Robust Decision-Making for Long-Term Energy Transitions

Advancing methods to address deep uncertainty in energy system models

by
Antonio F. Rodríguez Matas

supervised by
Prof. Dr. Pedro Linares Llamas
Prof. Dr. Jose Carlos Romero Mora

ICAI School of Engineering
Comillas Pontifical University

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The future's name is uncertainty - Edgar Morin

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

Antonio F. Rodríguez Matas
Madrid, 2025

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Abstract

Energy system transitions are increasingly shaped by uncertainty about future technological, climate, economic, and social developments. Under such deep uncertainty, traditional energy planning models—typically based on deterministic or probabilistic assumptions—can produce strategies that are fragile or misaligned with real-world complexity. This thesis develops and applies a set of methodological frameworks to improve the robustness, credibility, and decision relevance of long-term energy planning.

A central contribution of the thesis is the development of openMASTER, a modular, open-source, and structurally detailed national energy system optimization model. openMASTER incorporates advanced features such as energy service-based demand, endogenous behavioral dynamics, technology vintages and decommissioning, operational flexibility through technology hibernation and reactivation, and raw material constraints. The model enables transparent, extensible, and reproducible analyses of transition pathways while supporting the integration of advanced decision-support methodologies.

Building on this modeling platform, the thesis introduces three methodological approaches. The first is a hybrid optimization algorithm that combines robust optimization and minimax regret, allowing decision-makers to apply differentiated preferences across uncertainties that affect system feasibility (e.g., demand or resource availability) and those that affect performance (e.g., costs). This framework avoids both excessive conservatism regarding economic uncertainty and protection against vulnerability to infeasibility, resulting in more balanced and credible transition strategies.

The second contribution addresses a common oversimplification in energy models: the assumption of independence among uncertain parameters. A PCA-based method is applied to incorporate empirically-informed correlations between variables such as technology costs and fuel prices into robust planning frameworks. By preserving the internal structure of uncertainties, this approach significantly alters the design of robust strategies and highlights the importance of modeling structurally consistent futures.

The third methodological advance is a scenario-based decision-support framework to design robust policy packages across multiple objectives. It combines exploratory modeling, SHAP-based feature importance analysis, and multi-objective robustness metrics to systematically construct policy portfolios that perform satisfactorily even under adverse conditions. Applied to a national case study, this approach identifies coherent policy combinations—rather than isolated instruments—that support decarbonization, air quality, cost, and energy security under uncertainty.

Together, these contributions form a coherent and original toolbox for robust energy planning, grounded in both conceptual innovation and practical applicability. The thesis demonstrates how combining structural modeling advances with rigorous treatment of uncertainty enhances the robustness, interpretability, and credibility of decision support. The methodologies developed in this thesis offer significant potential for application to pressing real-world challenges, such as the decarbonization of hard-to-abate sectors, the design of robust strategies for sustainable mobility—including the planning of charging infrastructure, modal shifts, and behavioral transitions under uncertainty—, or the strategic management of dependencies on critical materials. By bridging methodological innovation and practical decision needs, this work contributes to the development of more resilient, transparent, and adaptive energy transition strategies capable of withstanding deep and evolving uncertainty.

Resumen extendido

Las transiciones de los sistemas energéticos están cada vez más condicionadas por la incertidumbre sobre la evolución futura de las tecnologías, el clima, la economía y los factores sociales, entre otros. Esta incertidumbre no se limita a funciones de probabilidad cuantificables, sino que es de carácter epistémico. En este contexto, se habla de incertidumbre profunda, entendida como la situación en la que los tomadores de decisiones no tienen suficiente conocimiento o información para describir las probabilidades de ocurrencia de los diferentes futuros posibles. Esta concepción contrasta con el concepto clásico de "estocasticidad", en el que las probabilidades de cada posible desenlace son conocidas o pueden ser estimadas con cierta confianza.

La incertidumbre profunda es especialmente relevante en el ámbito energético, donde las decisiones de inversión en infraestructuras, tecnologías o políticas públicas tienen horizontes temporales de décadas y comprometen trayectorias tecnológicas y de descarbonización difíciles de revertir. Bajo estas condiciones, el uso de modelos que dependen de supuestos en distribuciones probabilísticas ajustadas a datos pasados puede conducir a estrategias frágiles, optimizadas para futuros que pueden no materializarse, y que resultan inadecuadas frente a escenarios adversos o disruptivos. A pesar del creciente reconocimiento de esta problemática, muchos marcos de planificación energética siguen sin integrar de forma sistemática las herramientas y enfoques desarrollados en campos como la teoría de la decisión bajo incertidumbre profunda o el análisis exploratorio de escenarios.

Esta tesis doctoral se enmarca en este hueco metodológico, con el objetivo de desarrollar y aplicar un conjunto de metodologías que permitan mejorar la robustez, la credibilidad y la utilidad práctica de los modelos de planificación energética a largo plazo. Se trata de una tesis con una clara orientación metodológica, pero firmemente anclada en problemas reales de decisión. El trabajo se estructura en torno a cuatro grandes bloques, que corresponden a los capítulos centrales de la tesis. El primer bloque aborda el diseño y desarrollo de openMASTER, una herramienta de modelado del sector energético, concebida para representar de forma realista la evolución de sistemas energéticos complejos y facilitar la integración de metodologías avanzadas de toma de decisiones. El segundo bloque se centra en la formulación de un algoritmo híbrido que combina criterios diferenciados de robustez para representar preferencias específicas frente a distintos tipos de incertidumbre. El tercer bloque aplica un nuevo enfoque metodológico para incorporar correlaciones entre parámetros inciertos en modelos de planificación energética, superando la hipótesis convencional de independencia. Finalmente, el cuarto bloque desarrolla un marco para el diseño sistemático de paquetes de políticas robustos, integrando modelado exploratorio y métricas multiobjetivo para apoyar decisiones bajo múltiples fuentes de incertidumbre.

Desarrollo del modelo openMASTER

La primera gran contribución de la tesis es el desarrollo de openMASTER (the open-source Model for the Analysis of SusTainable Energy Roadmaps), un modelo nacional de optimización energética modular y de código abierto. Este modelo constituye una reescritura profunda y ampliada del modelo MASTER, desarrollado originalmente en GAMS y utilizado en anteriores proyectos de planificación energética. A diferencia de su predecesor, que era estático y cerrado, openMASTER ha sido reconstruido en Pyomo-Python y cuenta con una estructura dinámica multianual, lo que permite una mayor transparencia y facilidad de integración con nuevas metodologías. Entre las mejoras introducidas destaca una amplia gama de funcionalidades adicionales. Su diseño responde a la necesidad de contar con un entorno de modelado que permita representar de forma más realista la complejidad de los sistemas energéticos modernos —incluyendo sus dinámicas tecnológicas, comportamentales, y materiales— al mismo tiempo que facilita la integración de metodologías avanzadas de toma de decisiones bajo incertidumbre profunda.

openMASTER se estructura como un modelo de planificación a largo plazo de tipo bottom-up, con una resolución tecnológica detallada y un horizonte multianual configurable. El modelo resuelve un problema de optimización lineal (LP), con posibilidad de incorporar incertidumbre mediante conjuntos de escenarios y formulaciones robustas. Su arquitectura ha sido diseñada de forma modular, con distintos bloques funcionales que permiten representar demanda, conversión, transporte, almacenamiento y balances de energía y materiales, así como la contabilidad de emisiones de distinto tipo. Esta estructura modular no solo favorece la extensibilidad del modelo, sino que facilita su uso, pudiendo adaptar cada bloque sin necesidad de modificar el código del modelo.

Entre las capacidades avanzadas de openMASTER destacan: la formulación de la demanda exógena en términos de servicios energéticos (lo que permite una mayor coherencia en la competición técnológica y uso de energías finales); la representación endógena del comportamiento de usuarios—incluyendo la elección modal y la adopción tecnológica, así como dinámicas de comportamiento social que inciden en el consumo energético—; la incorporación de tecnologías con vintages y procesos de retirada, lo que permite capturar los efectos de obsolescencia tecnológica; la modelización de flujos de materiales y su reciclaje en la industria; y la posibilidad de activar y desactivar tecnologías a lo largo del horizonte de planificación, reflejando decisiones de hibernación y reactivación.

openMASTER se convierte así en una herramienta orientada a la comunidad, pensada no solo como un modelo operativo, sino como un entorno experimental para el desarrollo y validación de metodologías de planificación energética robusta. Su publicación como herramienta de código abierto y su documentación completa buscan promover la transparencia, la reproducibilidad y la cooperación entre investigadores, instituciones y responsables públicos.

Algoritmo híbrido para el tratamiento diferenciado de la incertidumbre

La segunda gran contribución metodológica de la tesis es el desarrollo de un algoritmo híbrido que permite aplicar diferentes criterios de robustez según el tipo de incertidumbre presente. Esta idea parte del reconocimiento de que las incertidumbres no son homogéneas: algunas afectan a las restricciones físicas o de viabilidad del sistema (como la demanda o la disponibilidad de recursos), mientras que otras inciden sobre el desempeño del sistema (como los costes del sistema). Sin embargo, la mayoría de los modelos energéticos aplican, en el caso de que lo hagan, un único criterio de decisión para todas las incertidumbres, lo que puede conducir a estrategias poco realistas con las preferencias reales de los decisores.

El algoritmo híbrido desarrollado en esta tesis combina la optimización robusta propuesta por Bertsimas y Sim para aquellas incertidumbres que afectan a la viabilidad del sistema, y la minimización del arrepentimiento máximo (minimax regret) para aquellas que afectan al objetivo de optimización (el coste total del sistema, lo que puede incluir costes sociales como el de las emisiones). Esta integración se formula en un único algoritmo, resoluble con una carga computacional razonable, que permite reflejar preferencias diferenciadas del decisor y evita los extremos de conservadurismo económico excesivo o de exposición inaceptable a la inviabilidad.

Los resultados empíricos muestran que este enfoque conduce a decisiones más equilibradas: se protegen los elementos críticos del sistema mediante estrategias robustas, mientras se permite cierta exposición al cambio o la variabilidad en aspectos como los costes.

Incorporación de correlaciones entre incertidumbres

La tercera contribución metodológica se refiere a la representación estructurada de la incertidumbre. La mayoría de los modelos energéticos tratan los parámetros inciertos como independientes entre sí, ya sea por simplicidad analítica o por falta de información. Sin embargo, esta asunción puede conducir a escenarios poco plausibles o internamente inconsistentes. En la realidad, existen multitud de incertidumbres correladas, como los precios de combustibles (los precios del gas, el petróleo y el carbón tienden a moverse conjuntamente) o los costes de tecnologías renovables que pueden estar influenciados por factores macroeconómicos o por el precio de materias primas comunes, entre otros. Ignorar estas correlaciones puede generar decisiones que, si bien parecen robustas sobre el papel, son frágiles en su aplicación real.

La tesis propone la aplicación de un enfoque basado en el análisis de componentes principales (PCA) para construir conjuntos de incertidumbre que introduzca las correlaciones existentes. El método reduce la dimensión del espacio de incertidumbre a partir de datos históricos y genera conjuntos poliédricos que pueden integrarse en formulaciones de optimización robusta. Este enfoque respeta las relaciones observadas entre parámetros y se adapta a distintas escalas y dominios de aplicación.

Aplicado a un caso de estudio nacional, el uso de este método revela que las estrategias cambian significativamente cuando se incorporan las correlaciones entre incertidumbres. Por ejemplo, en escenarios donde se modela una alta correlación positiva entre precios de combustibles y costes de tecnologías renovables, el modelo prioriza tecnologías con menor dependencia o diversifica la cartera tecnológica para amortiguar los efectos de la correlación. Esta capacidad para representar las correlaciones entre incertidumbres constituye un avance clave en la coherencia de los ejercicios de planificación energética.

Diseño de paquetes de políticas robustos

La cuarta gran aportación de la tesis se refiere al diseño de paquetes de políticas que sean robustos para múltiples objetivos frente a escenarios inciertos. En la práctica, las decisiones políticas no se implementan de forma aislada: las políticas interactúan, se solapan, se refuerzan o se anulan entre sí. Sin embargo, la mayoría de los modelos aplican análisis comparativos entre políticas individuales o utilizan combinaciones ad hoc, sin una lógica sistemática que permita diseñar paquetes coherentes y evaluar su desempeño conjunto.

La metodología desarrollada en esta tesis combina modelado exploratorio, análisis de importancia mediante valores SHAP (Shapley Additive Explanations) y métricas sobre la robustez de las políticas. Esto se traduce en un nuevo método de decisión que consiste en la generación de grandes conjuntos de escenarios con diferentes combinaciones de políticas e incertidumbres exógenas, el entrenamiento de modelos de aprendizaje automático sobre los resultados de los escenarios (en este caso, utilizamos Random Forest), y la identificación de las políticas más influyentes en cada objetivo. A partir de estos datos, se construyen carteras de políticas que ofrecen protección frente a escenarios adversos mediante el uso de indicadores agregados sobre la protección que aportan las políticas.

Aplicado a un caso nacional, el enfoque permite identificar combinaciones de políticas que simultáneamente cumplen objetivos de descarbonización, seguridad energética, calidad del aire y coste del sistema. Por ejemplo, se observa que el impacto de un precio al carbono aumenta con su combinación con medidas complementarias como políticas de movilidad urbana. Este tipo de análisis ofrece a los responsables de políticas una herramienta útil para diseñar estrategias más coherentes y efectivas.

Aplicaciones, relevancia práctica y proyección futura

Más allá de sus contribuciones teóricas y metodológicas, esta tesis ofrece un conjunto de herramientas con un elevado potencial de aplicación práctica a distintos retos contemporáneos de la transición energética. Aunque cada una de las metodologías ha sido aplicada a un caso de estudio nacional con fines ilustrativos y de validación, su diseño es generalizable y su integración en el modelo openMASTER muestra que es extensible a otros contextos geográficos, temporales o sectoriales.

Uno de los campos con mayor potencial de aplicación es la descarbonización de sectores difíciles de abatir, como la industria pesada (acero, cemento, refino, etc.), donde las decisiones de inversión son intensivas en capital, los horizontes temporales son largos y la incertidumbre sobre tecnologías y mercados es especialmente pronunciada.

Otro ámbito en el que estas metodológicas pueden aplicarse es la movilidad sostenible, donde la interacción entre avances tecnológicos, infraestructuras públicas y políticas reguladoras genera un sistema altamente dinámico y sujeto a múltiples fuentes de incertidumbre. La planificación de paquetes de políticas robustos puede aplicarse a estrategias que combinen infraestructuras de recarga, incentivos fiscales, restricciones al uso del automóvil y medidas de planificación urbana como las zonas de bajas emisiones. Las herramientas de análisis desarrolladas permiten evaluar qué combinaciones de políticas son más eficaces y resilientes.

Un tercer campo de aplicación es la gestión de la dependencia en materiales críticos, cada vez más relevante en un contexto de electrificación acelerada y de tensiones geopolíticas en las cadenas de suministro. Las metodologías desarrolladas permiten incorporar restricciones sobre disponibilidad de materias primas, explorar trayectorias tecnológicas alternativas y evaluar la robustez de distintas estrategias ante interrupciones o cambios en los precios relativos.

Por último, existe una oportunidad importante para integrar estas herramientas en marcos de planificación más amplios, que consideren no solo el sistema energético sino su acoplamiento con otros sistemas: agua, uso del suelo u otros sectores de la economía. La estructura modular de openMASTER y la generalidad de las metodologías permiten vincularlas con modelos macroeconómicos, de evaluación integrada (IAMs), o modelos sectoriales, generando sinergias analíticas de alto valor.

Desde el punto de vista institucional, estas herramientas pueden ser utilizadas por agencias públicas de energía, operadores del sistema, reguladores, y organismos de planificación climática para mejorar la calidad del apoyo a la decisión. También pueden servir de base para procesos participativos y deliberativos, en los que se requiera explorar alternativas bajo diferentes visiones del futuro y prioridades sociales.

Conclusión

En conjunto, esta tesis contribuye al campo de la planificación energética bajo incertidumbre profunda mediante el desarrollo de herramientas, innovación metodológica y orientación práctica. El modelo openMASTER proporciona una base sólida y flexible sobre la que construir ejercicios de análisis rigurosos, transparentes y reproducibles. Las metodologías desarrolladas —el algoritmo híbrido de robustez, el tratamiento estructurado de correlaciones, y el diseño de paquetes de políticas robustos— representan avances tanto en términos técnicos como conceptuales para el tratamiento de incetidumbres en la planificación energética a largo plazo.

Esta tesis no propone respuestas cerradas ni estrategias óptimas en un sentido clásico. Más bien, ofrece instrumentos para navegar la incertidumbre de forma informada, plural y adaptativa. Frente a un futuro cada vez más incierto y cambiante, no se trata de predecir, sino de prepararse. No se trata de optimizar en base a futuros poco probables de materializarse, sino de construir decisiones sólidas, flexibles y capaces de resistir a las incertidumbres.

Acronyms

AARO	Affinely Adjustable Robust Optimization
AF	Activity Factor
ARO	Adjustable Robust Optimization
B&S	Bertsimas and Sim (2004)
BM	Behavioral Measure
BT&N	Ben-Tal and Nemirovski (1999)
CAPEX	Capital Expenditure
CART	Classification and Regression Trees
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CE	Conversion Energy technologies
CHP	Combined Heat and Power
CMR	Candidate Maximum Regret
CNG	Compressed Natural Gas
CPU	Central Processing Unit
CSP	Concentrated Solar Power
CSV	Comma-Separated Values file
DAPP	Dynamic Adaptive Policy Pathways
DC	Demand Characterization
Det	Deterministic
DM	Demand Shift
DMDU	Decision Making under Deep Uncertainty
ES	Energy Service
EV	Electric Vehicle
FRILP	Fuzzy Radial Interval Linear Programming
GDP	Gross Domestic Product
GEP	Generation Expansion Planning
I-O	Input-Output
IAM	Integrated Assessment Model

ICEV	Internal Combustion Engine Vehicle
IEA	International Energy Agency
IGCC	Integrated Gasification Combined Cycle
IGDT	Info-Gap Decision Theory
LB	Lower Bound
LCOE	Levelized Cost of Energy
LDR	Linear Decision Rules
LEZ	Low-Emission Zone
LNG	Liquefied Natural Gas
LP	Linear Programming
Max	Maximum
MD	Macro Data
MF	Membership Function
MGA	Modeling to Generate Alternatives
MILP	Mixed-Integer Linear Programming
Min	Minimum
MINLP	Mixed-Integer Nonlinear Programming
MIP	Mixed Integer Programming
MMR	Minimax Regret
MMR-RO	Minimax Regret–Robust Optimization (a novel hybrid decision support method that combines minimax regret and robust optimization)
NDC	Nationally Determined Contributions
NECP	National Energy and Climate Plan
Neg	Negative
NG	Natural Gas
Nom	Nominal
O&M	Operation and Maintenance
OCGT	Open Cycle Gas Turbine
PC	Personal Computer
PCA	Principal Component Analysis
PDF	Probability Density Function
PE	Primary Energy
PHEV	Plug-In Hybrid Electric Vehicle
PoR	Price of Robustness

Pos	Positive
PP	Power Plant
PRIM	Patient Rule Induction Method
PV	(Solar) Photovoltaic
R&D	Research and Development
RAM	Random Access Memory
RDM	Robust Decision Making
RM	Raw Material
RO	Robust Optimization
RoR	Run-of-the-River
SCPC	Supercritical Pulverized Coal
SHAP	SHapley Additive exPlanations
ST	Supply Technologies
TE	Transformed/final energy
Th	(Solar) Thermal
Unc	Uncorrelated
VaR	Value at Risk
WFH	Work-from-home

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1 Introduction

1.1 Motivation

The transition to sustainable energy systems is central to addressing global challenges such as climate change, energy security, public health, and affordability (United Nations, 2015). Achieving this transition requires coordinated decisions about what types of energy investments are needed, when they should be made, and which policy instruments can effectively guide them. These decisions must go beyond shaping the energy mix: they involve navigating a complex interplay of technological trajectories, policy design, social behavior, and market dynamics—each subject to profound and evolving uncertainty.

Long-term energy planning is particularly difficult due to the structural inertia of energy systems. Investments in infrastructure and technologies are capital-intensive, long-lived, and difficult to reverse, often locking in specific technological, economic, and institutional pathways for decades. These decisions carry implications not only for system performance but also for broader societal outcomes, involving a wide range of actors—governments, regulators, market operators, firms, and citizens—who operate under diverse constraints and goals.

Critically, the long-time horizon of energy planning exposes decisions to deep uncertainty about key drivers such as future demand, resource availability, or technological development. In this context, uncertainty is predominantly epistemic (Marchau et al., 2019): it stems from limited knowledge about how these factors may evolve, and from the fact that historical data may not be representative of future dynamics. Consequently, relying on probabilistic forecasts is not appropriate, as it presumes knowledge of probability distributions that cannot be credibly specified. Instead, planning requires decision-making frameworks that can account for a wide range of plausible futures and enable the design of robust strategies—that is, strategies that perform satisfactorily even under adverse or unexpected conditions.

Several dimensions of uncertainty are particularly relevant. Climate change introduces long-term environmental risks whose impacts and feedbacks are not fully understood (Shukla et al., 2022). Technological innovation can rapidly reshape the feasibility and cost of transition options, as seen in the recent dramatic cost reductions in solar PV and wind power (IRENA, 2024). Social, geopolitical, and economic shifts—including changes in consumer behavior or disruptions in global supply chains—can also destabilize long-term plans (Balcilar et al., 2019; Schlindwein et al., 2023; Z. Zhao et al., 2023).

To navigate this complexity, energy system optimization models have become essential analytical tools (Pfenninger et al., 2014). These models provide a structured representation of the energy system, capturing its technological, economic, and environmental dimensions over time. This enables planners to evaluate alternative strategies, anticipate trade-offs, and identify potential vulnerabilities and opportunities. When properly designed and applied, they help clarify the consequences of decisions, enhance transparency in policy discussions, and support more informed and structured deliberation among stakeholders (Trutnevyte, 2016).

Yet, despite the growing recognition of uncertainty as a central feature of long-term energy planning, many modeling efforts continue to fall short in capturing its full scope and implications (Fodstad et al., 2022). This is not merely a technical shortcoming, but a fundamental limitation that affects the credibility and relevance of model-based insights. When long-term planning does not adequately account for the scope and structure of uncertainty surrounding future energy systems, it can lead to recommendations that are overly narrow, fragile, or misaligned with the complex realities that decision-makers must address. In such cases, even carefully designed strategies may fail if they are based on assumptions that do not hold when confronted with deeply uncertain or rapidly changing conditions.

For energy system models to truly support strategic planning in this context, they must move beyond static, deterministic, or probabilistic assumptions and embrace deep uncertainty as a core design consideration. This means developing approaches that help identify not just optimal solutions under expected conditions, but strategies that remain credible across a wide range of plausible futures. Addressing this challenge is not just a methodological refinement—it is a practical imperative for guiding energy transitions that are inherently uncertain. As such, improving how energy models represent and respond to uncertainty is a critical step toward ensuring that long-term energy decisions are both robust and aligned with broader sustainability goals.

1.2 Research Gaps

Building on the motivation outlined above, this thesis identifies and addresses four key research gaps in the way long-term energy planning models address deep uncertainty and support robust decision-making. These gaps are grounded in a critical examination of the existing literature, with a detailed review carried out in each of the chapters of the thesis. Collectively, they reveal persistent limitations in current modeling tools, in the conceptual and operational treatment of uncertainty, and in the integration of policy analysis into robust planning frameworks.

First, there is a fundamental gap in how energy system models define and implement robustness under deep uncertainty. Although the literature offers multiple interpretations—such as robustness as performance under the worst case (Wald) (Majewski, Wirtz, et al., 2017; Majewski, Lampe, et al., 2017), as minimization of regret (Savage) (Ribas et al., 2010; Trachanas et al., 2018; Yokoyama et al., 2014), or as insensitivity to variation across scenarios (Rabiee et al., 2018)—these are rarely distinguished or consistently applied. This conceptual ambiguity has methodological consequences. In most energy system models, robustness is typically addressed by selecting a single decision criterion—often based on worst-case performance—and applying it uniformly to all considered uncertainties (Moret, Babonneau, et al., 2020a; Patankar et al., 2022). This approach neglects a critical distinction: not all uncertainties affect the system in the same way, nor do they lead decision-makers to adopt the same preferences or attitudes toward them. Some uncertainties affect feasibility constraints (e.g., energy demand levels or resource availability), where the consequences of failure can be severe or unacceptable. In such cases, conservative strategies may be the most appropriate. Other uncertainties affect the cost-minimization objective (e.g., investment costs or fuel prices), where decision-makers may consider some performance loss as tolerable in exchange for greater flexibility or the potential to benefit from favorable outcomes.

Although decision theory has long emphasized this distinction (Lempert et al., 2003; Walker et al., 2003), energy system models seldom reflect it in practice: a single robustness formulation is applied across all uncertainties, regardless of their function in the system or the nature of the associated trade-offs. Electricity system models—particularly in unit commitment, dispatch, and transmission expansion—have pioneered differentiated treatments of uncertainty, distinguishing between short-term variability (e.g., in renewable output) and longer-term structural uncertainties (e.g., in investment or demand forecasts) (e.g., Morales et al. (2013) and Ruiz et al. (2015)). However, these advances remain largely confined to the electricity domain. A systematic and integrated application of differentiated uncertainty treatment across broader multi-energy systems remains largely absent.

This limits the model's ability to reflect the differentiated priorities of decision-makers, who may accept deviations in some outcomes while requiring stricter safeguards in others. Integrated modeling approaches that can distinguish between uncertainties affecting constraints and those influencing the objective function—and apply appropriate robustness criteria to each in a consistent and tractable way—remain scarce. Addressing this gap requires both conceptual clarity and modeling frameworks that can incorporate these distinctions into the structure and logic of the planning process without sacrificing structural or technological detail.

Second, the widespread assumption of independence among uncertain parameters remains a critical limitation in energy system models, not only for robust approaches but also for scenario-based planning frameworks more broadly (Abdalla, Abu Adma, et al., 2020; M. Cao et al., 2019). While this assumption simplifies model formulation, it is increasingly incompatible with empirical evidence from energy markets, global supply chains, and technology manufacturing processes. Key uncertainties—such as fossil fuel prices and investment costs of energy technologies—are frequently interdependent. These correlations can arise from different circumstances, such as the use of common materials or components across multiple technologies (Gailani et al., 2024; Gerres, 2022), macroeconomic conditions that simultaneously affect several sectors, or the widespread dependence on fossil fuels throughout the production, transportation, and deployment of energy technologies (Mensi et al., 2021).

Although some recent studies have begun to acknowledge and incorporate such correlations, their application has been largely restricted to specific subsectors such as electricity generation or transmission expansion planning (e.g., Roldan et al. (2019) and W. Wang et al. (2021)). These studies often focus on narrow cases, using simplified correlation structures or limiting the analysis to temporal autocorrelation. As a result, they do not provide a comprehensive assessment of how interdependencies across multiple uncertain parameters can affect long-term system behavior and the robustness of transition pathways.

Therefore, most energy system optimization models, when addressing uncertainty, continue to treat them as independent, without integrating correlations into the structure of the uncertainty space. This simplification undermines the internal consistency of scenario analysis and may bias the results towards strategies that seem robust under implausible or internally inconsistent futures. To date, no robust energy planning study has systematically incorporated multi-dimensional correlation structures within a multi-energy system model, nor examined how such interdependencies across uncertainties influence planning outcomes. Addressing this gap is critical to ensure that model-based decision support better reflects the complexity of real-world systems and provides more credible and policy-relevant insights.

Third, current approaches to energy policy modeling lack systematic frameworks for designing robust policy packages under deep uncertainty. Although energy transitions in practice depend on interacting combinations of instruments—such as carbon pricing, subsidies, efficiency standards, and mandates—most energy planning models continue to evaluate policies in isolation or assume additive effects (Rogge et al., 2016). This limits the ability to identify synergies, trade-offs, and reinforcing dynamics that shape real-world transitions.

Recent developments have improved the capacity to test predefined strategies under a wide range of futures (Wessel et al., 2024; Woodard et al., 2023). However, these approaches do not provide a systematic basis for constructing and evaluating policy combinations that are robust across multiple objectives and uncertain conditions. Moreover, most applications rely on different modeling frameworks, such as integrated assessment or macroeconomic models (Campigotto et al., 2024; Wessel et al., 2024), which lack the technological and temporal resolution needed to capture the detailed implications of policy interaction.

To date, no established decision-support framework combines exploratory modeling techniques with robustness analysis within energy system optimization to systematically design policy packages that are robust to a wide range of adverse and uncertain future conditions. Bridging this gap is essential to move from testing individual strategies to proactively identifying policy combinations capable of supporting robust energy transitions under uncertainty.

Taken together, these gaps point to a broader need for integrated approaches that combine rigorous treatment of uncertainty with energy system models capable of representing the technological, economic, and policy complexity of long-term transitions. Despite important conceptual advances in the literature on decision-making under deep uncertainty, their practical application in strategic energy planning remains limited. There is a pressing need for modeling frameworks that endogenously incorporate robustness criteria, account for interdependencies among uncertainties, and support the design and evaluation of coherent policy packages—ultimately bridging the gap between methodological innovation and real-world decision support.

Fourth, there is an ongoing lack of open-source energy system optimization models that are structurally and procedurally equipped to support the kind of robust, uncertainty-aware planning described above (Groissböck, 2019). While a growing number of open-source models exist, most were not designed from the outset to accommodate the specific methodological requirements of robustness analysis or to endogenously represent uncertainty-handling mechanisms. Essential modeling capabilities—such as representing exogenous demand in terms of energy services, endogenously modeling behavioral responses and modal choice, explicitly tracking technology vintages and retirement processes, and integrating material constraints and recycling processes—are still largely absent or implemented only in simplified ways.

These capabilities are essential not only for a more realistic energy system representation but also for evaluating the dynamic performance of strategies across a wide range of plausible futures. In their absence, many models rely on fixed input trajectories or externally defined scenarios for key variables, limiting the system's ability to respond endogenously to uncertainty and policy interventions. This significantly limits the ability to experiment with methodological innovations—such as alternative decision criteria or robustness formulations—and to evaluate their implications.

Advancing robust decision-making under deep uncertainty requires not only conceptual innovation but also modelling tools that are structurally and procedurally aligned with these ambitions. While several open-source energy models are available, few offer the combination of transparency, extensibility, and structural flexibility needed to represent robustness criteria and uncertainty-handling mechanisms as endogenous components of the planning process. In practice, limitations related to model architecture, proprietary dependencies, or restricted adaptability can hinder the implementation of alternative formulations and the integration of emerging decision frameworks. In this context, there is growing value in developing open and modular modelling platforms that can serve both as analytical instruments and as testbeds for methodological innovation—enhancing reproducibility and supporting more credible, policy-relevant planning under deep uncertainty.

1.3 Research Scope and Objectives

The main objective of this thesis is **to develop and apply methodological frameworks that enable robust decision-making in the context of long-term energy planning under deep uncertainty, using energy system optimization models**.

This central objective responds to the need for decision-support approaches that can explicitly account for the limitations of traditional modeling practices in long-term energy planning under epistemic uncertainty. In particular, the thesis seeks to improve how energy models represent different types of uncertainty, reflect their distinct implications for decision-making, and support the formulation of decisions that are robust to a wide range of plausible and evolving futures.

In line with the research gaps identified, the thesis is organized around the following interrelated research questions:

1. **How can robustness be addressed in energy system optimization models to reflect differentiated decision-making preferences across distinct sources of uncertainty?**
   This question addresses the core methodological gap identified in the literature: the lack of a consistent framework for representing robustness when uncertainties play different roles in the system. Some uncertainties may compromise system feasibility and require precautionary strategies, while others primarily affect performance outcomes and may allow for more flexible responses. The objective is to develop an algorithm that integrates multiple robustness formulations within a single optimization process, enabling the model to represent diverse decision-making preferences depending on the nature of each uncertainty.

2. **How can correlations between uncertain parameters be systematically integrated into energy system models, and what is their impact on energy transition pathways?**
   This question addresses the widespread simplification of treating uncertain parameters as independent, even in models that aim to support robust decision-making. In practice, key sources of uncertainty are often interdependent due to structural relationships across technologies, sectors, and supply chains. The aim is to examine how such correlations can be formally incorporated into the uncertainty space of energy system models and to assess how their inclusion affects the design of long-term energy transition pathways.

3. **How can combinations of energy policy instruments be designed to protect against adverse futures across multiple energy transition objectives?**
   This question stems from the recognition that real-world energy transitions are shaped by interacting combinations of policy instruments, not isolated measures. However, most existing applications of energy system optimization models focus on the evaluation of individual policy instruments or predefined strategies, often overlooking how instruments interact with each other and with uncertainty. The aim is to explore how energy system models can support the systematic design of policy portfolios that are robust to uncertainty and capable of achieving satisfactory outcomes across a diverse set of transition goals.

In order to explore these questions, **an additional objective of the thesis is the development of an open, extensible, and transparent energy system optimization model that enables robustness-oriented planning under deep uncertainty**. Rather than relying on externally imposed assumptions, the model enables the endogenous representation of key system dynamics that are essential for analyzing how uncertainty affects long-term planning—such as demand evolution, behavioral adaptation, technological turnover, and material constraints. These features, which remain largely absent from existing open-source tools, are necessary to conduct the type of detailed and flexible analysis required to address the research questions posed in this thesis.

Together, the objective and questions of this thesis define a coherent research scope that seeks to improve the methodological foundations of robust energy planning. The aim is to contribute to more realistic, flexible, and transparent modeling approaches that are better aligned with the actual complexity of decision-making in the context of long-term energy transitions under deep uncertainty.

1.4 Conceptual and Analytical Framework

The methodological approach of this thesis is structured around four core research questions that explore how energy system optimization models can better support robust decision-making under deep uncertainty. Each chapter develops a specific component of a broader analytical framework, progressively extending the ability to address different dimensions of uncertainty and robustness in energy systems modeling.

Chapter 2 develops the modeling infrastructure of the thesis, responding to the need for a dedicated platform capable of addressing the structural and analytical challenges associated with robustness in energy planning. The model developed—**openMASTER**—is a national energy system optimization model, designed to be open, modular, and extensible, and readily adaptable to other geographic scales. It represents a significantly enhanced and open-source version of the previous MASTER model, which was implemented in GAMS. In contrast, openMASTER has been entirely reprogrammed in Python and incorporates several methodological and structural advancements. Notably, while MASTER relied on a static formulation, openMASTER supports dynamic planning, and introduces additional capabilities that are rarely found together in existing open-source models, including detailed representations of demand in terms of energy services, endogenous behavioral and modal choices in transport, technology vintages and decommission processes, and material constraints, including material recycling. These structural capabilities allow the model to represent key features of energy system transitions and to explore how energy decisions interact with complex and deeply uncertain dynamics. openMASTER serves as the computational foundation for all subsequent chapters and makes it possible to implement and test the methodological innovations required to answer the three main research questions of the thesis.

Chapter 3 addresses the first research question: How can robustness be addressed in energy system optimization models to reflect differentiated decision-making preferences across distinct sources of uncertainty? At the core of this chapter lies the development of a novel algorithm that enables the endogenous application of multiple robustness formulations within a single decision-making framework. Drawing on decision theory, the algorithm combines a robust optimization formulation (Bertsimas et al., 2004) to protect against violations of feasibility constraints, with a minimax regret formulation that captures the desirability of flexibility in cost-related outcomes. This hybrid framework allows the model to treat different types of uncertainty according to their systemic role—more conservatively in the case of constraints, and more flexibly in the case of performance metrics. The algorithm is fully integrated into the energy system model, offering a tractable yet conceptually rigorous approach for representing differentiated decision-making preferences in long-term energy planning under deep uncertainty.

Chapter 4 responds to the second research question: How can correlations between uncertain parameters be systematically integrated into energy system models, and what is their impact on energy transition pathways? This chapter focuses on the often-overlooked role of interdependencies among uncertain parameters in shaping energy planning outcomes. While most existing models assume that uncertain parameters vary independently, this chapter demonstrates how such simplifications can bias the identification of robust decisions. To address this issue, it applies a principal component analysis (PCA)-based methodology to construct uncertainty sets that preserve empirically-informed correlation structures across parameters. This is the first application of such an approach within a national-scale multi-energy system optimization model. The analysis compares how robust plans differ under three correlation settings: independence, positively correlated uncertainties (e.g., cost increases occurring simultaneously across multiple options due to shared drivers), and negatively correlated uncertainties (e.g., a cost increase in one option being offset by a decrease in another due to trade-offs or substitutability). By integrating correlations directly into the uncertainty space, this chapter shows how the internal consistency and credibility of scenario exploration can be significantly improved, and how the resulting pathways are affected.

Chapter 5 addresses the third research question: How can combinations of energy policy instruments be designed to protect against adverse futures across multiple energy transition objectives? The chapter builds on the foundations established in previous chapters to explore how multiple policy levers—such as carbon pricing, efficiency standards, or renewable energy incentives—can be systematically combined into robust policy packages. This chapter develops a structured method to explore, evaluate, and select coherent combinations of policies under uncertainty. The approach leverages exploratory modeling to sample a wide range of uncertainty-policy combinations, machine learning-based feature importance analysis (e.g., SHAP values) to identify key policy drivers, and robustness indicators to evaluate performance across multiple objectives—including cost, emissions, and system reliability—under worst-case outcomes. It involves an iterative procedure to assemble policy portfolios that are robust to deep uncertainty and capable of delivering satisfactory performance across competing transition goals.

Taken together, these chapters constitute a coherent analytical framework that progressively builds the methodological foundations for robust energy planning. Each chapter addresses a critical gap in the literature, and together they respond to the thesis's central objective: improving how energy system models account for deep uncertainty. By combining conceptual clarity, structural modeling capabilities, and robust analytical methods, the thesis aims to contribute to more credible and actionable tools for guiding energy transitions under uncertainty.

2 openMASTER: The open source Model for the Analysis of SusTainable Energy Roadmaps

This chapter is based on the article entitled *"openMASTER: The open-source Model for the Analysis of SusTainable Energy Roadmaps"*, authored by Antonio F. Rodriguez-Matas, Manuel Pérez-Bravo, Pedro Linares, and Jose Carlos Romero, and published in *Energy Strategy Reviews*, Volume 54, July 2024, Elsevier. DOI: 10.1016/j.esr.2024.101456.

2.1 Introduction

The transition to a carbon-neutral energy system represents a complex and urgent challenge that requires both technological and social transformations. To achieve this goal in a short timeframe, decision-makers must understand the behaviour of energy systems and anticipate the consequences of their decisions. Analytical tools such as strategic energy planning models are crucial to enable appropriate decision-making processes.

Although numerous energy models have been developed by academic, business, and institutional entities, the majority of these models are not publicly accessible. To address this issue, open-source energy models are being made available and published in peer-reviewed scientific journals, enabling collaboration and use within the scientific community. *Openmod - Open Energy Modelling Initiative* (2023) and *openENTRANCE – Open ENergy TRanstion ANalyses for a Low-Carbon Economy* (2023) are examples of platforms that facilitate and promote the development of open-source models in the field of energy modelling. Particularly, within the Openmod manifesto, it is stated that "*in the context of energy modelling, "open" means for us that data and code are published and shared*". This perspective coincides with our shared understanding of open models, where "*using open software licenses [...] is an important element*".

Within this framework, this chapter presents openMASTER, the novel open-source version of the Model for the Analysis of SusTainable Energy Roadmaps (MASTER), designed specifically for strategic energy planning. The MASTER model was first developed in 2012 by Lopez-Pena et al. (2012) using the GAMS programming language. This model has been continuously updated to address emerging needs and changing demands, described in several scientific works. Now, the open-source version, openMASTER, is implemented in Pyomo, offering improved usability, accessibility, and additional enhancements compared to prior versions of MASTER.

The remainder of this chapter is organised as follows. In Section 2.2, we examine the contribution of openMASTER compared to other open-source strategic energy planning models. In Section 2.3, we provide a detailed description of the model, including its fundamentals and formulation. In Section 2.4, we illustrate the model's applications and potential uses. Section 2.5 presents a brief illustrative case study to demostrate how openMASTER can be used to address real-world energy decision-making problems. Finally, Section 2.6 contains a discussion about the strengths and limitations of openMASTER as a decision-making tool within the context of the energy transition.

2.2 Literature review

This section presents an overview of existing open-source strategic energy planning models, and specifically focuses on the unique contributions offered by openMASTER. To be considered open-source for our purposes, a model must have publicly accessible code that can be used without any subscription requirements or additional costs. For instance, we have excluded the TIMES model (Loulou, 2016) from our consideration despite its code being accessible, as it operates through a paid environment (VEDA) and a fee-based optimisation software (GAMS).

Moreover, to ensure comparability with openMASTER's capacity to facilitate decision-making processes, our analysis only considers models that incorporate both operation and investment aspects within their scope. Additionally, we have included models that provide a multisectoral representation, while excluding models such as Balmorel (Wiese et al., 2018) that do not consider mobility demand.

In this context, we conducted a literature review, using the works of Limpens et al. (2019) and Groissböck (2019) as our point of departure. These studies examined energy models using several key attributes for comparability, including multi-sector representation (including, at least, electricity, heat and mobility sectors), open-source character, optimisation of operation and/or investment, temporal resolution, and computational characteristics and time.

Our first evaluation focused on extending the temporal scope of the original literature review, initially performed in 2019, to account for potential changes in model characteristics or the emergence of new models comparable to openMASTER. Our assessment did not reveal any significant changes that would alter the findings of this literature review. Therefore, based on the aforementioned criteria, we have considered three models as potentially comparable to openMASTER: EnergyScope, Oemof and OSEMOSyS.

But besides enlarging the temporal scope of the review, we also expanded its methodological scope considered by Limpens et al. (2019) and Groissböck (2019), looking in particular at 12 questions regarding these four models (including openMASTER) and extensively reviewed the available documentation to address them. This comprehensive comparison allows us to discern modelling gaps and highlight the contributions of openMASTER within the family of open-source strategic energy planning models.

Notably, this review doesn't account for the potential capability of these models to incorporate these features by introducing the corresponding modifications in the model structure and equations. Undoubtedly, open-source models offer the advantage of facilitating such changes more readily. However, this review considers whether there is existing literature evidence supporting the implementation of these advancements in the models under consideration. Significantly, the advantage of openMASTER is that these changes and features are already included in the code available. Being open-source, the elements in openMASTER modelling these features can be easily transferred to other platforms or models, contributing to the open model family and its collaborative spirit.

The following are the 12 issues upon which these models are analysed:

(i) Does the model have the ability to perform dynamic planning and solve the investment roadmap over the entire considered timeframe, rather than exclusively focusing on a goal year? The significance of integrating the dynamic character into an energy planning model stems from the fact that decision-making concerning the investment and operation of energy technologies occurs across the entire temporal period. Dynamic models allow planners to account for changes and understand the effects of decisions over time (Pizzuti et al., 2024).

(ii) Can the model effectively handle uncertainties? Does it utilise (a) probabilistic or (b) non-probabilistic methods? Strategic energy planning involves deciding on necessary energy investments to meet societal demands, considering factors such as timing and required policies. The extended lifespan of energy technologies (typically 20 to 50 years) introduces parametric uncertainties, including climate change, technological advances, and geopolitical stability (Filar et al., 2010). Managing uncertainties in strategic energy models is crucial but challenging in terms of both model formulation and computational burden (Moret, Babonneau, et al., 2020a). Prior successful applications of uncertainty methodologies in similar models offer a valuable comparative advantage (DeCarolis et al., 2017). Additionally, distinguishing between probabilistic and non-probabilistic methods is vital, impacting both conceptual considerations and computational aspects, making this differentiation critically important (Moret, Babonneau, et al., 2020a).

(iii) Does the model define exogenous demand in terms of energy services? Instead of defining energy demand as final energy consumption, there is a better alternative in considering the demand for specific services, such as the usage of appliances (e.g., washing machines or refrigerators), lighting or mobility, among others. This enables to model technological competition, innovation and efficiency improvements in the adoption of end-use technologies, which notably affects energy consumption (*IEA-ETSAP | Optimization Modeling Documentation* 2023).

(iv) Does the model have the capability to represent technological and modal choice? In the context of exogenous demand being defined as energy services, technological choice refers to the model's ability to make optimal decisions regarding the investment and operation of end-use technologies (e.g., gasoline cars vs electric cars for providing mobility). Modal choice refers to the ability to make decisions concerning the distribution of mobility modal shares (e.g., cars, motorcycles, buses, bicycles, or metro), instead of rigidly specifying predetermined quantities for them. Illustrating the complexity of modal choice, in the context of urban transport, when an optimisation model aims to minimise costs and determine mobility modes, it naturally leans toward pedestrian or cyclist-based solutions due to their lower costs and lack of emissions. Additionally, modal choices depend on various factors, including the availability of different transportation modes (e.g., subways, trams, or none for metropolitan distances) and the variations in modes based on the type of mobility (e.g., interurban distances allowing plane or high-speed train travel but not all routes, with no option for walking or tram). Incorporating these complexities requires defining structural aspects of the model to ensure realistic decision-making (see e.g. (Tattini et al., 2018)).

(v) Does the model incorporate an endogenous representation of agent behaviour, enabling modifications or reductions in energy consumption through behavioural changes (e.g., energy-efficient housing, car-sharing or remote work)? Considering changes in behaviour in an endogenous and linear manner poses a challenge in strategic energy planning models (Nguene et al., 2011).

(vi) Does the model include non-energy commodities, such as raw materials for the industrial sector? As emphasised by Fais et al. (2016), "*although energy systems models focus on energy flows, it is evident that materials are an important part of the system, especially in the industry sector*". Some models, like TIMES, integrate this feature. However, it is an aspect frequently overlooked in open-source models.

(vii) Is the model capable of capturing circularities, such as the incorporation of recycled materials? The circular economy involves optimising resource use across the production chain to achieve a closed loop in product life cycles, promoting self-regeneration by transforming waste into resources. This continual increase in recycling and reuse reduces the demand for raw materials, effectively containing waste (Suzanne et al., 2020). However, incorporating these circular flows into strategic energy planning entails complexity (Di Leo et al., 2020).

(viii) Does the model have the capability to activate and hibernate installed capacity of energy conversion technologies? For a more realistic modelling approach, the installed capacity of a technology can be put into hibernation (saving O&M costs but rendering it unusable) and then reactivated (bringing back O&M costs and making it available for use) with a reactivation cost. Considering this capability is highly relevant for policy design, as supported by literature and real-world events. For example, the European Commission's report (European Commission, 2022) on reactivating lignite-fired power plants in Germany highlights its significance for energy security, electricity cost, and emissions.

(ix) Does the model consider the vintages of demand technologies? This allows for the consideration of changes in technology characteristics based on their manufacturing year (e.g., cars have different efficiencies or emissions based on their age) (*IEA-ETSAP | Optimization Modeling Documentation* 2023).

(x) Does the model consider the decommissioning of technologies? As highlighted by Invernizzi et al. (2020), "*decommissioning of existing and future energy infrastructures is constrained by a plethora of technical, economic, social and environmental challenges that must be understood and addressed if such infrastructures are to make a net-positive contribution over their whole life*".

(xi) Does the model incorporate a realistic representation of the power generation sector? Does it possess an adequate temporal resolution to effectively incorporate these factors? This may include (a) the integration of reserve and adequacy constraints and (b) energy storage technologies and/or load shifting options. These aspects are crucial for realistically modelling the operation and installation of capacity (Ramos et al., 2022).

(xii) Is it possible to account for and impose carbon budget constraints? Specifically, is it possible to establish a cumulative limit on carbon emissions for a specified multi-year period? Considering the growing importance of the remaining carbon budget in national policy discussions, its incorporation into strategic energy planning models is imperative (Matthews et al., 2020).

The extent to which the different models examined respond to these inquiries is shown in the following Table 2.1.

Table 2.1: Open-source models comparison. Criteria are satisfied (✓), partially satisfied (–), no data were found (blank) or unsatisfied (✗).

Criterion	**EnergyScope** (Limpens et al., 2019)	**Oemof** (Hilpert et al., 2018)	**OSeMOSYS** (Gardumi et al., 2018)	**openMASTER**
(i) Dynamic planning	✗	–[a]	✓	✓
(ii.a) Probabilistic uncertainty	✗	✗	✓[b]	✗
(ii.b) Non-probabilistic uncertainty	✓[c]	✗	✗	✓[c]
(iii) Energy services demand	–[d]	–[d]	–[d]	✓
(iv) Technological and modal choice	✗[e]	✗	–[f]	✓
(v) Endogenous agent behaviour	✗	✗	✗[g]	✓
(vi) Non-energy commodities	✗	✓	✓	✓
(vii) Circular economy	✗	✗	✗	✓
(viii) Technology hibernation	✗	✗	✗	✓
(ix) Technology vintages	✗	✗	✗	✓
(x) Technology decommission	✗	–[a]	✓	✓
(xi.a) Power system reliability	✗	✓	✓	✓
(xi.b) Storage and load shifting	✓	✓	✓	✓
(xii) Carbon budget	✗	✗	✓	✓

[a] A feature for periodic investment decisions in oemof.solph is work in progress, although it is not part of any stable release. It includes a lifetime tracking.

[b] OSeMOSYS-PuLP incorporates a stochastic version (Dreier et al., 2019).

[c] These models incorporate a robust version that addresses uncertainties (Moret, Babonneau, et al., 2020a).

[d] Integrate the demand for final energy (e.g., electricity and heat) with the demand for energy services (e.g., mobility).

[e] It allows for decision in allocating passenger transport between public and private transportation, as well as freight transport by train. The model operates within predetermined ranges, excluding modal shift within private and public transportation.

[f] Grosso et al. (2017) introduce a novel approach for origin-destination optimisation in urban mobility, considering modal choice. Notably, this approach has not been applied to a national-scale system nor for mobility demand over other distances (metropolitan, inter-city, etc.), and there are no other existing applications that incorporate modal choice

[g] Fragnière et al. (2017) propose coupling OSeMOSYS with a top-down approach (i.e., discrete choice model), resulting in an exogenous behavioural modelling from the energy planning modelling perspective; Beltramo (2016) analyse this possibility, pointing out the difficulty of doing so because of the appearance of nonlinearities and the need of further research.

2.2.1 Limitations of openMASTER

Although openMASTER offers several contributions compared to other similar models, as shown in section 2.2.2, this section first introduces its limitations and current problems that warrants consideration. On the one hand, a notable limitation lies in its absence of spatial modelling for electricity and gas grids, as well as other critical infrastructures within the energy system. This deficiency hampers the model's ability to effectively represent regional or global energy systems with interconnected networks. To address this limitation, future iterations of openMASTER could explore integrating spatial modelling capabilities, akin to approaches seen in existing models such as TIMES (Loulou, 2016) or GENeSYS (Löffler et al., 2017). However, implementing spatial modelling would come at the expense of increased computational complexity due to the addition of variables required to represent regional interactions and energy flows.

Moreover, openMASTER's bottom-up approach, coupled with its detailed technological specifications and temporal resolution, results in a significant number of equations and variables. This intricate structure necessitates a delicate balance between model detail and computational complexity. While openMASTER has been successfully applied to real-world case studies, such as the Spanish national energy system, as presented in Chapter 3, extending its scope to encompass more complex applications may pose challenges. Such expansions may require adjustments to temporal resolution and could potentially strain computational resources. Therefore, future enhancements to openMASTER could focus on optimizing its computational efficiency while maintaining model fidelity.

Another area of limitation for openMASTER pertains to its lack of exploration into continent-wide or global applications. While structurally adaptable for such endeavors, openMASTER has yet to undergo comprehensive testing and validation on this scale. Additionally, scaling up openMASTER's application may necessitate compromises to manage computational demands effectively. Therefore, further research is warranted to explore the feasibility and performance of openMASTER in broader geographic contexts.

Overall, while openMASTER demonstrates significant promise in strategic energy planning, its limitations underscore the need for ongoing refinement and development to maximize its utility and applicability in addressing complex energy challenges.

2.2.2 The contribution of openMASTER

As may be seen in Table 2.1, the openMASTER model addresses significant gaps identified in the existing models.

Firstly, openMASTER is the only reviewed model that introduces all exogenous demand in the form of energy services (see Table 2.1, criterion iii). By energy service we refer to those activities that require energy, but which are not expressed in energy terms, but in activity terms (e.g. m2 to be heated, p.km to be travelled, tons of steel to be produced, etc.). When demand is introduced in this fashion, additional structure needs to be incorporated in the model to represent how energy is converted into energy services (which will require investment and operation expenses, and result in different emissions or energy consumption) and more importantly, how these energy services can be provided by competing technologies, how this competition may evolve with time, and also how its demand may be affected by changes in behaviour or technology, allowing for the implementation of energy efficiency or behavioral measures and emissions reduction through the investment and operation of end-use technologies. In this regard, it also enables modal shifts in transportation, a crucial aspect for effective decarbonisation of this sector. It is important to emphasise that defining all exogenous demand as energy services has significant structural implications (see Table 2.1, criterion iv). This approach necessitates the model to make decisions not only on energy conversion (CE) technologies, but also on end-use (ST) technologies. It means adding significant complexity in terms of computation, but also defining the processes (which differs in the case of CE technologies and ST technologies, as will be explained in the following) and input data (techno-economic characterisation of technologies, etc).

Secondly, our thorough literature review indicates that our proposal is the first to introduce behavioural changes in an endogenous and linear manner within an open-source energy planning model (see Table 2.1, criterion v). This novel approach allows the model to determine optimal agent behaviour considering intangible costs such as discomfort, as well as to assess trade-offs, as occurs in the case of remote work, where mobility demand is reduced at the cost of an increase in residential energy consumption. Unlike other proposals such as SOCIO-MARKAL (Nguene et al., 2011), our approach does not rely on virtual technologies, but directly allows to modify the energy services demand through a linear formulation applied in a novel way in this type of strategic energy models.

Additionally, openMASTER allows for the modelling of non-energy raw material consumption and circular economy in the industrial sector (see Table 2.1, criterion vii). It should be noted that this is possible because the industrial sector is also represented, like all other sectors, on the basis of the demand for energy services (in this case, tons of materials). OpenMASTER not only designs the data input, but also incorporates the formulation defining these technological processes and their relationships, including circular material flows, material requirements and recycling rates. Therefore, this not only facilitates modelling the reduction in material consumption through recycling but also energy and emissions savings through less energy-intensive processes.

Moreover, our literature review reveals that openMASTER is the first open-source model to incorporate such technological granularity by considering the vintage of end-use technologies (see Table 2.1, criterion ix). This approach facilitates the representation of technological innovation, including learning curves for efficiency improvements and emissions reductions. Consequently, improvements in vehicle emission standards or household appliances efficiency, among others, can be incorporated along with a detailed definition of technology decommissioning over their lifecycle.

Lastly, openMASTER offers a more realistic approach to the dynamics of investing in energy conversion technologies compared to existing literature. Its dynamic, multi-step character, which encompasses investments and decommissions, is advanced compared to most strategic energy planning models but still simplifies the real-world decision-making process for energy technologies. Managing energy assets can involve deactivating/hibernating technologies and reactivating them as needed, incurring reactivation costs but achieving substantial O&M savings. Thus, this attribute, overlooked in open-source strategic energy planning models, represents a substantial gap addressed by openMASTER (see Table 2.1, criterion viii).

All these modelling elements have been shown to convey significant advantages to energy planning exercises, as shown by the previous literature summarized in Table 2.1.

2.3 Model description

2.3.1 Overview

openMASTER is a Pyomo-based model designed for sustainable energy policy analysis. It operates as a dynamic, bottom-up, partial equilibrium, linear programming (LP) model, with the primary objective of meeting an exogenously-determined demand of energy services across various sectors. It achieves this by adhering to technical and policy constraints while minimising a comprehensive objective function. This function includes the total economic costs of energy supply, the social costs associated with greenhouse gas emissions and pollutant releases, as well as to intangible costs such as discomfort.

The openMASTER model is structured according to a scheme of processes and flows, which is detailed in Appendix 2.A. Figure 2.1 provides an overview of the structure of the model, which comprises the entire energy sector, including the import and domestic consumption of primary energy, energy conversion and storage technologies for final energy production, energy services supply technologies, and the exogenous demand for energy services from various sectors of the economy. Additionally, to aid comprehension, green text has been added as illustrative examples of elements that could constitute each part of this structure.

Regarding the definition of the exogenous energy services demand, it is important to note, as shown in Figure 2.1, that a top-down approach is followed. The exogenous demand is derived from Macro Data (MD), such as population (passengers) in different environments (e.g., rural or urban), weight of freight to be transported, dwellings and commercial area categorised by climate zone, and demand for materials. Based on these values, representative parameters called Demand Characterization (DC) and Activity Factor (AF) are applied for each sector to define the final demand for energy services.

For the residential and commercial sectors, the DC parameter represents the quotas of dwellings and commercial area classified by efficiency, while the AF parameter indicates the typical energy services demanded per dwelling and commercial space. In the case of transportation, the DC parameter captures the typical mobility demand based on distance for freight and passengers according to their residential environment. The AF parameter corresponds to the passenger vehicle occupancy rate (passengers per vehicle) and the freight vehicle load factor (tons per vehicle).

This structure has two main goals. Firstly, it aims to provide a transparent and reproducible data framework for application in different countries and contexts. Secondly, it allows for the endogenous inclusion of behavioural changes. Further details about the definition of the exogenous energy services demand can be found in Appendix 2.B.

Finally, it is important to note that Appendix 2.A also provides comprehensive information on the configuration of the openMASTER model, including the input, output, and visualiser modules. These modules serve to streamline and standardise tasks related to input data preparation and result extraction, including the representation of decision variables in intuitive formats. Designed with a user-friendly approach, these modules ensure that individuals with varying levels of technical expertise in optimisation can easily utilise the model. Alongside the model code, users have access to these modules, which play a vital role in guaranteeing interoperability, accessibility, and adaptability.

2.3.2 Main equations

This section describes the main equations that form the basis of the model, providing the reader with an understanding of its fundamental principles. A current stable version of openMASTER can be found in an open repository on GitHub (*IIT-EnergySystemModels/openMASTER* 2023).

Objective function

The model aims to minimise the objective function, which represents the costs of the energy sector. These costs include (i) the domestic consumption and import of primary energy (PE); (ii) fixed and variable O&M costs of conversion technologies (CE); (iii) the cost of raw materials (RM) consumed by industrial supply technologies (ST); (iv) fixed and variable O&M costs of supply technologies (ST); (v) the investment cost of new conversion technology capacity (CE); (vi) the cost of reactivating hibernated capacity of conversion technologies (CE); (vii) the investment cost of new supply technology capacity (ST); (viii) the penalty cost of slack variables, which include unsupplied energy services (ESNS), as well as exceeding emission caps and carbon budget constraints; and (ix) the cost of agents' behavioural measures, including both economic costs (such as housing insulation) and intangible costs (such as discomfort).

Balance equations

The balance equations are employed to guarantee the conservation of energy (and material within the industrial sector) across all the processes involved. Consequently, the energy transformations taking place in the CE, ST and TE processes are subject to ensuring that the energy output corresponds to the input, accounting for efficiency losses. These balances must be met in all the time slices defined by the model. An important consideration is the treatment of technologies capable of producing multiple outputs, such as refineries in CE technologies or vehicles in ST technologies. To provide a realistic modelling approach for these processes, minimum and maximum quotas are defined for each technology to determine the range of outputs they can produce. From this perspective, the model can simulate the behaviour of these processes in a more accurate and reliable manner. For instance, a refinery may vary its production of diesel, gasoline, or kerosene from crude oil within specified operational boundaries. Similarly, a vehicle can provide different energy services (e.g., metropolitan and inter-city mobility demands) within realistic ranges. These constraints enable the model to optimise the operation of these technologies while ensuring that the generated outputs align with practical considerations and limitations.

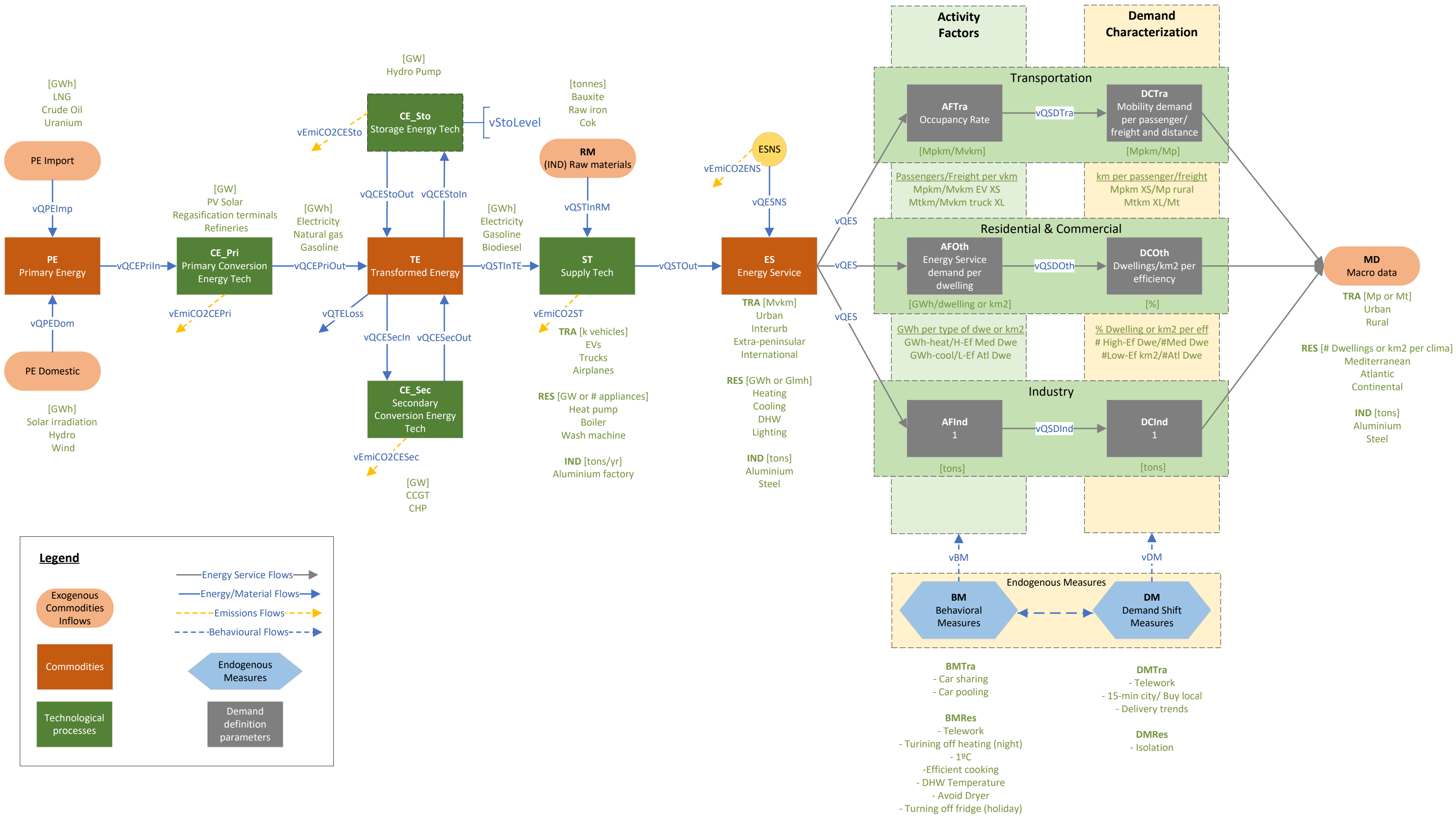

Figure 2.1: openMASTER core structure. To facilitate understanding, units and some examples of various processes, commodities, and flows are shown in green.

Storage equations

In the particular case of storage technologies, which store and release energy, the energy balance is not conducted on a per-time-slice basis. Rather, it is modelled daily, seasonally or annually. Furthermore, in order to ensure proper performance, storage technologies must adhere to a capacity restriction that limits their physical ability to store a specific amount of energy. This restriction must be considered when conducting the energy balance.

Capacity constraints

Capacity constraints are imposed to ensure that sufficient capacity is installed to enable operational functionality. Consequently, conversion technologies (CE) and supply technologies (ST) cannot exceed their respective installed capacity when conducting energy transformation processes.

The dynamic approach of openMASTER enables investment decisions to be made over the entire time horizon under consideration. This is achieved by considering the existing installed capacity and the decommissioning of technologies at the end of their operational lifespan on an annual basis. It is important to highlight that openMASTER incorporates the pre-existing installed capacity in the initial year of calibration, referred to as brownfield.

However, openMASTER treats the capacity installation of CE and ST technologies differently:

- Conversion Energy (CE) technologies are decommissioned at the end of their lifespan. Additionally, there is the possibility of decommissioning earlier if the model determines that the technology will no longer be required. Moreover, CE technologies can be hibernated and reactivated, which means that if a technology is not in use, it can be hibernated to save O&M costs. However, it cannot be utilised during this hibernation period. If the technology needs to be operational again, it can be reactivated.

- Supply technologies (ST) are modelled considering their vintage. This means that their technical characteristics, such as efficiency and emission factors, are subject to the year of manufacture. For instance, a diesel car manufactured before 2009, following European emission standards, should meet Euro 4 standards, while in later years, the standard to be met would be higher, such as Euro 5. In addition, modelling these technologies based on vintages allows for probabilistic decommissioning. In this manner, the entire vehicle fleet is not decommissioned at the end of its lifespan, but rather decommissioned over the considered period based on the probability of decommissioning.

Furthermore, maximum capacity constraints can be imposed to align the model's decisions with technical and policy considerations. For instance, the installation of new hydropower capacity may be restricted by the country's topography and water availability, whereas the introduction of new nuclear or coal capacity might be constrained by policy decisions.

On the other hand, a capacity constraint exists regarding the domestic consumption and import of primary energy. In this context, the energy resources available to the represented country or region are modelled, taking into account factors such as the absence of specific resources (e.g., Spain lacking oil resources) and the capacity for imports (e.g., the presence of gas pipelines or regasification plants for natural gas importation).

Finally, the availability of renewable energy resources is determined by CE technologies' availability factor. This factor enables the definition of operating profiles for these technologies across all time slices. For instance, solar photovoltaic plants operate according to solar irradiation availability. Additionally, the availability factor allows for considering levels below 100% for technologies not reliant on variable renewable sources, accommodating scheduled maintenance outages, among other factors.

Electricity generation reliability constraints

In the operation of large power systems, meeting certain reliability conditions at every time slice is essential to ensure smooth and secure functioning. For this reason, reserve and adequacy constraints on the electricity generation capacity are imposed.

The reserve constraint recognises that there is always uncertainty in the load that generators need to supply, such as imprecise demand forecasting, power plant failures, and the variability of power generation from renewable sources. Therefore, this constraint imposes that certain power plants must be capable of rapidly increasing their output in the event of a sudden imbalance.

The adequacy constraint ensures enough capacity to meet peak demand and maintain a reserve margin in power systems. The firmness concept quantifies the reliable capacity of technology. It stipulates that the firm capacity must exceed the peak demand multiplied by the required reserve margin (e.g., 10% excess capacity).

As previously stated, openMASTER presents a unique approach to defining exogenous demand in terms of energy services, where final energy consumption is a decision variable representing end-use technology consumption. This approach is particularly relevant for electricity generation reliability constraints as it requires treating the annual peak electricity demand as a decision variable instead of an input parameter. Although this introduces potential non-linearity, openMASTER addresses it by developing an auxiliary equation and using an additional variable.

By incorporating the annual peak electricity demand as a decision variable, openMASTER can provide a coherent and realistic reserve margin based on optimisation results, effectively capturing the intricate dynamics of electricity demand and supply. This feature enhances the accuracy and realism of strategic energy planning by accommodating evolving consumer preferences and industry trends, such as the growing adoption of electric vehicles and household electrification.

Technological and modal choice constraints

By integrating all exogenous demand as energy services in the model, informed decisions on supply technology investment and operation can be made, leading to technological competitiveness that allows to improve energy efficiency and emissions reduction.

In the particular context of the transport sector, supply technologies correspond to vehicles that supply passenger and freight mobility demands based on distance. Various options, such as electric cars, diesel cars, buses, metro, or bicycles, can be employed to meet the demand for metropolitan mobility. However, optimising the model to minimise costs would naturally favour lower marginal cost modes like walking or cycling, potentially overshadowing other modes. To address this, constraints are introduced to regulate the rate of modal shift, controlling changes in how mobility demand is met across different modes (e.g., car, bus, motorbike, bicycle, metro). Taking advantage of the dynamic approach of openMASTER, the model allows for annual limitations on the rate of change (e.g., a maximum of 2% annual change), preventing drastic shifts. It is important to note that within each mode, there may still be technological competition. For instance, if the electric car proves more competitive, it may replace traditional gasoline or diesel cars. Moreover, these constraints account for changes in mobility demand from year to year, ensuring that the imposed quota is not solely based on the previous year's demand, but adjusted for overall mobility growth or decline.

Endogenous behavioural measures equations

The openMASTER model introduces a formulation that incorporates behavioural changes of agents in a linear and endogenous manner. This is achieved by including additional variables and equations, as detailed in Appendix 2.C.

This comprehensive approach allows decision-makers to gain valuable insights into the impacts of specific measures across the energy value chain. The model considers four groups of behavioural measures:

- Passenger vehicle occupancy rate (passengers per vehicle) and Freight vehicle load factor (tons per vehicle), allowing to include phenomena such as car-sharing or car-pooling.

- Typical mobility demand by distance and passenger type, which could accommodate trends such as remote working, 15-minute cities, or changing delivery patterns.

- Typical demand for energy services by household type and commercial area, considering behaviours such as adjusting thermostat temperature, using cold water cycles for laundry, or increased remote work.

- Proportion of dwellings according to efficiency level, primarily representing improvements in building thermal insulation.

It should be noted that the scope of these behavioural change measures can be limited. However, by considering the interactions between different measures, the model enables optimal implementation strategies for behavioural changes. For instance, it allows for trade-off analysis of measures like remote work, which reduces mobility demand but increases energy services demand at home. The model facilitates determining the optimal level of remote work, considering investment and operational requirements in transportation and households, as well as the consumption of energy carriers and associated emissions throughout the energy supply chain.

These behavioural changes significantly impact the objective function, introducing both tangible (e.g., investment in housing insulation) and intangible costs (e.g., discomfort from reducing space heating temperature). Future advancements could incorporate income-based modelling to represent intangible costs experienced by different social groups in terms of passenger and household behaviours.

Emissions accounting equations

The openMASTER model considers emissions of CO_2, as well as pollutants such as NO_x, SO_x, and $PM_{2.5}$. By employing a bottom-up approach, openMASTER enables the calculation of emissions in the energy sector's processes with a high level of technological detail. This includes energy conversion (CE), energy transportation (TE), and final use in supply technologies (ST), ensuring a comprehensive and specific analysis of emissions. In the case of energy transportation (TE), special attention is given to emissions associated with methane leakages, which can be accounted for as equivalent CO_2.

Emissions are quantified by applying emission factors to the involved processes. Both conversion energy (CE) and supply technologies (ST) consider the fuel consumed when determining emission factors. For example, a hybrid plug-in gasoline car that can utilise either electricity or gasoline will have different emissions associated with the consumption of each fuel. Similarly, a combined cycle power plant may blend natural gas and biomethane.

Moreover, supply technologies (ST) not only consider emissions related to energy consumption but also take into account process emissions. These process emissions result from the use of these technologies regardless of the fuel source. Examples include emissions from tire wear in cars or chemical reactions in cement production. Consequently, the process emission factor of ST technologies depends on the energy service (ES) generated, meaning that emissions are calculated per vehicle-kilometre or tonne of cement. This allows for distinguishing between emissions generated by the same technology in different uses, such as a car emitting more when driving at higher speeds, resulting in higher emissions factors for inter-city distances than metropolitan ones.

Emission caps and carbon budget constraints

After accounting for emissions, it becomes feasible to establish global and sector-specific limits on emissions, including CO_2, NO_x, SO_x, and $PM_{2.5}$. In this regard, the dynamic approach of openMASTER enables the implementation of annual caps on key sectors, including transportation, industry, residential and commercial activities, power generation, and refining. Moreover, additional constraints can be readily established, such as pollution restrictions from the transportation sector could be implemented within urban areas to enhance air quality.

Moreover, this dynamic approach facilitates the effective implementation of a carbon budget constraint, which involves tracking the cumulative CO_2 emissions over a specific timeframe.

2.4 Applications

The MASTER model, known as such prior to the creation of openMASTER, has been utilised for over a decade to conduct several research projects across different fields of study. On one hand, the MASTER model has contributed to the publication of scientific papers in high-impact journals. These papers explore a range of topics, including a comparative analysis of energy efficiency measures versus renewable energy implementation

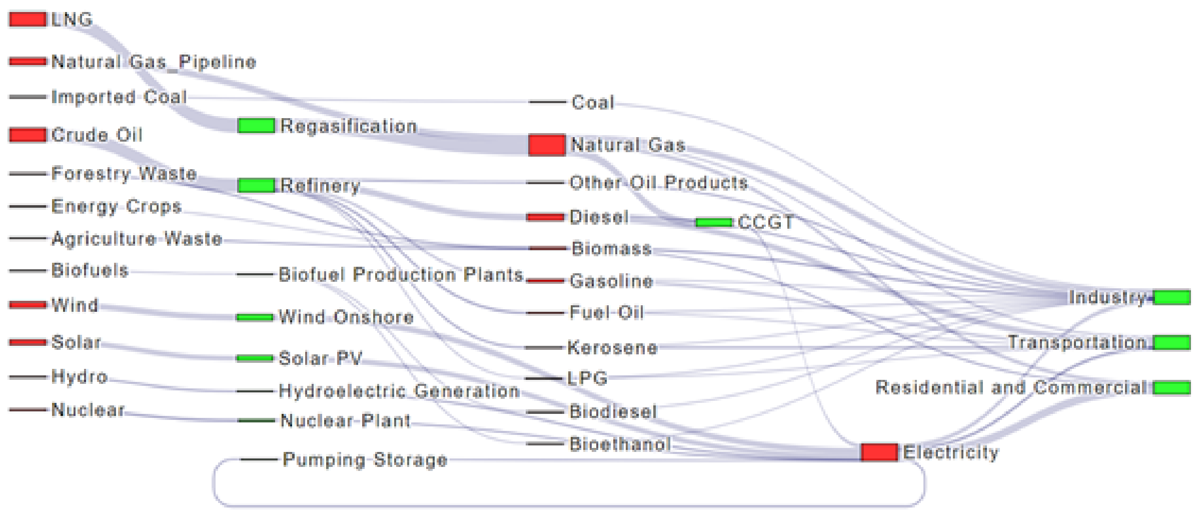

Figure 2.2: openMASTER results' visualizer: Energy Sankey diagram for 2030

(Lopez-Pena et al., 2012), the integration of water considerations into long-term energy planning models (Khan, Linares, Rutten, et al., 2018), the effects of water constraints on power generation in the face of climate change scenarios (Khan, Linares, and García-González, 2016), the utilisation of multicriteria decision-making to address sustainability indicators (Romero and Linares, 2021), the implications of the decarbonisation on energy poverty (Romero, Linares, et al., 2025), and the treatment of epistemic uncertainties through robust techniques, as shown in Chapter 3.

In addition, it has been employed in the preparation of public reports, with the objective of providing decision-makers with insights into the economic, environmental, and technological consequences of different potential pathways for the energy sector. This analytical tool enables informed discussions among stakeholders, facilitating the necessary consensus for the energy transition. Notably, these public reports includes an analysis of long-term (2030-2050) scenarios in the Spanish energy sector (Economics for Energy, 2017), strategies for decarbonising land transport in Spain (Economics for Energy, 2021), and the impact of climate change in water resource availability for electricity generation (Khan and Linares, 2015). This highlights that openMASTER is a flexible and adaptable model, making it a valuable tool for a wide range of research applications in the field of energy planning.

It is important to introduce the openMASTER results' visualiser, which is publicly accessible along with the model's entire code, and provides a user-friendly interface displaying comprehensive information on the energy system and its emissions. The visualiser allows users to access intuitive data, presented through graphs that can be customised for specific scenarios and years of interest.

In Figures 2.2, 2.3, 2.4 and 2.5, we showcase some graphs generated by the visualiser, including the Sankey diagram illustrating energy flows within the processes of the energy system, tracing them to their final consumption across various sectors through end-use technologies. Moreover, the visualiser offers the ability to track the evolution of primary energy consumption, assess the composition of renewable energy sources, and examine emission-related indicators such as their temporal changes and technological sources. These graphs are generated using Plotly, making them interactive and capable of being modified to represent different scenarios and years via selectors.

Another feature of this visualisation tool is the comparator, which facilitates intuitive comparisons between different years or scenarios. This empowers decision-makers to gain valuable insights through easily interpretable visualisations. Notably, the model offers comprehensive information related to the decision variables outlined in Section 2.3. This encompasses a wide range of details, including the evolution of the capacity of both energy conversion technologies and end-use technologies, the emissions sources, and the operational characteristics of technologies on a time-slice basis, among others.

Regarding the computational load, the model exhibits the features illustrated in Table 2.2. The optimisation is performed using Gurobi Optimizer version 10.0.1 on a PC equipped with a 64-bit Windows Operating

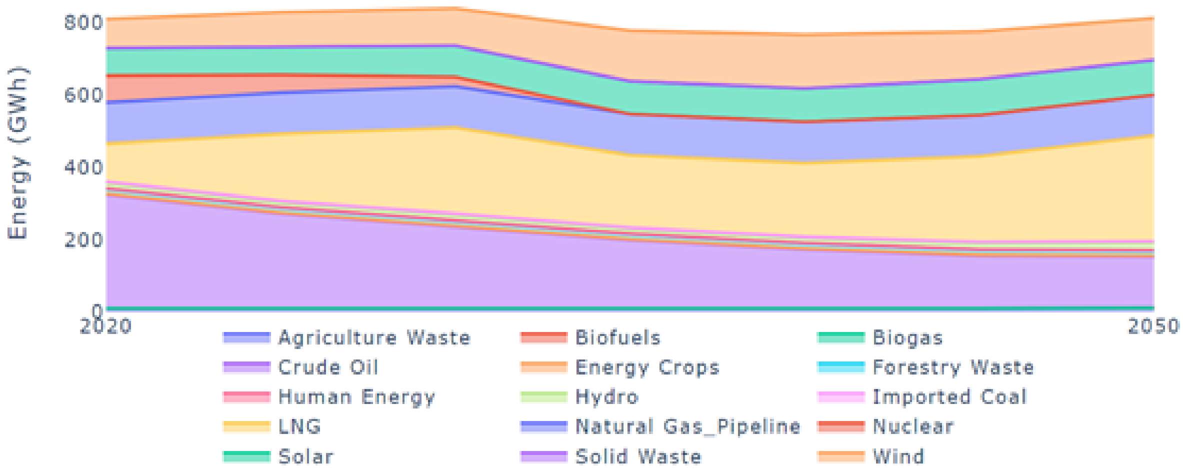

Figure 2.3: openMASTER results' visualizer: Evolution of primary energy consumption (2020-2050)

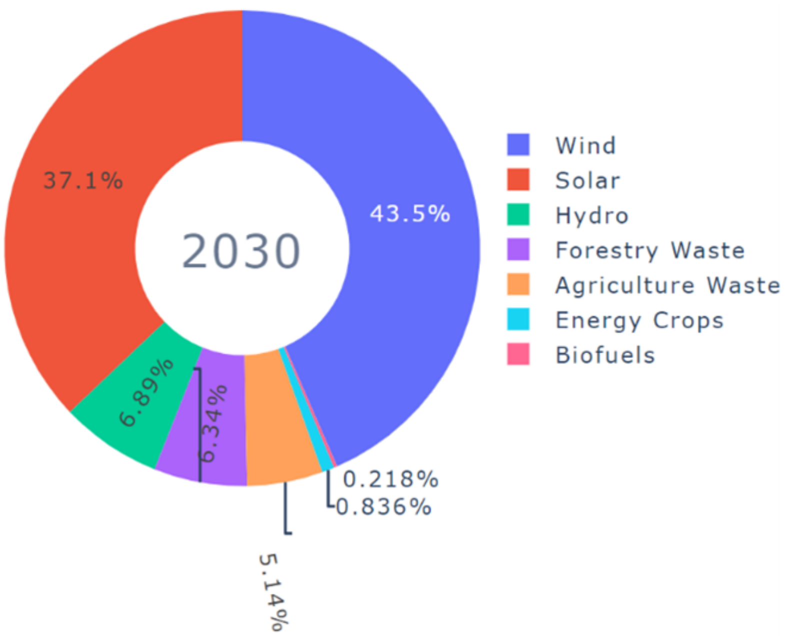

Figure 2.4: openMASTER results' visualizer: Renewable energy mix for 2030

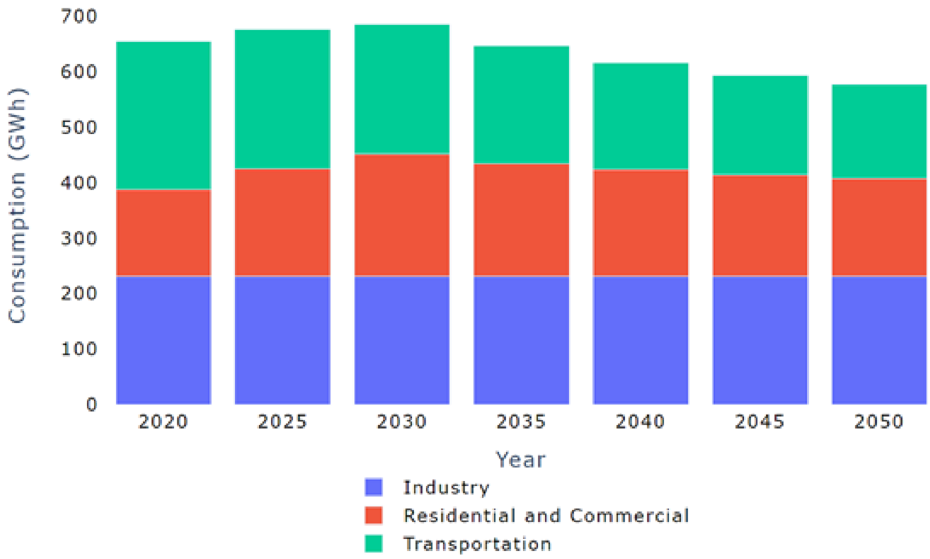

Figure 2.5: openMASTER results' visualizer: Evolution of final energy consumption (2020-2050)

System, an Intel(R) Xeon(R) Silver 4116 CPU @ 2.10GHz processor, and 128 GB RAM. The findings clearly indicate that the computational load and solving time are highly reasonable for strategic energy planning, and comparable to other similar models. In this context, it's essential to consider the computational load associated with the temporal resolution of the model. Most common openMASTER applications use configurations of 96 and 672 time slices per year, corresponding to hours in a typical day or week for each season. It's important to note that these temporal resolution scale up due to the time horizon in years, reflecting the dynamic character of openMASTER. Table 2.2 presents the computational results for utilising 96 time slices per year within a time horizon spanning from 2020 to 2070, with a representation of 5-year gaps.

Table 2.2: Computational characteristics of the case study (nominal LP case)

Type	**Variables**	**Equations**	**Solver time** [sec]
LP	2,087,907	3,042,005	131.31

2.5 Illustrative case study

This section presents a brief illustrative case study to demonstrate how openMASTER can be used to address real-world energy decision-making problems, and showing some of the results achievable with it. It is essential to emphasize that the interpretation of the results is not discussed here, but rather the model's capability to generate them.

This illustrative case study is calibrated for the Spanish energy system in the year 2020, representing a decarbonization scenario conducted under the constraint of annual emissions formulated by the Spanish government to achieve climate goals outlined in the Integrated National Energy and Climate Plan. Consequently, sectorial carbon cap constraints were imposed on all emissions during the 2020–2030 period. Detailed information regarding the calibration of this illustrative case study can be found in Appendix 2.D, including data on fuel prices, energy technology investment costs, technology efficiencies, and installed capacity for the 2020 calibration year.

Table 2.3 presents the installed capacity of conversion energy technologies for the year 2030 compared to the calibration year of 2020. It illustrates how the model resolves the investment planning of energy technologies for the years within the study horizon, not only for the electricity sector but for all energy vectors.

Table 2.3: Installed capacity of conversion energy technologies [GW]

Technology	**2020**	**2030**
Nuclear	7.4	3.2
Coal	10.2	0.0
CCGT	26.6	16.3
CCGT+CCS	0.0	14.6
OCGT	0.0	12.5
OCGT+CCS	0.0	0.0
Fuel Oil	3.7	0.0
Hydro	14.0	20.9
Wind Onshore	26.8	67.7
Wind Offshore	0.0	3.0
Solar PV	11.0	79.0
Solar Th	2.3	2.3
Biomass PP	1.4	0.0
Storage	6.4	16.3
CHP	5.3	2.6
TOTAL ELECT	115.0	238.4
Oil Refinery	47.9	26.1
Biofuel	56.2	51.0
Regasification	43.8	83.4

In addition to investment planning in conversion energy technologies, openMASTER also operates and invests in end-use energy technologies, referred to as supply technologies. In this regard, openMASTER considers three demand sectors (residential & services, industry, and transportation), where demand is defined as energy services (e.g., passenger and freight mobility, quantity of materials, or energy services in buildings such as heating, appliances, or lighting).

As an example of the installation of supply technologies, the results in Table 2.4 show the evolution of car fleet capacity. Similarly, it is worth noting that the model also provides this capacity for supply technologies of other mobility options (e.g., airplanes, trucks, buses, etc.) and sectors (e.g., gas boilers, heat pumps, or high and low-efficiency washing machines in residential areas, or various industrial processes such as Hall Heroult aluminum factories).

Furthermore, regarding Table 2.4, it is important to note that this car fleet corresponds to the total aggregate of each technology for the years 2020 and 2030, although the model disaggregates these technologies by vintage. Therefore, the number of each type of vehicle is disaggregated by its age, influencing its energy efficiency and emission factor. This allows for the inclusion of the learning curve, decommissioning after the end of their useful life, and compliance with environmental regulations of the supply technologies.

On the other hand, the operation of these technologies to meet the demand for energy services is another crucial aspect of openMASTER. In this regard, Figures 2.6 and 2.7 display the primary energy mix and final energy mix, respectively. It is noteworthy that the information in these Figures is aggregated for the year 2030 but is available for all time slices that configure the model.

As shown above, these results serve as a sample of the outcomes achievable through the utilization of openMASTER. Naturally, openMASTER can yield a diverse range of other results, including but not limited to CO_2 emissions, atmospheric pollutants (such as NO_x, SO_x, and $PM_{2.5}$), and behavioural measures, among others.

This comprehensive suite of outputs enables a holistic understanding of the impacts and implications of energy policies and scenarios analyzed using the openMASTER model.

Table 2.4: Car fleet [Million vehicles]

Fuel Type	**2020**	**2030**
Gasoline	10.67	9.095
Diesel	8.0063	2.563
CNG	0.0018	0.001
LPG	0.0091	0.003
Hybrid Gasoline	0.0077	4.363
Hybrid Diesel	0.0063	0.002
EV	0.01	1.512
TOTAL	18.711	17.539

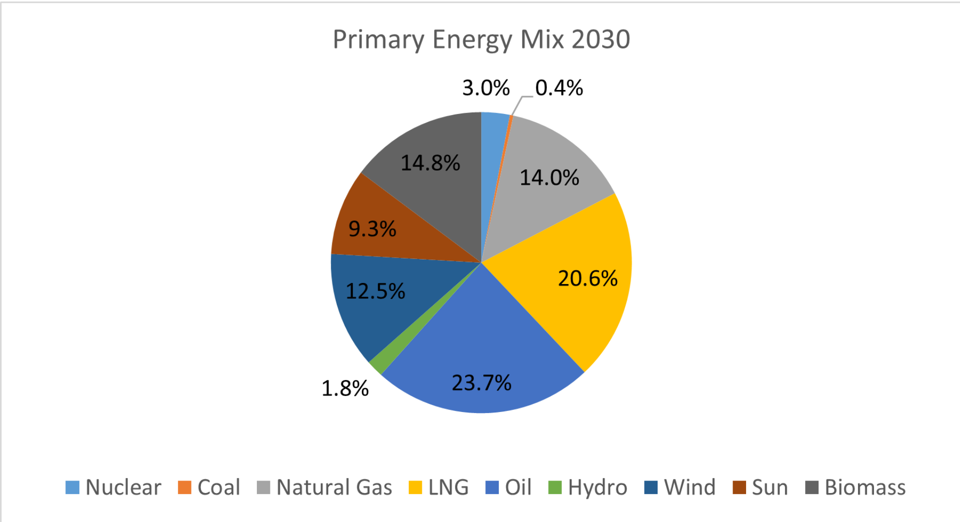

Figure 2.6: Primary energy mix for 2030

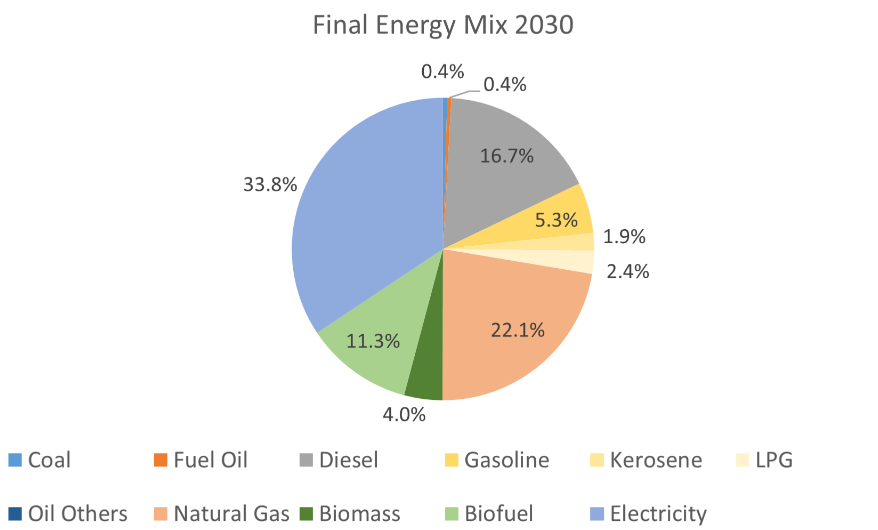

Figure 2.7: Final energy mix for 2030

2.6 Conclusions

Over the span of more than a decade, the MASTER model has demonstrated its reliability and adaptability across various research domains. In this context, we now introduce openMASTER, a valuable open-source tool for both public discussions about the energy transition and cutting-edge research. Through an extensive review of the literature, we have shown how openMASTER offers several advantages over similar models. The publication of the model as an open-source tool serves as an exercise in promoting transparency and replicability within the scientific community engaged in long-term energy system modelling.

Considerable efforts have been devoted to developing an accessible and modular tool, designed with user-friendly data treatment and visualisation modules. Additionally, the model offers a visualisation tool that proves instrumental for decision-makers. Importantly, all auxiliary modules associated with the model are also publicly available, further enhancing its usability and transparency.

Despite its strengths, the model does have limitations, as addressed in Section 2.2.1. It lacks spatial modelling for electricity and gas grids, crucial for representing regional or global models with energy interconnections. This could increase computational complexity. Additionally, the model's bottom-up approach and high level of detail entail a significant number of equations and variables, necessitating a trade-off between detail and computational complexity. While openMASTER has been applied to real-world case studies like the Spanish national energy system, expanding its scope to continent-wide or global applications remains unexplored and may require adjustments to temporal detail. Hence, improvement in these areas represents a potential avenue for enhancing the model's performance.

Ongoing research involving the openMASTER model is advancing in various directions, such as the consolidation of robust planning techniques for dealing with epistemic uncertainties, improving the representation of the transportation sector, integrating indicators of a just transition, and enhancing the level of detail in production processes and the circular economy within the industrial sector. These potential avenues hold promise for further leveraging the capabilities of the openMASTER model.

Appendix 2.A: openMASTER structure

The openMASTER model comprises distinct components that describe the different stages of energy conversion, from the utilization of natural resources to the energy services supply:

- **Primary Energy (PE)** accounts for the aggregate primary energy sources employed, encompassing both domestic and imported, renewable and non-renewable resources. Examples include uranium, coal, LNG, and solar irradiation.
- **Conversion Energy (CE)** processes represent the technologies responsible for transforming energy from one form to another, including storage and release mechanisms. While CE processes encompass electricity generation, they also incorporate activities like oil refining, biofuel production, and LNG regasification (considered as the transformation of primary energy, LNG, into final energy, natural gas), among others. This process consists of three subprocesses:
  - **Primary Conversion Energy (CE_{Pri})** processes, involving technologies that consume primary energy to produce final energy, such as solar PV, regasification plants, and refineries.
  - **Secondary Conversion Energy (CE_{Sec})** processes, involving technologies that consume final energy to produce another final energy commodity. Examples of such processes include CCGT or CHP, which may rely on regasified natural gas (originating from LNG) as their fuel source.
  - **Storage Energy (CE_{Sto})** processes, involving technologies that store and release final energy, such as hydro pumping.
- **Transportation Energy (TE)** pertain to the energy transportation and distribution networks responsible for delivering final energy to end-use technologies (supply technologies, ST). Each TE process exclusively transports a specific type of final energy, effectively representing the list of considered final energy types. Examples of TE sources include electricity, gasoline, and biodiesel.
- **Raw Materials (RM)** sources denote non-energy commodities consumed by supply technologies (ST) within the industrial sector. Examples of such materials encompass bauxite or raw iron.
- **Supply Technologies (ST)** processes represent devices that consume final energy, and in the case of industrial applications, also utilize raw materials, to deliver energy services. These technologies are designed to fulfill specific functions in various sectors. For instance, lamps utilize electricity to provide illumination, cars consume gasoline for transportation purposes, and boilers employ natural gas for heating applications.

Exogenous demand characterization

The characterization of demand within the model involves the implementation of specifically designed blocks to account for endogenous variables related to agents' behavioural changes. In this subsection, we will outline the processes utilized to define the demand:

- **Energy Service (ES)** represents the diverse range of energy services required within the modelled economy. It is important to note that the characterization of energy service demand is achieved by disaggregating the annual demand into distinct time slices using a load profile. This methodical approach enables a more refined representation of the temporal granularity within the model. Examples of energy services include demanded tonnes of aluminium, GWh of heating in the residential sector, or vehicles-km for metropolitan-distance mobility.
- **Activity Factor (AF)** serves as a parameter that characterizes the annual demand across various sectors of the economy:
  - In the **transportation** sector, the activity factor (AF_{Tra}) corresponds to the vehicle occupancy rate or load factor. For passenger transportation, this factor indicates the average number of passengers per vehicle. Similarly, for freight transportation, it represents the tonnes per vehicle.

- In the **residential and commercial** sector, the activity factor (AF_{Oth}) reflects the energy service demand per dwelling (for residential) or per square kilometer (for commercial). It captures the typical energy services demand for households or commercial spaces. For instance, in the case of Spain, it could represent the hot water demand for an Atlantic block dwelling, the required lumens for a Mediterranean single house, or the GWh of heating per square kilometer of continental commercial area.
- In the **industrial** sector, no AF is applied, as the demand for materials is externally determined and provided in Macro Data (MD).

• **Demand Characterization (*DC*)** serves as an additional factor that characterizes the annual demand within different sectors of the economy:

- In the **transportation** sector, the demand characterization (DC_{Tra}) factor captures the mobility demand per passenger and distance. It quantifies the distance, in kilometers, that a passenger demands based on their living context (urban or rural) and the type of travel distance (metropolitan, inter-city, etc.). For freight transportation, a similar factor is applied, but it represents the demand in terms of tonnage rather than passengers.
- In the **residential and commercial** sector, the demand characterization (DC_{Oth}) factor represents the percentage of dwellings (for residential) or square kilometers (for commercial) classified according to their efficiency level compared to the total. Therefore, this parameter quantifies the proportion of high and low-efficient dwellings based on their typology and climatic zone. For instance, in the case of Spain, 17% of single houses in the Atlantic climatic zone are classified as highly efficient.
- In the **industrial** sector, no specific DC factor is applied as the demand for materials is externally determined and provided through Macro Data (MD).

• **Macro Data (*MD*)** is a parameter that provides macro-level values for different sectors:

- In the **transportation** sector, it encompasses the number of residents in different types of environments (e.g. urban or rural).
- In the **residential and commercial** sector, it defines the total number of dwellings (for residential areas) and square kilometers (for commercial areas), categorized by climatic zones. In the specific context of the Spanish energy system, the climatic zones are represented as Mediterranean, Atlantic, and Continental, although alternative options can be readily applied.
- In the **industrial** sector, it indicates the demand in terms of tons of materials such as aluminium or steel.

openMASTER model configuration

The configuration of the openMASTER model primarily involves accurately and consistently defining the sets and parameters that constitute the model. On the one hand, the model operates dynamically, requiring the specification of a time horizon. One approach is to group the years, allowing optimization for representative years within each group (e.g., 2, 5, or 10 years) instead of optimizing for the entire time horizon, based on the modeller's discretion.

Furthermore, the temporal resolution, represented by time slices, must be determined. The model incorporates three sets for this purpose, representing seasons, days, and hours. Currently, the most commonly used configuration includes four seasons, seven days of a week, and 24 hours per day. This enables obtaining hourly granularity for a representative week in each season. Moreover, higher time granularity can be achieved, ranging from 8760 hours per year to even shorter time slices of 15 or 5 minutes. However, it is crucial to consider the trade-off between temporal resolution and computational load.

Defining the elements of the sets that represent processes and commodities in the model is essential. For example, the primary energy (PE) set should encompass all relevant primary energy vectors (e.g., coal, crude oil, solar irradiation), while the conversion technologies (CE) set should include corresponding conversion technologies (e.g., coal power plants, refineries, solar PV plants), and so forth.

Additionally, establishing consistent relationships between interconnected sets involving energy or matter flows (as illustrated in Figure 2.1) is crucial to avoid inconsistent flows. This is achieved through relational sets, ensuring that, for instance, a nuclear power plant consumes uranium instead of coal, or an aircraft produces vehicle-kilometres instead of lumens.

Moreover, subsets represent smaller groups of elements belonging to other sets. For instance, the renewable primary energy subset comprises renewable energy vectors from the primary energy set, excluding sources such as crude oil or natural gas. These subsets play a crucial role in defining equations within the model and must be consistently defined.

Moreover, the parameters' dimensions are determined based on the sets. For example, the parameter specifying the capital expenditure (CAPEX) cost of conversion technologies (CE) is defined for each individual CE technology. Therefore, any alterations made to the CE set must be accurately reflected in the corresponding parameter. Consequently, when making modifications, additions, or removals to a set, the modeller must ensure that all relevant changes are appropriately implemented across the associated parameters.

However, the openMASTER model has been developed in a modular and easy to use format for all users. In this way, along with the model code, the input and output modules are also accessible, as well as a viewer to obtain several visual information about the results. The development of input and output data modules is crucial for ensuring interoperability, accessibility, and adaptability. These modules serve as a vital link between the energy optimization model and the data sources, facilitating data transmission and result generation.

Input data module

To create a user-friendly and versatile solution, we designed the data input and output system to be compatible with both CSV and Excel file formats. While CSV serves as the primary format for input and output, Excel offers a convenient means of modifying input data and visualizing output results. However, Excel is not essential for the model's functionality. We chose these formats due to their widespread usage and compatibility with various software applications. Moreover, it is particularly advantageous in environments where users may not have access to advanced data management tools.

Furthermore, we adopted a modular approach to data processing in Python. This design divides the data processing into separate modules, enabling easy modification or customization of specific components without affecting the overall system functionality. To store initial data, we consolidated them into an Excel spreadsheet with different tabs representing sets and parameters.

The data loading process in our Python model involves a two-step transition from Excel to CSV and then from CSV to Pyomo. This approach enhances modularity and allows for future modifications to the data format. Loading data from CSV files is faster and does not require repetition unless new data is created. This design accommodates changes or expansions in the data structure or format.

We developed a data-loading pipeline that automatically identifies and processes different types of tables in Excel. The pipeline involves (i) identifying the data type (sets or parameters) based on the sheet name, (ii) defining table boundaries (by the use of the $\sim BOUNDS \sim$ indicators), (iii) identifying table formats, and (iv) converting the input data into CSV format for Python processing.

Separating the initial data from the model's input data enables continuous loading of CSV data while updating or modifying the input. This modular design streamlines the data updating process, enhances flexibility and robustness, and allows for separate workflows for data preparation and model computation.

However, for the user's convenience, it is recommended to modify the model's input data using the $openMASTER\_Data.xlsm$ Excel file. This file includes an input index ($INDEX$ tab) where all sets, subsets, and parameters are defined, including table dimensions (this information is used for converting this data to CSV), units, descriptions, and other details. From this tab, users can navigate the data using the CTRL+Q and CTRL+W commands, as each element has its own sheet in the Excel file. This makes it easier for users to modify the data.

Output data module

The data loading process involves sets and parameters as the main data types, while the data output focuses on variables. Variables represent the results of the model and are used for result visualization and analysis. The data output can be divided into storing the model's output data and loading the stored data for visualization.

To store the model's output data, we reverse the input data pipeline. Information about the indices of parameters is obtained from the "*INDEX*" Excel sheet, while for output variables, it is obtained from the "*Output*" sheet. Python uses this information to understand the indices of each variable. The variables are stored in separate Python data tables, organized in a dictionary format for easy representation and visualization. Simultaneously, the data is exported in CSV format for convenient access. To improve visual interpretation, the CSV files can be converted to a consolidated Excel format.

Once the model is executed and the results are stored, there is no need for recomputation unless there are changes in the input data. Loading the data from CSV files is designed to be user-friendly and accessible. A script iterates over each output file, storing the information in a dictionary for future use. This modular input and output data system enhances accessibility, adaptability, and streamlines the workflow for managing and visualizing the model's outputs.

Visualizer

In order to facilitate user-friendly data representation, a series of advanced templates were pre-programmed to allow for easy visualization of the data, as well as some of the most relevant and standard energy result graphics.

By replacing the data and making simple changes such as the title, axis labels, or units, advanced representations of future executions can be quickly obtained without the need for advanced technical knowledge. The pre-programmed graphics include (i) Sankey diagram, (ii) Bar chart and stacked bar chart, (iii) Area chart and stacked bar chart, (iv) Sectors diagram, and (v) Evolutionary line.

This data representation can be found in the dashboard, an essential component of the openMASTER toolset, offering an intuitive and interactive interface. It enables users to explore complex energy planning data across various scenarios and timeframes. Figure 2.8 showcases the dynamic manipulation and comparison of data visualizations, empowering users to generate actionable insights. It highlights key functionalities of the dashboard, including the ability to customize chart types, zoom in on specific time periods, and switch between different scenarios. These features enhance the user's analytical capabilities and facilitate a deeper understanding of the data.

Additionally, integrating a Plotly dashboard in the openMASTER model facilitates the selection and comparison of various scenarios, periods, and graph types, promoting a user-friendly comprehension of the data. Figure 2.9 emphasizes the significance of the "COMPARATOR" tab, which empowers users to compare data from different scenarios within the same time period and track the evolution of a single scenario across multiple time periods. This adaptability offers valuable insights for strategic decision-making and policy assessment in the energy planning domain, enhancing the overall effectiveness of the tool.

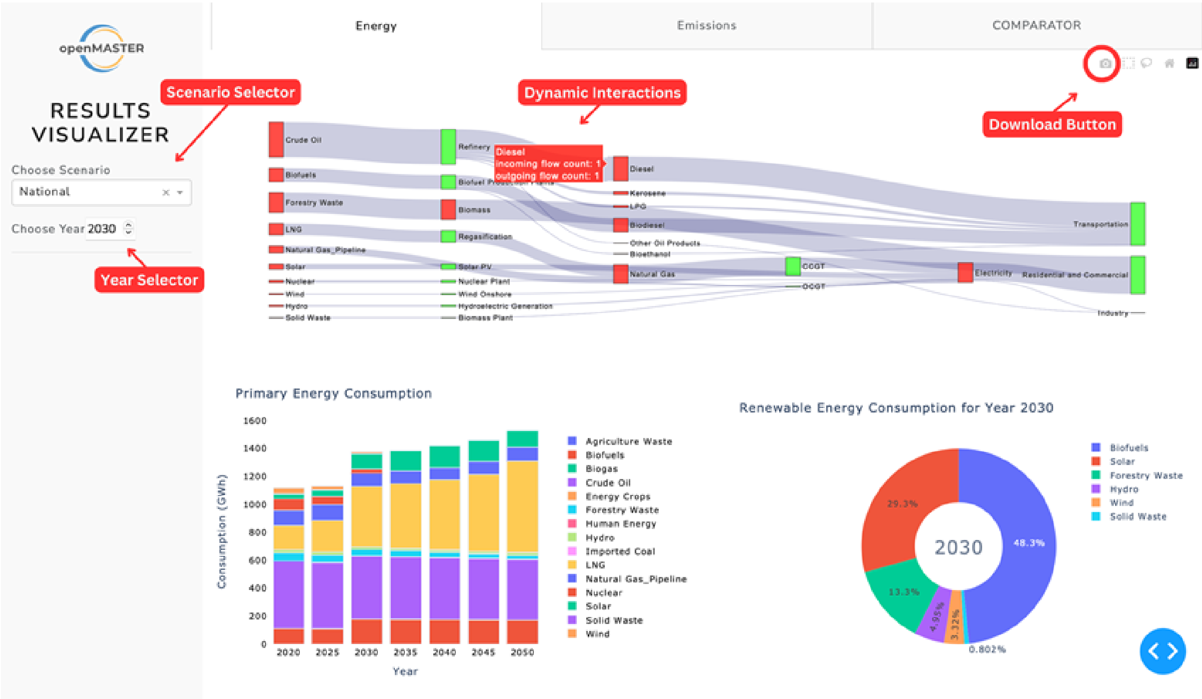

Figure 2.8: Plotly dashboard integration

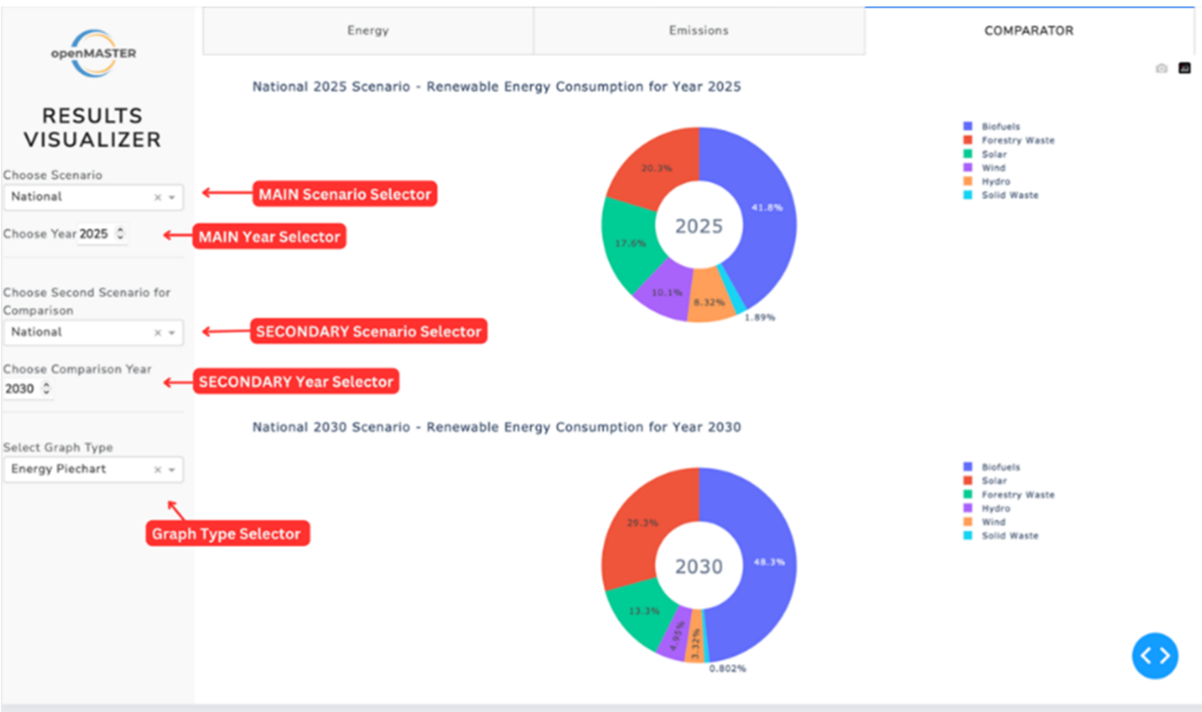

Figure 2.9: Plotly dashboard "COMPARATOR" tab

Appendix 2.B: Definition of exogenous energy services demand in openMASTER

According to the disaggregation of openMASTER, the exogenous annual demand for energy services can be derived by multiplying these parameters (Activity Factor, Demand Characterization and Macro Data).

In the case of the **transportation** sector, the exogenous annual demand for mobility energy services could be expressed as follows:

$$\sum_{ST,ES}\left(\text{vQES}_{ST,ES,y}\cdot \text{pAFTra}_{ST,ES,SD}\right) \geq \text{vQSD}_{SD,y} \tag{2.1}$$

$$\text{vQSD}_{SD,y} \geq \sum_{MD}\left(\text{pDCTra}_{SD,MD}\cdot \text{pMD}_{MD,y}\right) \tag{2.2}$$

As depicted in Figure 2.10, the mobility data is derived from the Macro Data (MD) parameter, which represents the population characterized by their residential environment. Currently, for passenger mobility, this characterization involves distinguishing between urban and rural populations, as the demand for mobility significantly varies between these population types. However, this disaggregation can be further extended by differentiating populations living in large, medium, or small cities, as well as rural areas with varying degrees of isolation from urban centres.

The Demand Characterization (DC) parameter indicates the mobility demand in terms of distance for a typical citizen based on their residential environment. This disaggregation is based on the understanding that a typical resident in a large city like Madrid or Barcelona requires much longer commuting distances compared to a resident in a rural municipality. By multiplying the population (Macro Data) by the typical distance (Demand Characterization), we obtain the number of kilometres demanded by a passenger for different distances, such as metropolitan or inter-city distances.

Moreover, mobility demand can be met by various modes and technologies. For instance, within a large city, mobility can be covered by car, moped or metro, while mobility between two cities could be made by car, train or airplane. As a result, the Activity Factor (AF), which represents the occupancy rate or load factor of vehicles, varies significantly depending on the technology and type of distance. For example, the occupancy rate of a car during a metropolitan trip is usually lower compared to an inter-city trip, where it may transport more passengers. Simultaneously, a bus has the capacity to transport a significantly larger number of passengers compared to a car.

On the other hand, it is worth noting that the available technologies and modes also differ based on the environment and distance type. For instance, the metro is not available in rural areas. Moreover, the same technology can supply to different mobility demands (e.g., a car can be used for metropolitan and inter-city trips).

For the case of the **residential and commercial** sector, the idea is similar, being the formulation:

$$\sum_{ST}\text{vQES}_{ST,ES,y} \geq \sum_{ST,ES}\left(\text{vQSD}_{SD,MD,y}\cdot \text{pAFOth}_{ES,SD,MD}\right) \tag{2.3}$$

$$\text{vQSD}_{SD,MD,y} \geq \text{pDCTra}_{SD,MD}\cdot \text{pMD}_{MD,y} \tag{2.4}$$

As illustrated in Figure 2.11, Macro Data (MD) categorize the number of dwellings (or km2 for the commercial sector) by typology (single house and block house) and climatic zone (Mediterranean, Atlantic, and Continental). The Demand Characterization (DC) factor defines the weights that each of these housing groups represents in terms of energy efficiency. Thus, we obtain a classification of these households based on typology, climatic zone, and efficiency. The Activity Factor (AF) determines the energy service demand per household (or km2) based on this classification. Consequently, the energy service demand is expressed in terms of GWh for heating, lumens for lighting, or cycles for hot or cold laundry washing, among others.

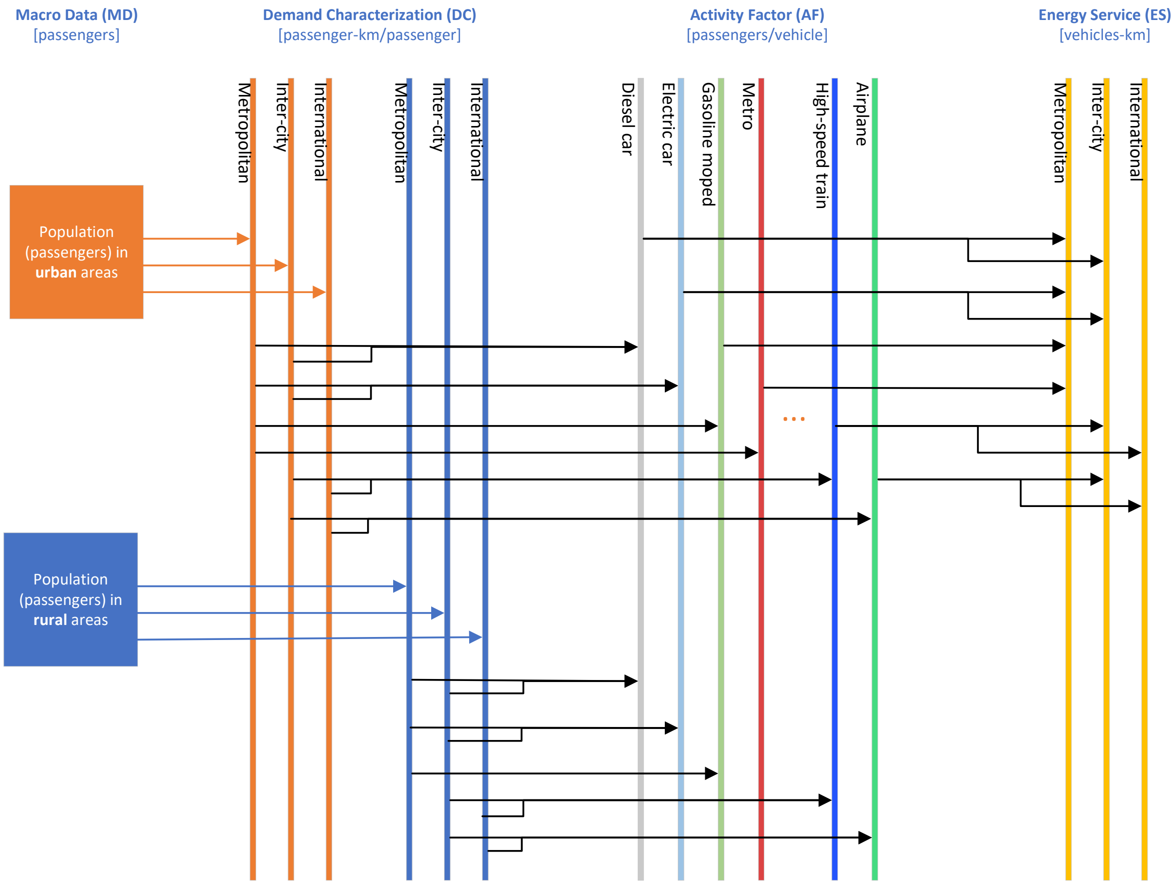

Figure 2.10: Structure of the exogenous demand in the transportation sector in openMASTER

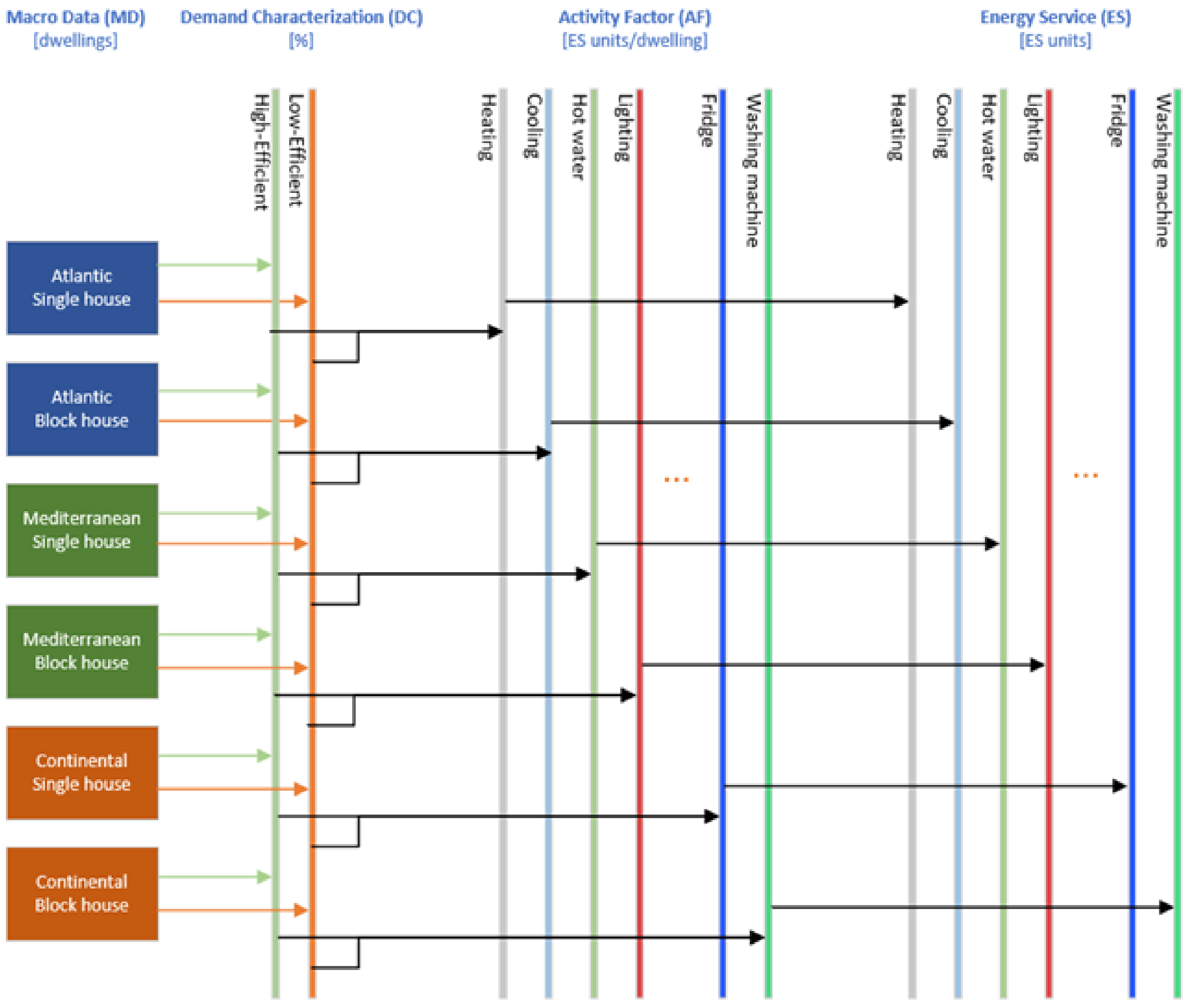

Figure 2.11: Structure of the exogenous demand in the residential sector in openMASTER

Appendix 2.C: Endogenous behavioural measures linear formulation

Historically, modifications or reductions in demand within energy models have typically incorporated measures of changes in agent behaviour through an exogenous approach. This involved creating scenarios of behavioural change and calculating the resulting effect on the demand parameter, subsequently implementing these changes in the input data for model optimization. This novel approach allows for an endogenous and more integrated representation of behavioural measures within the model framework. It is important to note that this formulation is possible as all exogenous demand is stated as energy services.

In the case of transportation, and building upon the framework presented in the previous section that elucidated the model structure for representing exogenous demand, we derive the following formulation:

$$\sum_{ST,ES}\left(\text{vQES}_{ST,ES,y} \cdot \text{pAFTra}_{ST,ES,SD}\right) + \sum_{ST,ES} \text{vBMTra}_{ST,ES,SD,y} \geq \text{vQSD}_{SD,y} \tag{2.5}$$

$$\text{vBMTra}_{ST,ES,SD,y} = \sum_{n} \text{vBMTra}_{nST,ES,SD,y} \tag{2.6}$$

$$\text{vBMTra}_{nST,ES,SD,y} \geq 0 \quad \forall n \tag{2.7}$$

$$\text{vBMTra}_{nST,ES,SD,y} \leq \text{p}\delta\text{AFTra}_{nST,ES,SD} \cdot \text{vQES}_{ST,ES,y} \quad \forall n \tag{2.8}$$

$$\text{vQSD}_{SD,y} \geq \sum_{MD}\left(\text{pDCTra}_{SD,MD} \cdot \text{pMD}_{MD,y}\right) - \sum_{MD} \text{vDMTra}_{SD,MD,y} \tag{2.9}$$

$$\text{vDMTra}_{SD,MD,y} = \sum_{n} \text{vDMTra}_{nSD,MD,y} \tag{2.10}$$

$$\text{vDMTra}_{nSD,MD,y} \geq 0 \quad \forall n \tag{2.11}$$

$$\text{vDMTra}_{nSD,MD,y} \leq \text{p}\delta\text{DCTra}_{nSD,MD} \cdot \text{pMD}_{MD,y} \quad \forall n \tag{2.12}$$

We have introduced two additional sets of variables to the original equations presented in Appendix 2.B. The first set, denoted as vBMTra_n (Behavioral Measures in Transportation), captures variations in the parameter pAFTra, which represents the vehicle occupancy rate. The subscript n corresponds to the number of measures that aim to increase the number of passengers per vehicle, facilitating modelling of phenomena such as car-sharing or car-pooling.

To maintain linearity in the model, we define this variable using a mathematical formulation that enables optimization of changes in the parameter. By doing so, we avoid introducing non-linearities that would arise from directly defining pAFTra as a variable. Additionally, equation 2.8 illustrates that the variable vBMTra_n is bounded by the parameter $\text{p}\delta\text{AFTra}_n$, which denotes the maximum allowable change in vehicle occupancy rate for each measure.

The second set of variables, denoted as vDMTra_n (Demand Shift Measures in Transportation), follows a similar mathematical formulation to ensure linearity in the problem. These variables allow the model to optimize variations in the parameter pDCTra, which represents mobility demand in passenger-kilometers per distance and environment. In consequence, vDMTra_n allows to represent changes related to trends like remote work, the 15-minute city concept, or delivery trends, among others. The variable is constrained by the parameter $\text{p}\delta\text{DCTra}_n$.

These changes significantly impact the objective function, introducing tangible or intangible costs. Future advancements in the model could incorporate income-based passenger and household modelling to represent intangible costs experienced by different social groups.

For the residential sector, a similar formulation is applied:

$$\sum_{ST} \text{vQES}_{ST,ES,y} \geq \sum_{SD,MD} \left(\text{vQSD}_{SD,MD,y} \cdot \text{pAFRes}_{ES,SD,MD}\right) - \sum_{SD,MD} \text{vBMRes}_{ES,SD,MD,y} \tag{2.13}$$

$$\text{vBMRes}_{ES,SD,MD,y} = \sum_{n} \text{vBMRes}_{nES,SD,MD,y} \tag{2.14}$$

$$\text{vBMRes}_{nES,SD,MD,y} \geq 0 \quad \forall n \tag{2.15}$$

$$\text{vBMRes}_{nES,SD,MD,y} \leq \text{p}\delta\text{AFRes}_{nES,SD,MD} \cdot \text{vQSD}_{SD,MD,y} \quad \forall n \tag{2.16}$$

$$\text{vQSD}_{SD,MD,y} \geq \sum_{MD} \left(\text{pDCRes}_{SD,MD} \cdot \text{pMD}_{MD,y}\right) - \sum_{MD} \text{vDMRes}_{SD,MD,y} \tag{2.17}$$

$$\text{vDMRes}_{SD,MD,y} = \sum_{n} \text{vDMRes}_{nSD,MD,y} \tag{2.18}$$

$$\text{vDMRes}_{nSD,MD,y} \geq 0 \quad \forall n \tag{2.19}$$

$$\text{vDMRes}_{nSD,MD,y} \leq \text{p}\delta\text{DCRes}_{nSD,MD} \cdot \text{pMD}_{MD,y} \quad \forall n \tag{2.20}$$

In the context of the residential sector, we introduce the variable vBMRes_n, which represents behavioral changes influencing the parameter pAFRes. This parameter quantifies the demand for energy services per household, considering typology (single house or block), climate zone, and efficiency. Therefore, vBMRes_n enables the incorporation of behavioural adjustments related to household consumption, such as reducing thermostat temperatures for heating and cooling space, or increasing consumption through remote work.

Additionally, the variable vDMRes_n affects the parameter pDCRes, which defines the proportion of dwellings categorized by energy efficiency. This variable allows modeling improvements in building efficiency, including investments in thermal insulation for dwellings, thereby accounting for associated investment costs.

Trade-offs in measures: Interactions and optimal implementation of behavioural measures strategies

This formulation enables to model the relationships between different measures. For instance, we have observed that remote work impacts two potential sets of measures. On one hand, it reduces mobility demand through the utilization of the variable vDMTra_n, thus decreasing the amount of passenger-kilometers traveled in metropolitan distances. On the other hand, it increases the demand for energy services at home, as captured by the variable vBMRes_n, leading to augmented energy requirements for heating or the use of household appliances (e.g., computers). To model this relationship, the following lineal formulation is proposed:

$$\sum_{MD} \left(\text{vDMTra}_{\text{telework}SD,MD} \cdot \text{pTO}_{\text{telework}ES,SD,MD}\right) \leq \text{vBMRes}_{\text{telework}ES,SD} \tag{2.21}$$

The parameter $\text{pTO}_{\text{telework}}$ represents the trade-off associated with the remote work measure. It defines the increase in demand for energy services at home per unit reduction in mobility demand. Thus, the model facilitates the determination of the optimal level of remote work, considering investment and operational requirements in both transportation and households, as well as the consumption of energy carriers and associated emissions across the entire energy supply chain necessary to fulfill these energy services.

Appendix 2.D: Illustrative case study calibration

Section 2.5 of Chapter 2 features an illustrative case study that was conducted to demonstrate some interesting outputs from openMASTER.

The time-varying parameters are specified with their initial and final values, which are set to correspond to the years 2020 and 2030, 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. Hourly demand is derived by utilizing a load curve applied to the annual demand.

In the following, some parameters are defined. More information can be found on openMASTER's GitHub webpage (*IIT-EnergySystemModels/openMASTER* 2023).

Table 2.5: Fuel cost assumptions for primary energy sources in 2020 and 2030

Primary Energy	**2020 Fuel Cost**[€/MWh]	**2030 Fuel Cost**[€/MWh]
Nuclear	2.88	2.88
Imported Coal	10.00	7.00
Natural Gas	18.40	18.40
Liquefied Natural Gas	37.00	37.00
Crude Oil	40.00	30.00
Hydro Run off the River	0.00	0.00
Hydro with Reservoir Capacity	0.00	0.00
Mihi Hydro	0.00	0.00
Wind Onshore	0.00	0.00
Wind Offshore	0.00	0.00
Solar Photovoltaic	0.00	0.00
Solar Thermoelectric	0.00	0.00
Solar Thermal	0.00	0.00
Biomass Energy Crops	21.00	21.00
Biomass Agriculture Waste	17.00	17.00
Biomass Forestry Waste	8.00	8.00
Solid Waste	21.00	21.00
Bioethanol Production Inputs	54.00	54.00
Biodiesel Production Inputs	46.00	46.00
Biogas	104.00	104.00

Table 2.6: CAPEX, installed capacity, and conversion losses of conversion technologies (2020–2030)

Conversion Technology	**2020 CAPEX** [€/kW]	**2030 CAPEX** [€/kW]	**Prev. Cap.** [GW]	**Losses** [%]
Nuclear Power	4800	4500	7.40	0.62
Imported Coal Traditional	1450	1450	3.00	0.58
Imported Coal IGCC	1950	1900	3.00	0.52
Imported Coal SCPC	1650	1650	1.00	0.55
Imported Coal SCPC + CCS	3400	2850	0.50	0.64
CCGT Traditional	550	530	26.60	0.42
CCGT + CCS	1750	1500	0.00	0.54
OCGT Traditional	450	450	0.00	0.55
OCGT + CCS	900	750	0.00	0.65
Fuel Oil Traditional	784	784	3.70	0.62
Hydro RoR	1715	1650	2.15	0.00
Hydro w/ Reservoir	2100	2100	12.00	0.00
Hydro Pumping Storage	3804	3804	3.30	0.30
Mini Hydro	1715	1650	0.00	0.00
Wind Onshore	1300	1000	28.00	0.00
Wind Offshore	2800	1900	0.00	0.00
Solar PV Centralised (Tracking)	463	355	8.40	0.00
Solar PV Distributed Industry	645	500	0.00	0.00
Solar PV Distributed Other	645	500	0.00	0.00
Solar Thermoelectric Centralised	3000	2800	2.30	0.00
Solar Thermal Industry	848	848	0.00	0.00
Solar Thermal Other	848	848	0.00	0.00
Biomass Energy Crops Centralised	2517	2517	0.32	0.61
Biomass Agri Waste Centralised	2517	2517	0.68	0.61
Biomass Forestry Waste Centralised	2517	2517	0.00	0.61
Solid Waste	5503	5503	0.70	0.61
CHP Industry (Gas)	1425	1425	2.40	0.26
CHP Other (Gas)	2093	2093	2.40	0.27
CHP Industry (Biomass)	2137.5	2137.5	0.00	0.26
CHP Other (Biomass)	3139.5	3139.5	0.00	0.27
Refinery Low Complexity	114	114	62.20	0.07
Refinery High Complexity	330	330	24.30	0.09
Refinery Very High Complexity	653	653	0.00	0.17
Bioethanol Production Plant	1040	1040	0.40	0.00
Biodiesel Production Plant	510	510	6.70	0.00
Regasification Terminal	35	35	76.00	0.01

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

This chapter is based on the article entitled *"Improving robustness in strategic energy planning: A novel decision support method to deal with epistemic uncertainties"*, authored by Antonio F. Rodriguez-Matas, Pedro Linares, Manuel Pérez-Bravo, and Jose Carlos Romero, and published in *Energy*, Volume 292, April 2024, Elsevier. DOI: 10.1016/j.energy.2024.130463.

3.1 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 (Perez-Arriaga et al., 2008). 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 Appendix 3.A) has shown that, although there is a significant amount of literature dealing with probabilistic uncertainties in energy models, in particular stochastic approaches (e.g. (Kanudia et al., 1998; Usher et al., 2012)), 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) (Moret, Babonneau, et al., 2020a; Patankar et al., 2022), 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 (Marchau et al., 2019), 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 chapter 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 chapter is structured as follows. As a preamble, Section 3.2 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 3.3 introduces the novel robust decision support method. Section 3.4 offers the results of applying and validating the novel methodology to a real-size strategic energy planning model. Section 3.5 presents conclusions and future work.

3.2 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 (Marchau et al., 2019). 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 (Hüllermeier et al., 2021).

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 (Majewski, Wirtz, et al., 2017). Another way of understanding it is as the least sensitive decision to changes in the environment (Rabiee et al., 2018). 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 (Trachanas et al., 2018): 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.

3.2.1 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 (Shapiro et al., 2007), 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 (Soroudi and Amraee, 2013). More detailed information about these methodologies' inputs, advantages, disadvantages and applications can be found in Table 3.1.

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 (Schnaars, 1987). 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 (Moret, Codina Gironès, et al., 2017). 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 (1973), 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 (Gorissen et al., 2015), 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 et al. (2004) (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.

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 (Tutsoy, 2022).

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.

3.2.2 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 (Loulou and Lehtila, 2016). These models usually incorporate uncertainty through stochastic programming, with examples such as those developed for Quebec (Kanudia et al., 1998), the United Kingdom (Usher et al., 2012), and Belgium (Nijs et al., 2011). Some models, such as TIAM, have also incorporated stochastic approaches to deal with uncertain parameters (Loulou, Labriet, et al., 2009). However, models become intractable when they incorporate too many uncertainties, which has led to alternative proposals such as the TEMOA model (Hunter et al., 2013), which uses a Modeling to Generate Alternatives (MGA) approach in order to explore near-optimal solutions (Pfenninger et al., 2014). Other approaches, such as Monte Carlo simulation, have also been used in several models. Some examples can be found in MESSAGE (Gritsevskii et al., 2000), ESME (Pye et al., 2015) and OSeMOSYS (Dreier et al., 2019). Another option is that proposed by trial-and-error models, which has been applied in various case studies, such as the analysis of Jacobson, Krauland, et al. (2022), 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 (Jacobson, Delucchi, et al., 2015). 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. Appendix 3.A 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, Babonneau, et al. (2020a), 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 Appendix 3.B, 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 et al. (2004) is the most widespread, likely because it provides a significant

Table 3.1: Overview of methods to handle uncertainty in energy planning

Type	Method	Input	Advantages	Disadvantages	Applications
Probabilistic	Stochastic Programming	PDF	Easy implementation	Computationally expensive. Large amount of historical data. Able to consider a few uncertainties.	Huang et al. (2016), Kanudia et al. (1998), Loulou, Labriet, et al. (2009), Loulou and Lehtila (2016), and Usher et al. (2012)
	Monte Carlo	PDF	Easy implementation	Computationally expensive. Large amount of historical data. Able to consider a few uncertainties. Slow convergence.	Baležentis et al. (2017), Koltsaklis et al. (2017), and Pilpola et al. (2020)
	Point-estimate	PDF	Very easy implementation	Simplistic method. Large amount of historical data.	Sannigrahi et al. (2020)
	Possibilistic	MF	Converting linguistic knowledge to numerical values	Complex implementation. Historical data and expertise. Ambiguous results.	Erdoğan et al. (2016), Kaya et al. (2019), and Momoh et al. (1995)
	Hybrid	PDF & MF	Dealing with both possibilistic and probabilistic uncertainty types simultaneously	Computationally expensive. Complex implementation. Large amount of historical data.	Soroudi (2012) and Soroudi and Ehsan (2011)
Non-Probabilistic	Interval Analysis	Intervals	Useful when just an interval is available	The correlations among intervals are neglected. Conservative.	Z. H. Fu et al. (2017) and Shaalan et al. (1993)
	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.	Aghahosseini et al. (2023), Gracceva et al. (2013), Hansen et al. (2019), and Lopez-Pena Fernandez (2014)
	IGDT	Forecasted values	Robustness. Accurate for severe uncertainties. Useful when no PDFs or MF available.	Does not find the optimal, but most robust solution. Extremely conservative.	Rabiee et al. (2018)
	Robust Optimization	Uncertainty sets	Robustness. Accurate for severe uncertainties. Useful when no PDFs or MF available.	Conservative.	Moret, Babonneau, et al. (2020a), Moret, Babonneau, et al. (2020b), B. Chen et al. (2014), and Zhong et al. (2021)

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.

3.2.3 Current status and challenges of robust strategic energy planning

The studies conducted by Moret, Babonneau, et al. (2020a) and Patankar et al. (2022) have contributed significantly to the advancement of strategic energy planning models, introducing innovative robust approaches to address uncertainties in a practical manner.

Moret, Babonneau, et al. (2020a) 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. (2022) 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. (2022) 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, Babonneau, et al. (2020a), 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, Babonneau, et al. (2020a): "*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, Babonneau, et al. (2020a) 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. (2022) 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 (Rabiee et al., 2018). 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 (Trachanas et al., 2018). 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 (Inuiguchi et al., 1995).

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.

3.3 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 3.4, employing both a real-size energy model and a simplified version to verify and interpret the results.

3.3.1 Robust optimization in the constraints

As previously argued, the B&S (Bertsimas et al., 2004) 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 T (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 Appendix 3.D.

$$\sum_{g \in \mathrm{GEN}} x_{\mathrm{op}}(g,t) + x_{\mathrm{ens}}(t) \geq \sum_{s \in \mathrm{DS}} D(s,t) \quad \forall t \in \mathrm{TS} \tag{3.1}$$

Equation 3.1 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 $x_{\mathrm{op}}(g,t)$, and the sum of the energy not supplied slack variable $x_{\mathrm{ens}}(t)$.

$$\sum_{g \in \mathrm{CE}} x_{\mathrm{op}}(g,t) + x_{\mathrm{ens}}(t) - \sum_{s \in \mathrm{DS}} D(s,t) - W(t) \cdot \tau - \sum_{s \in \mathrm{DS}} P(s,t) \geq 0 \quad \forall t \in \mathrm{TS} \tag{3.2}$$

$$W(t) + P(s,t) \geq \delta_D(s,t) \quad \forall s \in \mathrm{DS},\ \forall t \in \mathrm{TS} \tag{3.3}$$

The energy demand balance constraint 3.1 is transformed into its robust counterpart in 3.2 and 3.3, 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.

3.3.2 Minimax regret in the objective function

Inuiguchi et al. (1995) 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 et al. (1998) 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 by Mausser et al. (1998) is based on a linear maximization problem, in which uncertain costs are defined as interval coefficients:

$$c \in \Gamma = \left\{ c \in \mathbb{R}^n \;\middle|\; \underline{c}_i \leq c_i \leq \overline{c}_i \quad \text{for } 1 \leq i \leq n \right\},$$

where $\underline{c}_i$ and $\overline{c}_i$ are the lower and upper bounds, respectively, also known as extremals. The uncertainty set for uncertain costs can be defined as:

$$\Psi = \left\{ i \;\middle|\; \underline{c}_i < \overline{c}_i \right\}.$$

The goal is to find $x \in \Omega$ 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 c is:

$$R(c,x) = \max_{y \in \Omega} \left(c^T y - c^T x \right) = \left(\max_{y \in \Omega} c^T y \right) - c^T x.$$

It immediately follows that $y = x_c$, where x_c is the optimal solution under cost vector c.

If

$$R_{\max}(x) = \max_{c \in \Gamma} \{ R(c,x) \}$$

is the maximum regret for x considering any possible uncertain cost c, the objective is to find x^* satisfying:

$$R_{\max}(x^*) \leq R_{\max}(x) \quad \text{for all } x \in \Omega.$$

Therefore, x^* is the optimal solution to the Minimax Regret problem (MMR) (Mausser et al., 1998).

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

$$\begin{aligned}
& \min r \\
\text{s.t.} \quad & c^k x + r \geq c^k x_{c^k} \qquad \forall c^k \in C \\
& x \in \Omega \\
& r \geq 0
\end{aligned} \tag{3.4}$$

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

The set of cost scenarios C needs to be built iteratively. The idea consists of finding the cost scenario that maximizes regret for a candidate solution $\hat{x}$. This is done by solving the Candidate Maximum Regret problem (CMR) (Mausser et al., 1998).

As previously discussed, x^* is the solution that minimizes the maximum regret for all $x \in \Omega$, so $R_{\max}(\hat{x}) \geq R_{\max}(x^*)$ 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 via CMR, as illustrated in Figure 3.1. As soon as the CMR upper bound $R_{\max}(\hat{x})$ is equal to or lower than the MMR lower bound $\hat{r}$, the algorithm has converged to $\hat{x} = x^*$.

However, a significant issue is that CMR results in a quadratic objective function. Mausser et al. (1998) describe a mathematical programming procedure—improving upon the original formulation from (Inuiguchi et al., 1995)—which leads to the following formulation for the CMR problem:

$$\begin{aligned}
& R_{\max}(\hat{x}) \equiv \max \quad \bar{c}z - \underline{c}y \\
\text{s.t.} \quad & x \in \Omega \\
& x + y - z = \hat{x} \\
& y_i - \hat{x}_i b_i \leq 0 && \forall i \in \Psi \\
& z_i - (M_i - \hat{x}_i)(1 - b_i) \leq 0 && \forall i \in \Psi \\
& z_i - y_i \geq -\hat{x}_i && \forall i \notin \Psi \\
& z_i - y_i \leq M_i - \hat{x}_i && \forall i \notin \Psi \\
& y, z \geq 0 \\
& b_i \in \{0, 1\} && \forall i \in \Psi
\end{aligned} \tag{3.5}$$

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

This formulation uses the c-consistency property (Inuiguchi et al., 1995), which limits the consideration of uncertain costs c to only their extremal values. Combined with x-optimality, this allows the decision variable x to be restricted to only those vertices of the feasible region Ω that are optimal under such extremal cost realizations.

Moreover, c-consistency implies that the additional constraints involving y_i, z_i, and b_i are only required for $i \in \Psi$, since the regret term is already linear for certain cost coefficients. However, for simplicity, the equations are included for all i. Note that the regret-maximizing cost vector $\hat{c}$ is set as:

$$\hat{c} = \bar{c} + b_i(\underline{c} - \bar{c}).$$

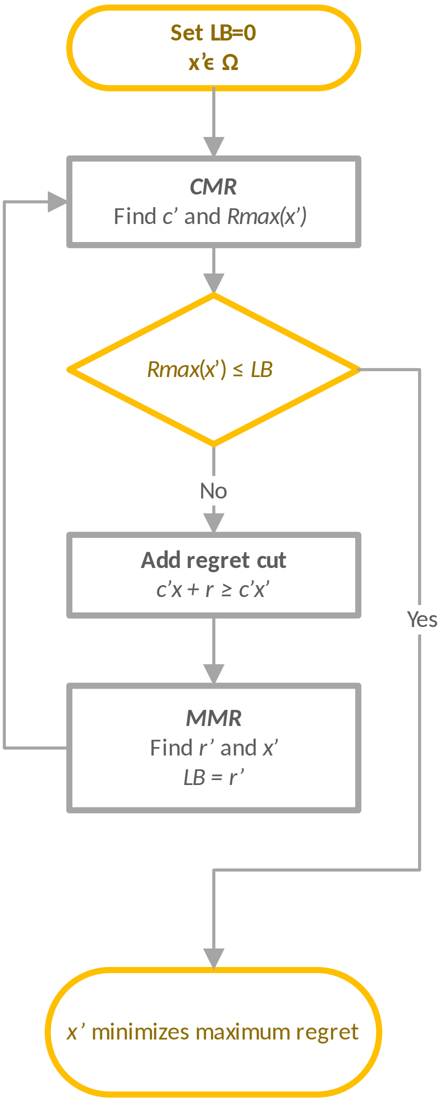

Figure 3.1: Minimax regret algorithm flowchart, which obtains the minimax regret for linear programs with interval objective function coefficients: Lower Bound parameter (LB), Minimizing maximum regret decision (x'), Candidate Maximum Regret problem (CMR), Maximizing cost scenario (c'), Maximum regret (Rmax), Minimax Regret problem (MMR), Minimax regret (r)

Thus, the minimax regret algorithm integrated into the novel decision-making approach is depicted in Figure 3.1. 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.

3.3.3 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.

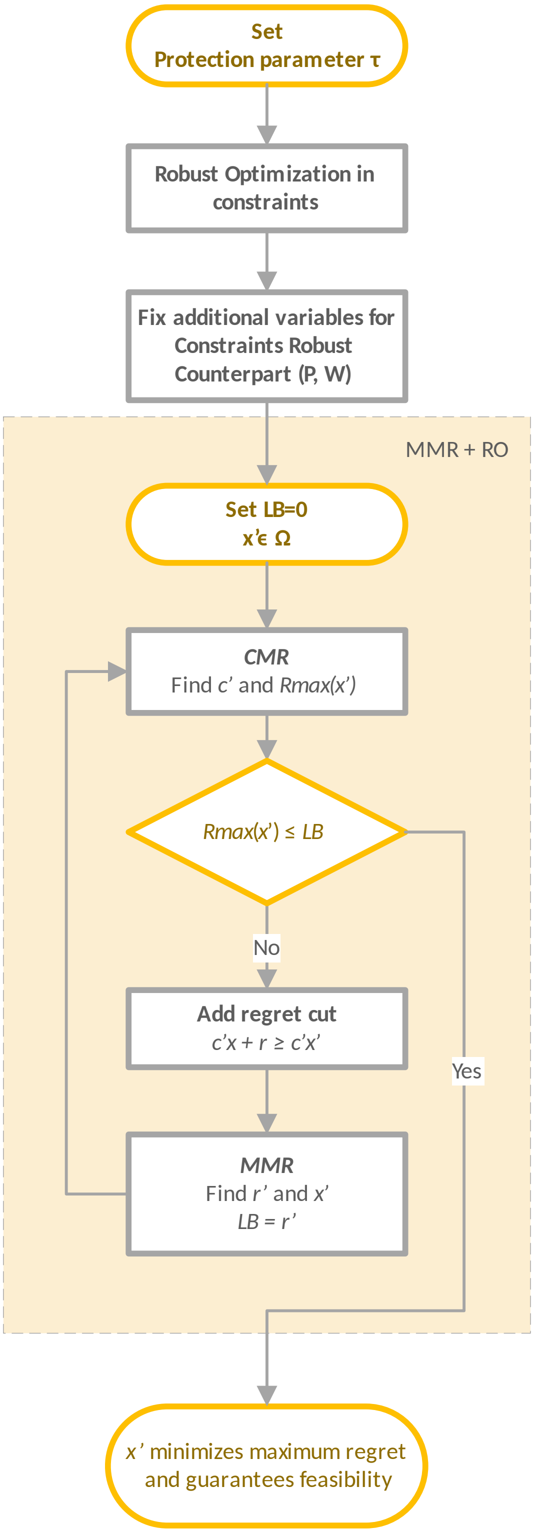

Figure 3.2: Flowchart of the decision support method, which enables the determination of the minimax regret decision for optimality while ensuring feasibility in the constraints: Protection parameter (τ), Robust optimization additional parameters (P, W) Lower Bound parameter (LB), Minimizing maximum regret decision (x'), Candidate Maximum Regret problem (CMR), Maximizing cost scenario (c'), Maximum regret (Rmax), Minimax Regret problem (MMR), Minimax regret (r)

Figure 3.2 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 3.4.

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.

3.4 Assessment of the robust, minimax regret algorithm proposed

The novel decision support method has been implemented in the context of openMASTER[a], a real-size strategic energy planning model similar to MARKAL-TIMES. openMASTER is a bottom-up, partial equilibrium, linear programming (LP) model that operates to facilitate sustainable energy policy analysis. openMASTER seeks to minimize an objective function representing the total private economic costs of energy supply, while conforming to technical and policy limitations, including greenhouse gas emission reduction targets. Further information about the openMASTER model can be found in Chapter 2.

It is worth noting that since openMASTER 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.

3.4.1 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

[a] Although the original version of this work, published in *Energy* (Elsevier), referred to the model as *MASTER*, the model has since been made publicly available under the name *openMASTER*. The version used here is an initial—and therefore more simplified—one compared to the extended formulation presented in Chapter 2. In particular, the exogenous demand corresponds to final energy consumption in each sector.

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 (Moret, Codina Gironès, et al., 2017).

The case study was conducted under a constraint of annual emissions of 29 MtCO_2 from 2050, which aligns with the Long Term Strategy 2050 formulated by the Spanish government for achieving climate neutrality (Gobierno de España, 2020). Additionally, a carbon budget constraint was imposed on all emissions during the 2020-2050 period, i.e., cumulative CO_2 emissions cannot exceed a certain limitation. Detailed information about the calibration of this case study can be found in Appendix 3.D.

In terms of computational load, incorporating the proposed algorithm increases the size of the model substantially, but it is still feasible and solvable within reasonable times. The iterative method (named MMR-RO in Table 3.2), which comprises both MMR and CMR, as presented in section 3.3, 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 $\tau = 0$ is significantly higher than those required for subsequent protection levels, as shown in Table 3.3. 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 3.2: Model 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 3.3: Execution time and iterations for different levels of protection

Tau	**Time (sec)**	**Iterations**
Det	117	N/A
$\tau = 0$	196,479	11
$\tau = 1$	14,506	2
$\tau = 2$	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 3.4. The Price of Robustness (PoR) indicator, presented in (Bertsimas et al., 2004), 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 3.4.2, 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 3.4: 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%
$\tau = 0$	575.74	1.60	0.3%
$\tau = 1$	619.01	44.87	7.8%
$\tau = 2$	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 3.5. 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 $\tau = 0$, 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.

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.

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

Table 3.5: Capacity for energy conversion technologies in the case study of the Spanish energy system

Conversion energy capacity	**2020**	**2050**					
[GW]		Det (Nom.)	$\tau = 0$[b]	$\tau = 1$	$\tau = 2$	Det (Worst)	Det (Best)
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

3.4.2 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 based on Monte Carlo simulation for the detailed problem presented in the case study (section 3.4.1), a simplified version was employed.

The simplified version of the openMASTER model used in this chapter 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 3.6), 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 3.6) 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.

[b] For $\tau = 0$, 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.

Table 3.6: Simulation results for feasibility analysis for different levels of protection

	$\tau = 0$		$\tau = 1$		$\tau = 2$		$\tau = 3$	
	MMR-RO	RO	MMR-RO	RO	MMR-RO	RO	MMR-RO	RO
Infeasibilities [%]	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 3.6 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.

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 3.6, 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 3.3, 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 3.7) is incorporated, and build the payoff matrix, which in turn yields the regret matrix.

Table 3.7 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 3.7) are presented along with its ranking position relative to the other 64 decisions.

Table 3.7: 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 $10^t h$ 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.

3.5 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 chapter 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 chapter 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 (Mausser et al., 1999).

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.

Appendix 3.A: Review of application of uncertainty treatment methods to the main energy models

Authors	Model family	Method	Uncertain parameters	Application	Time dimension
Kanudia et al. (1998)	MARKAL	Stochastic programming	Carbon mitigation measures implementation	Quebec energy-environment system	Multi-stage
Usher et al. (2012)	MARKAL	Stochastic programming	Fossil fuel prices, biomass availability	UK energy system	Two-stage
Loulou and Lehtila (2016)	TIMES	Stochastic programming	Demand, capacities, costs	National energy systems framework	Multi-stage
Nijs et al. (2011)	TIMES	Stochastic programming	Fuel price	Belgium energy system	Static
Loulou, Labriet, et al. (2009)	TIAM	Stochastic programming	Climate sensitivity	Worldwide energy and emissions market	Static
Hunter et al. (2013)	TEMOA	Stochastic optimization	Import prices of coal, oil, diesel and gasoline	Utopia energy system	Two-stage
Gritsevskii et al. (2000)	MESSAGE	Monte Carlo simulation, Own algorithm	Technology costs	Global (single-region) energy system	Two-stage
Pye et al. (2015)	ESME	Monte Carlo simulation	Costs, prices, resource availability	UK energy system	Static
Dreier et al. (2019)	OSeMOSYS	Monte Carlo simulation	Costs, CO_2 emissions, electricity and diesel consumption	Utopia energy systems	Static
Lopez-Pena Fernandez (2014)	MASTER.SO	Scenario analysis	Electricity generation (firmness), hydraulicity	Spanish energy system	Static

Appendix 3.B: 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 dimension
Mulvey et al. (1995)	Own (scenarios)	Energy demand	Power capacity expansion (LP)	Pessimistic Wald (Cost)	Multi-stage
Janak et al. (2007)	Own	Processing time, demand, prices	Chemical plant scheduling (MILP)	Pessimistic Wald (Cost)	Dynamic (continuous-time)
Babonneau et al. (2010)	BT&N, LDR, Own	Pollutant transfer, demand	Environmental and energy planning (LP)	Pessimistic Wald (Cost)	Dynamic (3 periods)
Ribas et al. (2010)	Scenarios (Kouvelis et al., 1997)	Oil production, demand, prices	Oil supply chain planning (LP)	Savage and Pessimistic Wald (Profit)	Two-stage
Hajimiragha et al. (2011)	B&S	Electricity prices	Plug-in Hybrid Electric Vehicles (MILP)	Pessimistic Wald (Cost)	Static
Koo et al. (2011)	Scenarios (C.-S. Yu et al., 2000)	Fuel prices, emission targets	Sustainable energy planning (LP)	Pessimistic Wald (Cost)	Static
Jiang et al. (2012)	B&S, Own	Wind power production	Wind/hydro unit commitment (MILP)	Pessimistic Wald (Cost)	Two-stage
Parisio et al. (2012)	B&S	Conversion efficiencies	Energy hub management (MILP)	Pessimistic Wald (Cost)	Dynamic
L. Zhao et al. (2012)	Own	Wind production	Wind unit commitment (MILP)	Pessimistic Wald (Cost)	Two-stage
Dong et al. (2013)	B&S, Own	Prices, cost, efficiencies	Energy management planning (FRILP)	Pessimistic Wald (Cost)	Dynamic (3 periods)
Street et al. (2014)	ARO	Gen./trans. outages	Electricity market scheduling (MILP)	Pessimistic Wald (Cost)	Static (1 period)
Akbari et al. (2014)	B&S	Demand, fuel costs	Building energy system (MILP)	Pessimistic Wald (Cost)	Static
Yokoyama et al. (2014)	Own	Energy demand	Energy supply systems (MILP)	Savage	Static
Rager (2015)	B&S, Own	Cost, demand, efficiencies	Urban energy system (MILP)	Pessimistic Wald (Cost, CExD)	Static
Grossmann et al. (2015)	LDR	Reserve demand	Air separation unit scheduling (MILP)	Pessimistic Wald (Cost)	Multi-stage
Ruiz et al. (2015)	B&S, ARO, Own	Demand, generator availability	Electricity transmission (bilevel MILP)	Pessimistic Wald (Cost)	Two-stage
Moret, Bierlaire, et al. (2016)	B&S	Fuel prices	Household supply (MILP, conceptual)	Pessimistic Wald (Cost)	Static

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Authors	Method(s)[a]	Uncertain parameters	Application and model type[b]	Criteria and indicator	Time dimensioning
Sy et al. (2016)	Own (Ng & Sy, 2014)	Selling prices, demand	Polygeneration (MILP)	Pessimistic Wald (Profit)	Static
Nicolas (2016)	B&S	Fuel prices, investment cost, climate	Integrated Assessment Model (LP)	Pessimistic Wald (Cost)	Dynamic
Gong et al. (2016)	Own	Feedstock price, biofuel demand	Biomass conversion pathways (MINLP)	Pessimistic Wald (Cost)	Two-stage (ARO)
Majewski, Wirtz, et al. (2017)	Soyster, Own	Demand, fuel prices, emissions	Decentralized energy supply (MILP)	Pessimistic Wald (Cost)	Two-stage
Majewski, Lampe, et al. (2017)	Soyster, Own	Energy demand, fuel prices	Decentralized energy supply (MILP)	Pessimistic Wald (Cost)	Two-stage
Ning et al. (2018)	AARO, Own	Feedstock supply, demand	Process network planning (MILP)	Bi-criterion: Wald and Savage	Two-stage
Caunhye et al. (2018)	ARO	Generator outputs	Power-grid expansion (MILP)	Pessimistic Wald (Cost)	Two-stage
Trachanas et al. (2018)	Own	Energy saving factors	Efficiency strategies (LP)	Savage	Static
C. Chen, Sun, et al. (2019)	Own	Renewables, multi-load demand	Energy hub operation planning	Pessimistic Wald (Cost)	Two-stage
Moret, Babonneau, et al. (2020a)	B&S	Costs, discount, lifetime, demand	Swiss strategic planning (MILP)	Pessimistic Wald (Cost)	Static
Jeong et al. (2020)	B&S	Capacity, power fluctuation	Korean power system planning (LP)	Pessimistic Wald (Cost)	Static
Y. Cao et al. (2020)	B&S	Market price	EV aggregator (MILP)	Pessimistic Wald (Profit)	Static
Moret, Babonneau, et al. (2020b)	B&S	Costs, lifetime, demand, efficiency, renewables	European power planning (MILP)	Pessimistic Wald (Cost)	Static
Xie et al. (2020)	Own (Zeng and L. Zhao, 2013)	Load, traffic demand	Expansion planning (MINLP)	Pessimistic Wald (Cost)	Two-stage

[a] Abbreviations: BT&N = Ben-Tal and Nemirovski (1999), B&S = Bertsimas and Sim (2004), LDR = Linear Decision Rules, ARO = Adjustable Robust Optimization, AARO = Affinely Adjustable RO. "Own" indicates custom robust formulation.
[b] Model types: LP = Linear Programming, MILP = Mixed-Integer Linear Programming, MINLP = Mixed-Integer Nonlinear Programming, FRILP = Fuzzy Radial Interval LP.

Appendix 3.C: The application of the MMR-RO algorithm formulation to the case study of the openMASTER model

Below is the mathematical formulation of the main equations that were modified and added to the openMASTER 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:

$$\mathrm{vGen}_{f,t} + \mathrm{vENS}_{f,t} \geq \sum_{d \in D} \mathrm{pDem}_{d,f,t} \quad \forall f \in F,\ \forall t \in T \tag{3.6}$$

where $f \in F$ represents the final energy vectors, $d \in D$ the demand sectors, and $t \in T$ 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 et al. (2004) method to this balance, the resulting robust counterpart is given by the following two equations:

$$\sum_{g \in G} \mathrm{vGen}_{g,f,t} + \mathrm{vENS}_{f,t} - \sum_{d \in D} \mathrm{pDem}_{d,f,t} - \tau \cdot \mathrm{vZ}_{f,t} - \sum_{d \in D} \mathrm{vP}_{f,d,t} \geq 0 \quad \forall f \in F,\ \forall t \in T \tag{3.7}$$

$$\mathrm{vZ}_{f,t} + \mathrm{vP}_{f,d,t} \geq \mathrm{pDeltaDem}_{f,d,t} \quad \forall f \in F,\ \forall d \in D,\ \forall t \in T \tag{3.8}$$

Equations 3.C and 3.C 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.

$$
\begin{aligned}
\min \text{vTotCost} = \sum_{t \in T} \text{pDisRate}_t \cdot \Big(& \sum_{p \in P} \text{pFuelCost}_{p,t} \cdot (\text{vImp}_{p,t} + \text{vDom}_{p,t}) \\
& + \sum_{g \in G} \text{pFixom}_{g,t} \cdot \text{vTotCap}_{g,t} \\
& + \sum_{g \in G} \text{pVarom}_{g,f} \cdot \text{vGen}_{g,f,t} \\
& + \sum_{g \in G} \text{pCapex}_{g,t} \cdot \text{vNewCap}_{g,t} \\
& + \sum_{g \in G} \text{pDecom}_{g,t} \cdot \text{vDecCap}_{g,t} \\
& + \sum_{f \in F} \text{pENS}_{f,t} \cdot \text{vENS}_{f,t} \\
& + \text{pCO2Exc}_t \cdot (\text{vCapExc}_t + \text{vBudgetExc}_t) \Big)
\end{aligned}
\tag{3.9}
$$

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

Table 3.10: 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	CO_2 excess cost	€/tCO_2e

Table 3.11: 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	tCO_2e
vBudgetExc	Excess emissions beyond the budget limit	tCO_2e

To apply the iterative minimax regret algorithm, it is necessary to generate the set of equations corresponding to 3.4 and 3.5 in section 3.3.2 of this Chapter. The implementation of this methodology to the objective function 3.9 of this version of openMASTER 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

$$\max \ \mathrm{vCMR} \tag{3.10}$$

s.t.

$$\begin{aligned}
\mathrm{vCMR} = \sum_{t\in T} \mathrm{pDisRate}_t \cdot \Big[& \sum_{p\in P} \mathrm{pFuelCost}^{\mathrm{Max}}_{p,t} \cdot (\mathrm{vImp}^{W}_{p,t} + \mathrm{vDom}^{W}_{p,t}) \\
& + \sum_{g\in G} \mathrm{pFixom}_{g,t} \cdot \mathrm{vTotCap}^{W}_{g,t} \\
& + \sum_{g\in G} \mathrm{pVarom}_{g,f} \cdot \mathrm{vGen}^{W}_{g,f,t} \\
& + \sum_{g\in G} \mathrm{pCapex}^{\mathrm{Max}}_{g,t} \cdot \mathrm{vNewCap}^{W}_{g,t} \\
& + \sum_{g\in G} \mathrm{pDecom}_{g,t} \cdot \mathrm{vDecCap}^{W}_{g,t} \\
& + \sum_{f\in F} \mathrm{pENS}_{f,t} \cdot \mathrm{vENS}^{W}_{f,t} \\
& + \mathrm{pCO2Exc}_t \cdot (\mathrm{vCapExc}^{W}_t + \mathrm{vBudgetExc}^{W}_t)\Big] \\
- \sum_{t\in T} \mathrm{pDisRate}_t \cdot \Big[& \sum_{p\in P} \mathrm{pFuelCost}^{\mathrm{Min}}_{p,t} \cdot (\mathrm{vImp}^{Y}_{p,t} + \mathrm{vDom}^{Y}_{p,t}) \\
& + \sum_{g\in G} \mathrm{pFixom}_{g,t} \cdot \mathrm{vTotCap}^{Y}_{g,t} \\
& + \sum_{g\in G} \mathrm{pVarom}_{g,f} \cdot \mathrm{vGen}^{Y}_{g,f,t} \\
& + \sum_{g\in G} \mathrm{pCapex}^{\mathrm{Min}}_{g,t} \cdot \mathrm{vNewCap}^{Y}_{g,t} \\
& + \sum_{g\in G} \mathrm{pDecom}_{g,t} \cdot \mathrm{vDecCap}^{Y}_{g,t} \\
& + \sum_{f\in F} \mathrm{pENS}_{f,t} \cdot \mathrm{vENS}^{Y}_{f,t} \\
& + \mathrm{pCO2Exc}_t \cdot (\mathrm{vCapExc}^{Y}_t + \mathrm{vBudgetExc}^{Y}_t)\Big]
\end{aligned} \tag{3.11}$$

$$\mathrm{vImp}_{p,t} + \mathrm{vImp}^{Y}_{p,t} - \mathrm{vImp}^{W}_{p,t} = \mathrm{pImp}^{\mathrm{MMR}}_{p,t} \tag{3.12}$$

$$\mathrm{vDom}_{p,t} + \mathrm{vDom}^{Y}_{p,t} - \mathrm{vDom}^{W}_{p,t} = \mathrm{pDom}^{\mathrm{MMR}}_{p,t} \tag{3.13}$$

$$\mathrm{vTotCap}_{g,t} + \mathrm{vTotCap}^{Y}_{g,t} - \mathrm{vTotCap}^{W}_{g,t} = \mathrm{pTotCap}^{\mathrm{MMR}}_{g,t} \tag{3.14}$$

$$\mathrm{vGen}_{g,f,t} + \mathrm{vGen}^{Y}_{g,f,t} - \mathrm{vGen}^{W}_{g,f,t} = \mathrm{pGen}^{\mathrm{MMR}}_{g,f,t} \tag{3.15}$$

$$\mathrm{vNewCap}_{g,t} + \mathrm{vNewCap}^{Y}_{g,t} - \mathrm{vNewCap}^{W}_{g,t} = \mathrm{pNewCap}^{\mathrm{MMR}}_{g,t} \tag{3.16}$$

$$\mathrm{vDecCap}_{g,t} + \mathrm{vDecCap}^{Y}_{g,t} - \mathrm{vDecCap}^{W}_{g,t} = \mathrm{pDecCap}^{\mathrm{MMR}}_{g,t} \tag{3.17}$$

$$\mathrm{vENS}_{f,t} + \mathrm{vENS}^{Y}_{f,t} - \mathrm{vENS}^{W}_{f,t} = \mathrm{pENS}^{\mathrm{MMR}}_{f,t} \tag{3.18}$$

$$\mathrm{vCapExc}_{t} + \mathrm{vCapExc}^{Y}_{t} - \mathrm{vCapExc}^{W}_{t} = \mathrm{pCapExc}^{\mathrm{MMR}}_{t} \tag{3.19}$$

$$\mathrm{vBudgetExc}_{t} + \mathrm{vBudgetExc}^{Y}_{t} - \mathrm{vBudgetExc}^{W}_{t} = \mathrm{pBudgetExc}^{\mathrm{MMR}}_{t} \tag{3.20}$$

$$\mathrm{vImp}^{Y}_{p,t} - \mathrm{vB}^{\mathrm{FuelCost}}_{p} \cdot \mathrm{pImp}^{\mathrm{MMR}}_{p,t} \leq 0 \tag{3.21}$$

$$\mathrm{vDom}^{Y}_{p,t} - \mathrm{vB}^{\mathrm{FuelCost}}_{p} \cdot \mathrm{pDom}^{\mathrm{MMR}}_{p,t} \leq 0 \tag{3.22}$$

$$\mathrm{vGen}^{W}_{g,f,t} - \mathrm{vGen}^{Y}_{g,f,t} \geq -\mathrm{pGen}^{\mathrm{MMR}}_{g,f,t} \tag{3.23}$$

$$\mathrm{vENS}^{W}_{f,t} - \mathrm{vENS}^{Y}_{f,t} \geq -\mathrm{pENS}^{\mathrm{MMR}}_{f,t} \tag{3.24}$$

$$\mathrm{vTotCap}^{W}_{g,t} - \mathrm{vTotCap}^{Y}_{g,t} \geq -\mathrm{pTotCap}^{\mathrm{MMR}}_{g,t} \tag{3.25}$$

$$\mathrm{vNewCap}^{Y}_{g,t} - \mathrm{vB}^{\mathrm{Capex}}_{g} \cdot \mathrm{pNewCap}^{\mathrm{MMR}}_{g,t} \leq 0 \tag{3.26}$$

$$\mathrm{vDecCap}^{W}_{g,t} - \mathrm{vDecCap}^{Y}_{g,t} \geq -\mathrm{pDecCap}^{\mathrm{MMR}}_{g,t} \tag{3.27}$$

$$\mathrm{vCapExc}^{W}_{t} - \mathrm{vCapExc}^{Y}_{t} \geq -\mathrm{pCapExc}^{\mathrm{MMR}}_{t} \tag{3.28}$$

$$\mathrm{vBudgetExc}^{W}_{t} - \mathrm{vBudgetExc}^{Y}_{t} \geq -\mathrm{pBudgetExc}^{\mathrm{MMR}}_{t} \tag{3.29}$$

$$\mathrm{vImp}^{W}_{p,t} - (pM - \mathrm{pImp}^{\mathrm{MMR}}_{p,t}) \cdot (1 - \mathrm{vB}^{\mathrm{FuelCost}}_{p}) \leq 0 \tag{3.30}$$

$$\mathrm{vDom}^{W}_{p,t} - (pM - \mathrm{pDom}^{\mathrm{MMR}}_{p,t}) \cdot (1 - \mathrm{vB}^{\mathrm{FuelCost}}_{p}) \leq 0 \tag{3.31}$$

$$\mathrm{vGen}^{W}_{g,f,t} - \mathrm{vGen}^{Y}_{g,f,t} \leq pM - \mathrm{pGen}^{\mathrm{MMR}}_{g,f,t} \tag{3.32}$$

$$\mathrm{vENS}^{W}_{f,t} - \mathrm{vENS}^{Y}_{f,t} \leq pM - \mathrm{pENS}^{\mathrm{MMR}}_{f,t} \tag{3.33}$$

$$\mathrm{vTotCap}^{W}_{g,t} - \mathrm{vTotCap}^{Y}_{g,t} \leq pM - \mathrm{pTotCap}^{\mathrm{MMR}}_{g,t} \tag{3.34}$$

$$\mathrm{vNewCap}^{W}_{g,t} - (pM - \mathrm{pNewCap}^{\mathrm{MMR}}_{g,t}) \cdot (1 - \mathrm{vB}^{\mathrm{Capex}}_{g}) \leq 0 \tag{3.35}$$

$$\mathrm{vDecCap}^{W}_{g,t} - \mathrm{vDecCap}^{Y}_{g,t} \leq pM - \mathrm{pDecCap}^{\mathrm{MMR}}_{g,t} \tag{3.36}$$

$$\text{vCapExc}_t^W - \text{vCapExc}_t^Y \leq pM - \text{pCapExc}_t^{\text{MMR}} \tag{3.37}$$

$$\text{vBudgetExc}_t^W - \text{vBudgetExc}_t^Y \leq pM - \text{pBudgetExc}_t^{\text{MMR}} \tag{3.38}$$

MMR

$$\min \ \text{vRegret} \tag{3.39}$$

s.t.

$$\begin{aligned}
\text{vRegret} + \sum_{t\in T} \text{pDisRate}_t \cdot \Big(& \sum_{p\in P} \text{pFuelCost}_{p,t,k}^{\text{CMR}} \cdot (\text{vImp}_{p,t} + \text{vDom}_{p,t}) \\
& + \sum_{g\in G} \text{pFixom}_{g,t} \cdot \text{vTotCap}_{g,t} + \sum_{g\in G} \text{pVarom}_{g,f} \cdot \text{vGen}_{g,f,t} \\
& + \sum_{g\in G} \text{pCapex}_{g,t,k}^{\text{CMR}} \cdot \text{vNewCap}_{g,t} + \sum_{g\in G} \text{pDecom}_{g,t} \cdot \text{vDecCap}_{g,t} \\
& + \sum_{f\in F} \text{pENS}_{f,t} \cdot \text{vENS}_{f,t} + \text{pCO2Exc}_t \cdot (\text{vCapExc}_t + \text{vBudgetExc}_t)\Big) \\
\geq \sum_{t\in T} \text{pDisRate}_t \cdot \Big(& \sum_{p\in P} \text{pFuelCost}_{p,t,k}^{\text{CMR}} \cdot (\text{pImp}_{p,t,k}^{\text{CMR}} + \text{pDom}_{p,t,k}^{\text{CMR}}) \\
& + \sum_{g\in G} \text{pFixom}_{g,t} \cdot \text{pTotCap}_{g,t,k}^{\text{CMR}} + \sum_{g\in G} \text{pVarom}_{g,f} \cdot \text{pGen}_{g,f,t,k}^{\text{CMR}} \\
& + \sum_{g\in G} \text{pCapex}_{g,t,k}^{\text{CMR}} \cdot \text{pNewCap}_{g,t,k}^{\text{CMR}} + \sum_{g\in G} \text{pDecom}_{g,t} \cdot \text{pDecCap}_{g,t,k}^{\text{CMR}} \\
& + \sum_{f\in F} \text{pENS}_{f,t} \cdot \text{pENS}_{f,t,k}^{\text{CMR}} + \text{pCO2Exc}_t \cdot (\text{pCapExc}_{t,k}^{\text{CMR}} + \text{pBudgetExc}_{t,k}^{\text{CMR}})\Big)
\end{aligned} \tag{3.40}$$

$$\text{vRegret} \geq 0 \tag{3.41}$$

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 $pImp_{p,t}^{MMR}$ represents the resulting value of the variable $vImp_{p,t}$ in the previously solved MMR problem. Similarly, in the MMR problem, the parameter $pImp_{p,t}^{CMR}$ 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 3.3 of this Chapter involves the set of equations 3.10-3.38 and 3.39-3.41 respectively.

Appendix 3.D: Spanish case study calibration

Section 3.4.1 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.

Table 3.12: Fuel cost assumptions for primary energy sources (2020 and 2050)

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

Table 3.13: Assumptions for conversion technologies

Conversion Technology	**2020 CAPEX** [€/kW]	**2050 CAPEX** [€/kW]	**Installed Capacity** [GW]	**Conversion Losses** [%]
Nuclear Power	4800	4500	7.4	0.62
Imported Coal Traditional	1450	1450	3	0.58
Imported Coal IGCC	1950	1900	3	0.52
Imported Coal SCPC	1650	1650	1	0.55
Imported Coal SCPC with CCS	3400	2850	0.5	0.64
CCGT Traditional	550	530	26.6	0.42
CCGT with CCS	1750	1500	0	0.54
OCGT Traditional	450	450	0	0.55
OCGT 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 PV Centralised w/ Tracking	463	355	8.4	0
Solar PV Distributed in Industry	645	500	0	0
Solar PV Distributed in Other Uses	645	500	0	0
Solar Thermoelectric Centralised	3000	2800	2.3	0
Solar Thermal in Industry	848	848	0	0
Solar Thermal in Other Uses	848	848	0	0
Biomass Energy Crops Centralised	2517	2517	0.32	0.61
Biomass Agri. 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 Industry (NG)	1425	1425	2.4	0.26
Cogeneration Other Uses (NG)	2093	2093	2.4	0.27
Cogeneration Industry (Biomass)	2137.5	2137.5	0	0.26
Cogeneration 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

Table 3.14: 2020 Annual final energy demand by sector and vector [GWh/year]

Vector	**Industry: Chemical**	**Industry: Mining, Constructions and Materials**	**Industry: Other**	**Primary Sector**	**Resid. Sector**	**Serv. Sector**	**Transp. Air**	**Transp. Land**	**Transp. Sea**
Biodiesel	4.4	172	233	48.4	–	97.2	–	9476	5.3
Bioethanol	4.4	172	233	48.4	–	97.2	–	9476	5.3
Biomass	57.8	3220	14345	952	29303	1332	–	–	–
Coal	1414	9039	295	862	755	–	–	–	–
Electricity	6131	25462	19045	4804	51087	50197	–	3937	–
Heat Distributed	3065	12731	9522	2402	25543	25098	–	–	–
Natural Gas	30158	44330	23372	2632	34997	27014	–	2777	–
Diesel	477	10069	3619	24032	17355	11860	–	250000	5494
Fuel Oil	404	2076	1133	145	56.1	101	–	6565	–
Gasoline	–	–	24	332	–	406	61.5	62894	–
Kerosene	–	–	–	–	–	–	84475	–	–
LPG	65.7	946	656	696	10471	2154	–	1129	–
Oil Product Other	–	14362	–	–	–	–	–	–	–

4 How energy strategies are shaped by the correlation of uncertainties

This chapter is based on the article entitled *"How energy strategies are shaped by the correlation of uncertainties"*, authored by Antonio F. Rodriguez-Matas, Carlos Ruiz, Pedro Linares, and Manuel Pérez-Bravo, and published in *Applied Energy*, Volume 382, March 2025, Elsevier. DOI: 10.1016/j.apenergy.2024.125257.

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4.1 Introduction

In response to the global climate crisis, numerous countries have pledged to achieve climate neutrality by 2050 as outlined in their Nationally Determined Contributions (NDC). This goal requires a profound transition from fossil fuels to renewable energy sources (Shukla et al., 2022). To meet this target, decision-makers must understand energy systems dynamics and anticipate the consequences of their actions. Strategic energy planning models are crucial for this task (Gambhir, 2019).

However, the energy transition faces significant uncertainties, including the development of key decarbonization technologies (Probst et al., 2021; Way et al., 2022), changes in energy demand behavior (Barrett et al., 2022), geopolitical instability affecting energy and material access (Ruhnau et al., 2023), or climate change impacts (Yalew et al., 2020; Craig et al., 2022). Accounting for these uncertainties in long-term energy planning is essential to avoid wrong decisions and potential lock-ins.

Many planning exercises have tried to address these uncertainties, through different approaches. However, most consider uncertainties as independent factors, which may result in significant errors. Relevant variables in energy planning are usually correlated, making it essential to incorporate these correlations to create coherent scenarios. A significant case is the correlation between uncertain primary energy prices and uncertain investment costs for energy technologies.

On the one hand, primary energy prices, such as natural gas and crude oil, often exhibit high positive correlations due to their substitutability and market indexation (D. Zhang et al., 2018). Therefore, it is important to consider scenarios where fuel prices align with their historical covariance. Ignoring these correlations may lead to incoherent pathway recommendations, such as favoring CNG and LNG as transport fuel substitutes during high petroleum prices, which is unlikely to be an optimal option since crude oil prices significantly impact natural gas prices (Mensi et al., 2021).

Similarly, the investment cost of energy conversion technologies is typically correlated due to shared materials or manufacturing processes. For instance, the use of steam turbines in both combined cycle and nuclear plants mean that an increase in their production costs, driven by rising steel prices, could impact investment costs for both technologies simultaneously. Conversely, technological advancements or economies of scale could reduce costs for both. This interdependency also applies to other technologies sharing components, materials, or manufacturing processes.

Lastly, cross-correlations between primary energy prices and investment costs of energy technologies mainly arise from the use of fossil fuels in various stages of technology production. Fossil fuels are involved in producing basic materials (Gerres, 2022), high-temperature industrial processes (Gailani et al., 2024), transporting technologies (e.g., sea transport from a Chinese factory to a photovoltaic plant site in Spain), and installation (e.g., ships and platforms for offshore wind). Including these cross-correlations provides a more comprehensive consideration of costs across supply chains, adding significant value and coherence to the analysis. Following previous examples, crude oil significantly affects natural gas prices, which in turn impacts steel production costs, affecting the investment costs for both nuclear and combined cycle plants through their reliance on steam turbines.

Thus, incorporating these correlations is crucial for capturing real market dynamics and cascading effects often ignored or treated as independent in energy planning, and hence to design consistent planning strategies.

This importance has already been recognized by several studies in the literature. For instance, Abdalla, Abu Adma, et al. (2020) highlights that including correlations between uncertainties can lead to less conservative outcomes and reduced generation expansion costs. Similarly, M. Cao et al. (2019) emphasizes that assuming independent uncertain parameters, as done in most studies, may lead to suboptimal results, underlining the need to consider correlations to ensure optimal solutions. Furthermore, Roldan et al. (2019) and W. Wang et al. (2021) also discuss the relevance of addressing correlated uncertainties in transmission network planning and the interplay between demand response and renewable energy sources, respectively. Collectively, these studies reinforce the necessity of incorporating correlations to improve the coherence and accuracy of energy planning scenarios.

Despite the importance of considering the correlation between uncertain parameters, the literature review (detailed in Appendix 4.A) shows that most existing energy-related works focusing on them address single subsectors such as electricity: generation expansion planning (Abdalla, Abu Adma, et al., 2020; Abdalla, Smieee, et al., 2020; Dehghan et al., 2016; Lei et al., 2020; Saxena et al., 2018), transmission network expansion planning (Roldan et al., 2019; S. Zhang et al., 2018), demand response planning (Zeng, Y. Liu, et al., 2021), and energy storage planning (M. Cao et al., 2019; Q. Wang et al., 2022). Notably, the work from Patankar et al. (2022) represents the first and only attempt to introduce correlations in strategic energy planning across the entire energy sector. Despite the significant gap this work addresses and its excellent methodological development, it only considers the autocorrelation of uncertainties, i.e., the correlation of a single parameter with its historical values (e.g., natural gas actual price with its past prices). It does not account for correlations between different parameters (e.g., crude oil and natural gas prices) or their cross-correlations (e.g., natural gas prices and combined cycle plant investment costs). It is worth noting that there are also other types of analyses and techniques used in the energy sector to explore relationships and interactions between energy sectors. For example, Input-Output (IO) analysis is one of the techniques used, which helps in understanding economic trends and interdependencies across various industries, providing valuable insights into how sectors influence each other (Shang et al., 2024). However, while these methods are effective for capturing relationships in sectoral dynamics, they do not directly apply to the optimization models typically used in long-term energy planning. Thus, no prior research has incorporated correlations between different uncertain parameters in a strategic energy planning model for multiple energy vectors. This gap likely exists due to the increased complexity of such optimization models and the traditional focus on minimizing computational complexity in energy planning.

Regarding the type of correlations considered in the literature, the vast majority considers uncertainties between (i) renewable generation and electricity demand (Dehghan et al., 2016; Lei et al., 2020; Saxena et al., 2018; Roldan et al., 2019; S. Zhang et al., 2018; Zeng, Y. Liu, et al., 2021; M. Cao et al., 2019; W. Wang et al., 2021; Y. Fu et al., 2021; H. Yu et al., 2022; L. Yu et al., 2020); and (ii.a) renewable generation from different plants (e.g., two PV plants in a different location) (Abdalla, Smieee, et al., 2020; Qiu et al., 2019; Xu et al., 2020), or (ii.b) the generation of different renewable technologies (i.e. PV and wind production) (Abdalla, Abu Adma, et al., 2020; Q. Wang et al., 2022; Zhu et al., 2020). However, correlations between fuel prices and energy technology investment costs have not been studied, despite their significant impact on the energy supply chain.

This study aims to address these gaps by analyzing the effects of incorporating correlations between primary energy prices and investment costs of energy technologies in energy planning. Uncertainties are incorporated in the model by a Robust Optimization (RO) approach. This technique is specifically designed to find optimal solutions that guarantee their feasibility for all possible realization of the uncertain parameters within an uncertainty set Ben-Tal et al. (1998). We focus on polyhedral uncertainty sets Soyster (1973) and Bertsimas et al. (2004) because they are versatile enough to model correlations and uncertainties among historical data, but also because they enable the obtention of tractable deterministic counterparts. However, the most typical data-driven polyhedral uncertainty sets, either fail to capture correlations (e.g. "box" or "budget" uncertainty sets) rendering over-conservative solutions, or result in larger counterpart formulations (e.g. "convex hull" uncertainty set), which are difficult to solve. To this end, in this chapter we employ the methodology proposed by Cheramin et al. (2021) which proposes to reduce the dimension of the polyhedral data driven uncertainty set, and hence improving its computational performance, while keeping the maximum amount of information regarding data correlations. In particular, they propose to use Principal Component Analysis (PCA), a well stablished linear dimensionality reduction technique Wold et al. (1987), that allows identifying the components of the data with that explain most of its variability. Moreover, Cheramin et al. (2021) show how the level of conservatism in the robust solution can be adjusted by including more or less PCA components to define the polyhedral uncertainty set. A case study focused on the decarbonization of the Spanish energy system by 2030 (Gobierno de España, 2021) illustrates the impact of considering these correlations. This case study shows the applicability of this analysis to real-size countries or regions. Furthermore, it addresses an additional complexity arising from the long-term evolution of these correlations: while fossil fuel prices and energy technology investment costs may remain correlated, technological and market developments might allow for their decoupling over time. By modifying these correlations into three scenarios, the study aims to explore how the degree of correlation affects decision strategies, and the impact of fossil fuel prices on renewable energy deployment.

We summarize the key contributions of this chapter as follows:

1. We apply an innovative robust optimization technique based on PCA to a strategic energy planning model, incorporating correlations between different uncertain parameters. According to the literature review, this research is the first to systematically incorporate these correlations within a strategic energy planning model that accounts for several energy vectors.

2. We present a case study focused on the decarbonization of the Spanish energy system in 2030, introducing for the first time the correlations between uncertain fuel prices and energy technology investment costs.

3. By varying the degree of these correlations, we assess the sensitivity of decisions to these correlations and evaluate their impact on the potential decoupling of fossil fuel prices from renewable energy costs.

4.2 Methods

4.2.1 The energy model: openMASTER

This study has been conducted within the framework of openMASTER, an open-source strategic energy planning model. This model can be used as a tool for supporting decision-making about designing public policies and investment pathways in the energy sector. It is especially useful for understanding the functioning of the energy sector as a whole, its vulnerabilities, opportunities, and trade-offs.

openMASTER is a Pyomo-based model. It operates as a dynamic (multi-stage), bottom-up, partial equilibrium, linear programming (LP) model, aiming to meet an exogenous demand for energy services across various sectors. It achieves this by adhering to technical and policy constraints while minimizing a comprehensive objective function that includes total economic costs of energy supply, social costs of greenhouse gas emissions and pollutants, and intangible costs such as discomfort of transport.

The model is built according to a scheme of processes and flows detailed in Figure 2.1 encompassing the entire energy sector, including primary energy import and domestic consumption, energy conversion and storage technologies for final energy production, and supply technologies to provide energy services. The energy services' exogenous demand is characterized using several parameters, including Activity Factors, Demand Characterization, and Macro Data.

The main equations of openMASTER include the objective function, balance equations, storage equations, capacity constraints, and electricity generation reliability constraints. Balance equations ensure the conservation of energy across all processes, while storage and capacity constraints ensure proper performance and operational functionality. The model also integrates constraints to ensure reliability in electricity generation and considers endogenous behavioral measures, capturing the impact of specific social measures across the energy value chain. Emissions accounting and constraints on emissions and carbon budgets further enhance the model's capability for comprehensive energy policy analysis. For a more comprehensive understanding of the openMASTER model, readers are encouraged to refer to Chapter 2.

For this study, a version of openMASTER that incorporates an algorithm based on robust optimization for handling uncertainties (Rodriguez-Matas, Linares, et al., 2024) has been used as a starting point. The model was then modified to include correlations based on the approach by Cheramin et al. (2021), as further explained in the next subsection.

4.2.2 A data-driven robust optimization technique for including correlations

Historically, various methodologies have been employed to address uncertainties in energy planning models. Prominent among these is scenario analysis, which constructs narratives for qualitatively studying uncertainties (Aghahosseini et al., 2023; Gracceva et al., 2013; Hansen et al., 2019; Lopez-Pena Fernandez, 2014); stochastic programming, which assigns probabilities to different potential scenarios (Huang et al., 2016; Loulou, Labriet, et al., 2009; Loulou and Lehtila, 2016); and robust optimization, which develops solutions based on worst-case scenarios, minimax regret, or least sensitivity (Rodriguez-Matas, Linares, et al., 2024; B. Chen et al., 2014; C. Chen, Li, et al., 2012; Zhong et al., 2021). Each approach, despite its merits, relies on constructing representative scenarios, or uncertainty sets, to support decisions but, in general, it is not straightforward to systematically incorporate the inherent correlations between multiple uncertainties. This often results in treating uncertainties as independent phenomena or requires manual handling, such as in scenario analysis.

The literature review shows that some studies have attempted to include correlations through various methodologies. However, none have applied these methods to different parameters in long-term energy planning models, especially in the crucial case of the correlation between fuel prices and technology costs. Popular approaches include the Cholesky Decomposition (Saxena et al., 2018; H. Yu et al., 2022), a mathematical technique that decomposes a covariance matrix into the product of a lower triangular matrix and its transpose, allowing for the construction of a set of correlated random variables. It is mainly reserved for sensitivity analysis and statistical applications, such as Monte Carlo simulations, to explore the range of possible outcomes and assess decision robustness under different scenarios. Additionally, some works utilize Copula functions to generate a joint probability function for two uncertainties initially modeled with independent probability functions (Q. Wang et al., 2022; Y. Fu et al., 2021; L. Yu et al., 2020; Qiu et al., 2019; Zhu et al., 2020; Mu et al., 2022). This approach could be applicable in models based on Distributionally Robust Optimization (Namakshenas et al., 2019), which extends the robust optimization approach by considering the uncertainty of a parameter's distribution function rather than its specific values. However, this technique is less suitable for dealing with epistemic uncertainties found in long-term energy planning, as these involve incomplete knowledge about the future, which traditional probabilistic methods cannot capture. Epistemic uncertainties encompass fundamental gaps in understanding the evolution of complex systems, making it difficult for past behaviors to represent future outcomes accurately.

Lastly, robust optimization, based on the Wald decision criterion, prepares for the most adverse scenarios. A critical requirement within this methodology is the definition of uncertainty sets, outlining the potential range of values for uncertain parameters (Moret, Codina Gironès, et al., 2017). The challenge in incorporating correlations lies precisely in the intricate design of these uncertainty sets. The first robust optimization approach, proposed by Soyster (1973), relies on box uncertainty sets (refer to the black rectangle in Figure 4.1), which represent uncertainties within a rectangular space, resulting in overly conservative outcomes due to the limited correlation space captured. Since then, various techniques have emerged, each attempting to mitigate the conservatism associated with this methodology. One widely adopted approach, proposed by Bertsimas et al. (2004), relies on budget uncertainty sets (refer to the green lozenge in Figure 4.1), which introduce a control parameter to balance robustness and conservativeness, reducing the number of uncertain parameters at their worst realization, but still do not consider correlations between uncertainties. A proposal aiming to incorporate correlations involves defining convex hull uncertainty sets (refer to the red polygon in Figure 4.1), which represent the smallest convex set encompassing all possible scenarios, capturing correlations but at a high computational cost, making them unsuitable for real-size strategic energy models.

A novel methodology, previously unapplied to energy models, presents an opportunity to reconcile reasonable computational costs with the integration of correlations among uncertain parameters. This innovative approach, proposed by Cheramin et al. (2021), is based on Principal Component Analysis (PCA). Unlike traditional robust optimization techniques based on box or budget uncertainty sets, this approach can use historical data to capture the interdependencies among uncertainties to build a more nuanced representation of the un-

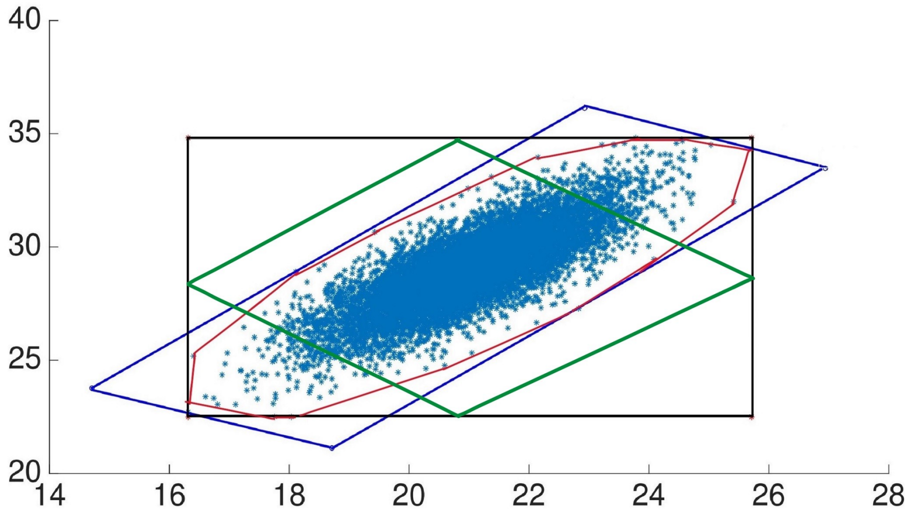

Figure 4.1: Definition of uncertainty sets for two correlated uncertain parameters. Black: Box (Soyster, 1973); Green: Budget (Bertsimas et al., 2004); Red: Convex hull; Blue: PCA-based uncertainty set including correlation (Cheramin et al., 2021). Source:(Cheramin et al., 2021)

certainty set (refer to the blue rectangle in Figure 4.1). Data-driven techniques have gained increasing popularity across various fields, including energy systems, where they enable more precise decision-making under uncertainty Kong et al. (2021), Z. Liu et al. (2023), Ma et al. (2022), and Yin et al. (2022). Therefore, PCA helps develop data-driven polyhedral uncertainty sets that address the limitations of conventional polyhedral sets by capturing the correlations and allowing direct trade-offs between tractability and conservativeness: incorporating more principal components can pose additional challenges in computational complexity, but in exchange, it yields a more robust solution.

Therefore, this PCA-based technique offers the potential to design robust decisions that address uncertainties while incorporating inherent correlations and maintaining computational feasibility. However, due to its novelty, it has only been used illustratively in the original work by Cheramin et al. (2021) showing simple examples of the formulation for the knapsack problem and the power grid problem. It has never been applied in a real case study analysis of investment uncertainty, or in a full-scale energy model. This study aims to bridge this gap by applying it to achieve robust decisions in strategic energy planning, aligning this methodological advance with its practical application.

Applying this method to the openMASTER model involves making the necessary modifications for its implementation. These modifications involved applying the scenario-induced uncertainty set proposed by Cheramin et al. (2021)[a]:

$$\mathcal{U}_{\mathrm{PCA}}(\mathcal{S}, m_1) = \left\{ \boldsymbol{u} : \boldsymbol{u} = \bar{\boldsymbol{s}} + \sum_{i=1}^{m_1} \left(\alpha_i \left(\frac{\overline{\omega}_i}{\|\boldsymbol{d}_i\|} \boldsymbol{d}_i \right) + (1-\alpha_i) \left(\frac{\underline{\omega}_i}{\|\boldsymbol{d}_i\|} \boldsymbol{d}_i \right) \right) + \sum_{i=m_1+1}^{m} \frac{\overline{\omega}_i + \underline{\omega}_i}{2\|\boldsymbol{d}_i\|} \boldsymbol{d}_i,\ 0 \le \alpha_i \le 1,\ \forall i \in [m_1] \right\},$$

where

$$\overline{\omega}_i = \max_{j=1}^{N} \left\{ \frac{\boldsymbol{s}_{j0} \cdot \boldsymbol{d}_i}{\|\boldsymbol{d}_i\|} \right\} \in \mathbb{R}, \quad \text{and} \quad \underline{\omega}_i = \min_{j=1}^{N} \left\{ \frac{\boldsymbol{s}_{j0} \cdot \boldsymbol{d}_i}{\|\boldsymbol{d}_i\|} \right\} \in \mathbb{R},$$

[a]Following notation from Cheramin et al. (2021), we denote scalar values by non-bold symbols, e.g., m_1, while we represent vectors by bold symbols in the column form (e.g., $\boldsymbol{u} = (u_1, \ldots, u_m)^\top$). Italic subscripts represent indices, e.g., c_g, while non-italic subscripts indicate simplified specifications, e.g., $\mathcal{U}_{\mathrm{PCA}}$. Symbol $\|\cdot\|$ denotes the Euclidean norm. The number of uncertain parameters, i.e., the size of random variable vector, is denoted by m and $\boldsymbol{u} = (u_1, \ldots, u_m)^\top \in \mathbb{R}^m$ represents the random variable vector. We adopt N to denote the number of available scenarios for $\boldsymbol{u}$. Symbol $\mathcal{S}$ represents the set of the N scenarios, where each scenario is denoted by $\boldsymbol{s}_j \in \mathbb{R}^m$, i.e., $\boldsymbol{s}_j \in \mathcal{S},\ \forall j \in [N]$. The number of utilized principal components in the scenario-induced uncertainty set is indicated by m_1.

meaning $(\frac{\overline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i)$ and $(\frac{\underline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i)$ are the largest and smallest projected centered scenarios onto the principal direction $\boldsymbol{d}_i$, respectively. The sample mean $\bar{\boldsymbol{s}}$ is added to $\mathcal{U}_{\text{PCA}}(\mathcal{S}, m_1)$ because the scenarios have already been centered at $\bar{\boldsymbol{s}}$.

This uncertainty set is applied to the uncertain parameters of primary energy prices and investment costs of energy technologies. These parameters are part of the objective function. Thus, Equation 4.1 has been modified, representing the annual cost variable affected by these uncertainties. This annual cost variable is integrated into the objective function in the openMASTER model:

$$\mathbf{vUncCost}_y = pYrGap \cdot \sum_{pe,s,d,h} \mathbf{pUnc}_{pe,y} \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce} \mathbf{pUnc}_{ce,y} \cdot \mathbf{vCENewCap}_{ce,y} \tag{4.1}$$

where **pUnc** represents both the primary energy price for the subset *pe* (i.e., Primary Energy) and the investment cost of energy technologies *ce* (i.e., Conversion Energy technologies). As these two subsets are part of the same parameter, they are indicated by subscripts in the equation. The parameter $pYrGap$ is a scalar representing the year gap for which each representative year of the model is solved, and for which operating costs, including the primary energy consumed, must be summed. In this case study, the gap used is 5 years. Regarding the variables, **vQPEImp** and **vQPEDom** are the imported and domestically consumed primary energy, respectively. The variable **vCENewCap** is the newly installed capacity of energy conversion technologies. The subscripts y, s, d, and h represent the temporal subsets year, season, day, and hour, respectively, given that openMASTER has been configured to work for this case study with a temporal horizon from 2020 to 2030, with four seasons and one representative day per season with 24 hours. In total, 288 time slices.

The following provides a step-by-step development of the mathematical formulation resulting from the application of the PCA-based uncertainty set (refer to Equations 4.3 and 4.4) to the uncertainties in Equation 4.2 of the objective function[b].

$$\max_{\mathbf{pUnc}\in\mathcal{U}_{pca}} pYrGap \cdot \sum_{pe,s,d,h} \mathbf{pUnc}_{pe,y} \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce} \mathbf{pUnc}_{ce,y} \cdot \mathbf{vCENewCap}_{ce,y} \tag{4.2}$$

s.t.

$$\boldsymbol{u}_m = \bar{\boldsymbol{s}}_{unc} + \sum_{m=1}^{m_1}\left(\alpha_m \gamma^{up}_{m,unc} + (1-\alpha_m)\gamma^{do}_{m,unc}\right) + \sum_{m=m_1+1}^{M} \rho_{m,unc},\; unc \in (pe \cup ce) \tag{4.3}$$

$$0 \leq \alpha_m \leq 1 \tag{4.4}$$

where $\gamma^{up}_{m,unc} = \left(\frac{\overline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i\right)_{unc}$ and $\gamma^{do}_{m,unc} = \left(\frac{\underline{\omega}_i}{\|\boldsymbol{d}_i\|}\boldsymbol{d}_i\right)_{unc}$.

The following maximization problem is obtained by applying 4.3 to 4.2:

$$\begin{aligned}\max_{\alpha_m} pYrGap \cdot \sum_{pe,s,d,h} (\bar{s}_{pe} + \sum_{m=1}^{m_1}\left(\alpha_m\gamma^{up}_{m,pe} + (1-\alpha_m)\gamma^{do}_{m,pe}\right) + \sum_{m=m_1+1}^{M} \rho_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} \\ +\mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce}(\bar{s}_{ce} + \sum_{m=1}^{m_1}\left(\alpha_m\gamma^{up}_{m,ce} + (1-\alpha_m)\gamma^{do}_{m,ce}\right) + \sum_{m=m_1+1}^{M} \rho_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}\end{aligned} \tag{4.5}$$

Factoring out α_m, we obtain the following equation with only the elements that depend on this variable:

[b] The following equations are shown to illustrate the key mathematical modifications introduced to incorporate the PCA-based uncertainty set. They represent only the modified or additional constraints required to define the robust formulation under correlated uncertainties. These expressions do not constitute the complete energy system optimization model, which also includes energy balances, investment dynamics, and operational constraints, among many other equations. For a full understanding of the model's mathematical structure, readers are referred to Chapter 2, which presents the core formulation of openMASTER. The complete code and mathematical formulation are publicly available in the project's open repository.

$$\max_{\alpha_m} \sum_{m=1}^{m_1} \alpha_m \cdot (pYrGap \cdot \sum_{pe,s,d,h} (\gamma^{up}_{m,pe} - \gamma^{do}_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce} (\gamma^{up}_{m,ce} + -\gamma^{do}_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}) \tag{4.6}$$

Considering the dual problem of minimizing the negative of equation 4.6, including constraint 4.4, results in:

$$\max \beta_m \tag{4.7}$$

s.t.

$$-\beta_m \leq -(pYrGap \cdot \sum_{pe,s,d,h} (\gamma^{up}_{m,pe} - \gamma^{do}_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce} (\gamma^{up}_{m,ce} + -\gamma^{do}_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}) \tag{4.8}$$

$$\beta_m \geq 0 \tag{4.9}$$

Applying the Strong Duality Theorem:

$$\sum_{m=1}^{m_1} \beta_m = \sum_{m=1}^{m_1} \alpha_m \cdot (pYrGap \cdot \sum_{pe,s,d,h} (\gamma^{up}_{m,pe} - \gamma^{do}_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce} (\gamma^{up}_{m,ce} + -\gamma^{do}_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}) \tag{4.10}$$

$$0 \leq \alpha_m \leq 1 \tag{4.11}$$

$$\beta_m \geq (pYrGap \cdot \sum_{pe,s,d,h} (\gamma^{up}_{m,pe} - \gamma^{do}_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce} (\gamma^{up}_{m,ce} + -\gamma^{do}_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}) \tag{4.12}$$

Substituting into the original problem, the following equations result from applying the PCA-based uncertainty set:

$$\begin{aligned} \mathbf{vUncCost}_y = \sum_{m=1}^{m_1} \beta_m + (pYrGap \cdot \sum_{pe,s,d,h} (\bar{s}_{pe} + \sum_{m=1}^{m_1} \gamma^{do}_{m,pe} + \sum_{m=m_1+1}^{M} \rho_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) \\ + \sum_{ce} (\bar{s}_{ce} + \sum_{m=1}^{m_1} \gamma^{do}_{m,ce} + \sum_{m=m_1+1}^{M} \rho_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}) \end{aligned} \tag{4.13}$$

s.t.

$$\beta_m \geq (pYrGap \cdot \sum_{pe,s,d,h} (\gamma^{up}_{m,pe} - \gamma^{do}_{m,pe}) \cdot (\mathbf{vQPEImp}_{pe,y,s,d,h} + \mathbf{vQPEDom}_{pe,y,s,d,h}) + \sum_{ce} (\gamma^{up}_{m,ce} + -\gamma^{do}_{m,ce}) \cdot \mathbf{vCENewCap}_{ce,y}) \tag{4.14}$$

$$\beta_m \geq 0 \tag{4.15}$$

Thus, Equation 4.13 is integrated into the objective function. Additionally, Equations 4.14 and 4.15 are constraints that have been incorporated into the model as a result of the mathematical development stemming from the application of the PCA-based uncertainty set.

4.2.3 Methodological procedure to apply the PCA-based uncertainty set to an energy model

The application's steps are shown in the flowchart in Figure 4.2. Starting with the correlated data, historical data must be collected and preprocessed in order to apply PCA, which reduces the dimensionality of the data matrix and generates the covariance matrix, eigenvectors, and eigenvalues. At this point, the number of principal components is determined to introduce the appropriate uncertainty set into the model. As mentioned earlier, the decision on the number of components allows the decision-maker to balance the trade-off between tractability and conservativeness: incorporating more principal components can increase computational complexity, but in return, it provides a more robust solution. This uncertainty set, with the selected number of principal components, is then incorporated into the energy model. In our case, which considers correlated uncertainties in the objective function, this equation is modified as detailed in the step-by-step formulation in the previous subsection. Once the results of applying this methodology are obtained, the analysis may prompt the decision-maker to consider increasing the number of principal components based on their conclusions. This process can be repeated, modifying the number of components as needed. In this way, a robust strategy is developed that not only protects against uncertainties but also accounts for the correlations between them.

It is important to note that during the data preprocessing stage, two key modifications can be applied to tailor the methodology to future trends. First, the correlation matrix can be adjusted to reflect updated correlation levels between pairs of uncertain parameters, allowing for the incorporation of potential changes in their relationships. Second, the mean values used to construct the uncertainty set, represented by the parameter $\bar{\mathbf{s}}_{unc}$, can be updated based on projected trends, ensuring the methodology aligns with forward-looking scenarios.

4.3 Case study

The case study examines the correlations between fuel prices and investment costs in energy technologies. Although the correlations of all fuels and technologies are considered, the study places special emphasis on fossil fuels and renewable technologies, as these are modified to create scenarios based on different levels of correlation. The objective is to understand how accounting for these correlations affects decision-making and how changes in these correlations impact the deployment of renewable energy sources.

While the analysis could be applied to any country or region, it focuses on the decarbonization of the Spanish energy system, which, in our opinion, provides a very interesting setting for this analysis. Spain features a relatively large and diverse energy system, rich in renewable resources, thus helping to show the applicability of our methodology to a real national energy planning exercise, and also showing the interactions among the many different technologies that may play a role in the energy transition. This, we believe, helps in generalizing the conclusions obtained in the study to other regions. Furthermore, Spain is already undergoing an ambitious transformation of its energy system, with a large share of renewables, and so the interactions and correlations, and their impacts, are better observed compared to other countries with lower shares of these technologies.

This case study aligns with the national CO_2 emission targets for 2030 as outlined in the Spanish National Energy and Climate Plan (NECP). The base year for calibration is 2020, with detailed calibration information provided in Appendix 4.B. As noted earlier, the data preprocessing stage allows for tailoring the methodology to future trends by updating the mean values and correlation levels. For this case study, the mean values used to construct the correlated uncertainty sets ($\bar{\mathbf{s}}_{unc}$) have been updated to reflect the expected projections of uncertainties for 2030. The number of principal components m_1 is 10.

The correlation matrix has also been adjusted to explore three different scenarios, capturing varying levels of correlation between uncertain parameters and evaluating their impact on investment strategies (correlation values are provided in Appendix 4.C):

- Uncorrelated scenario: This scenario uses the budget-based robust optimization technique proposed by Bertsimas et al. (2004), assuming no correlations. It serves as a baseline for comparison with other scenarios, providing a reference point to evaluate the impact of accounting for correlations.

- Positive correlation scenario: Historical data point to a positive correlation between primary energy prices and technology investment costs. In this scenario, this correlation is adjusted with a coefficient of 0.5. This scenario assumes that increases (or decreases) in fossil fuel prices lead to corresponding increases (or decreases) in renewable investment costs due to higher (or lower) costs associated with materials, production, transportation, and installation processes reliant on fossil fuels.

- Negative correlation scenario: This approach sets correlation coefficients to -0.5, indicating an inverse relationship: High (or low) fossil fuel prices accelerate (or slow down) the learning curve of renewables, reducing (or increasing) their costs and enhancing (or worsening) their competitiveness through greater (or lesser) R&D efforts.

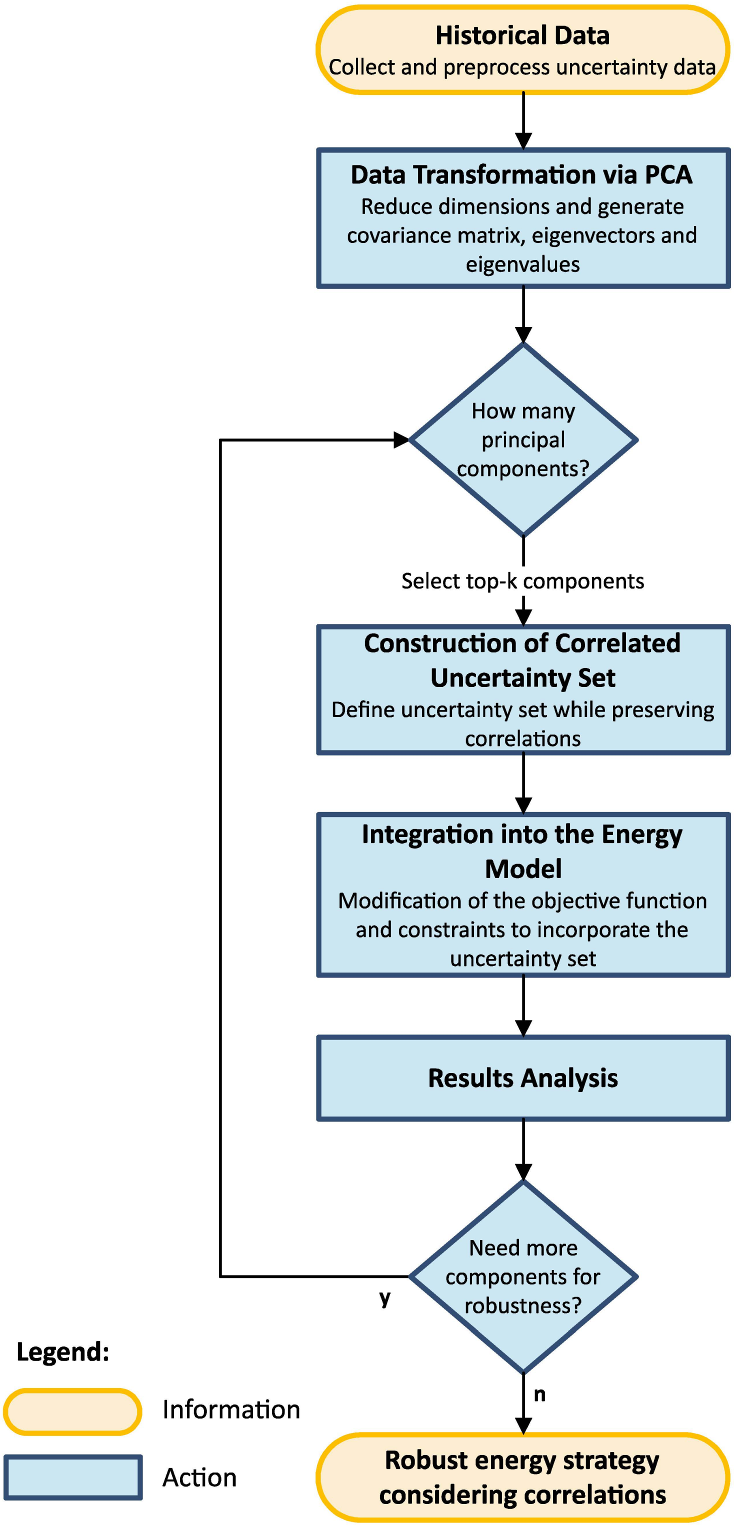

Figure 4.2: Flowchart illustrating the step-by-step application of PCA-based uncertainty set in an energy model

Please note that while these scenarios offer a basic framework, real-world correlations are more nuanced, with coefficients ranging from -1 to 1. The selected correlation coefficients are designed to be representative of their corresponding scenarios and provide meaningful insights. Additionally, we ran other scenarios with different correlation levels, and the results did not show significant differences to justify their inclusion for interpreting the differences between positive, negative, and no correlation scenarios. Therefore, to facilitate the analysis and the drawing of conclusions, these additional scenarios were not included.

Therefore, these scenarios provide a comprehensive view of how different correlations can influence the deployment of renewable energy technologies for achieving the decarbonization goals of Spain by 2030.

4.4 Results

The uncorrelated scenario serves as a baseline for comparison, with results for positive and negative correlations presented against it. However, common elements across scenarios are worth analyzing, as they reveal consistent patterns and useful insights regardless of correlation assumptions.

On the one hand, Table 4.1 highlights a significant reliance on gas power plants across all scenarios. This dependence on fossil fuel technologies can be attributed to reduced nuclear capacity in all scenarios, falling below 2 GW, and to the firmness and adequacy constraints of the openMASTER model, which require backup for increased variable capacity from wind and solar sources. To mitigate emissions from the electric mix, Carbon Capture and Storage (CCS) technologies play a notable role in reducing emissions from gas-based technologies in all scenarios.

Regarding renewable energies, hydroelectric capacity shows minimal expansion due to geographical constraints on maximum capacity. Pumped hydro also increases marginally across all scenarios, likely due to high costs of new capacity, which reduce its competitiveness compared to gas power plants, a trend expected to continue through 2030. Additionally, all three scenarios show a clear preference for wind power over solar. This preference may stem from the better adaptation of wind power's generation profile to demand, hence reducing the need for backup.

Concerning CO_2 emissions in 2030, total emissions are nearly identical across scenarios, around 100 Mt, complying with the emission cap set, as depicted in Figure 4.5. However, significant differences exist in the sectoral distribution of these emissions, particularly affecting the energy generation and transportation sectors.

Under the scenario in which we assume a **positive correlation**, the strategy varies notably from the uncorrelated baseline. It exhibits higher crude oil refinery capacity and minimal biofuel refining capacity, indicating a greater reliance on oil derivatives. This is supported by higher consumption of oil derivatives and natural gas, which together account for nearly 60% of the final energy mix, as depicted in Figure 4.3. In contrast, the uncorrelated baseline scenario relies more on biofuels, displacing both fossil fuels and conventional electricity generation.

In the transportation sector, which accounts for the highest greenhouse gas emissions in Spain, the total final energy consumption indicates a strong preference for emission reduction through natural gas and electrification over biofuels, as shown in Figure 4.4. However, it exhibits around 10 TWh higher consumption of oil derivatives compared to the uncorrelated baseline, as well as the highest natural gas consumption, leading to the highest emissions in this sector. This underscores the greater competitiveness of fossil fuels in a scenario where

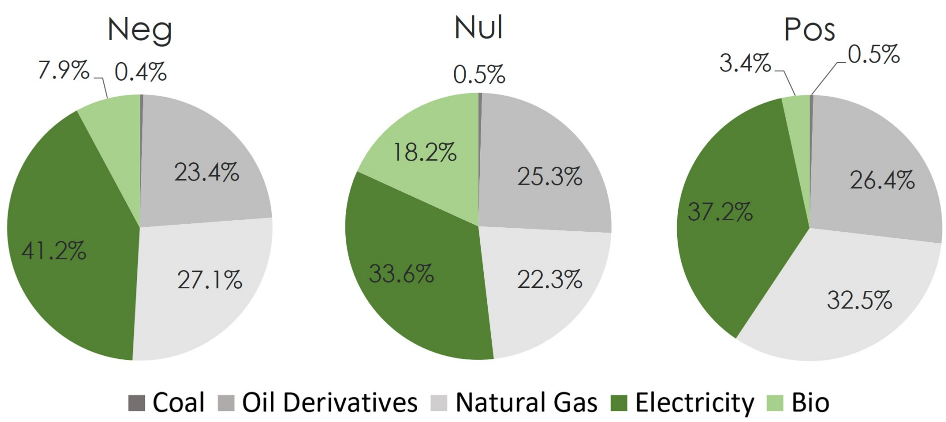

Figure 4.3: Final energy mix in 2030 as a percentage of total final energy consumption. Final energy vectors are aggregated into categories

Conversion energy capacity [GW]	**2020**	**2030**		
		Neg	**Unc**	**Pos**
Nuclear	7.4	1.9	1.9	1.9
Coal	10.2	0	0	0
CCGT	26.6	18.8	16.4	13.1
CCGT+CCS	-	14	7.7	12.1
OCGT	-	8.7	6	9.5
OCGT+CCS	-	0	0	0
Fuel Oil	3.7	0	0	0
Hydro	14	14	14	14
Wind Onshore	26.7	90.8	67.6	75.7
Wind Offshore	-	3	3	0
Solar PV	11	40.3	30.7	18.7
Solar Th	2.3	0	0	0.6
Biomass PP	1.4	0	0	0
Pumping storage	6.4	6.5	6.5	6.5
CHP	5.5	0	0	0
TOTAL ELECT	**115**	**198**	**153.7**	**152**
Oil Refinery	28	24	24.5	26.1
Biofuel	7	4.4	14.3	0.1
Regasification	76	81.5	48.2	75.2

Table 4.1: Capacity of installed energy conversion technologies (GW). The heatmap colors facilitate comparison between the three scenarios (Neg: Negative correlation scenario; Unc: Uncorrelation scenario; Pos: Positive correlation scenario) by highlighting the relative capacities within each technology using an orange gradient. Abbreviations: Spanish National Energy and Climate Plan (NECP), Combined Cycle Gas Turbine (CCGT), Carbon Capture and Storage (CCS), Open Cycle Gas Turbine (OCGT), Photovoltaic (PV), Thermosolar (Th), Power Plant (PP), Combined Heat and Power (CHP), Total electricity generation capacity (TOTAL ELECT).

Final energy [TWh]	**2030**		
	Neg	**Unc**	**Pos**
Coal	3.0	3.0	3.0
Fuel Oil	2.6	2.9	2.9
Diesel	101.2	112.2	109.5
Gasoline	39.6	27.4	39.2
Kerosene	11.5	13.6	12.4
LPG	1.0	1.1	1.1
Oil Others	9.5	10.4	10.2
Natural Gas	191.4	147.8	215.9
Biomass	54.7	27.4	22.2
Biofuel	1.0	93.1	0.4
Electricity	291.6	222.5	247.0

Table 4.2: Total annual consumption detailed for final energy vectors for 2030 (TWh). The heatmap colors facilitate comparison between the three scenarios (Neg: Negative correlation scenario; Unc: Uncorrelation scenario; Pos: Positive correlation scenario) by highlighting the relative capacities within each technology using an orange gradient. Abbreviations: Liquified Petroleum Gas (LPG), Other petroleum derivatives (Oil Others).

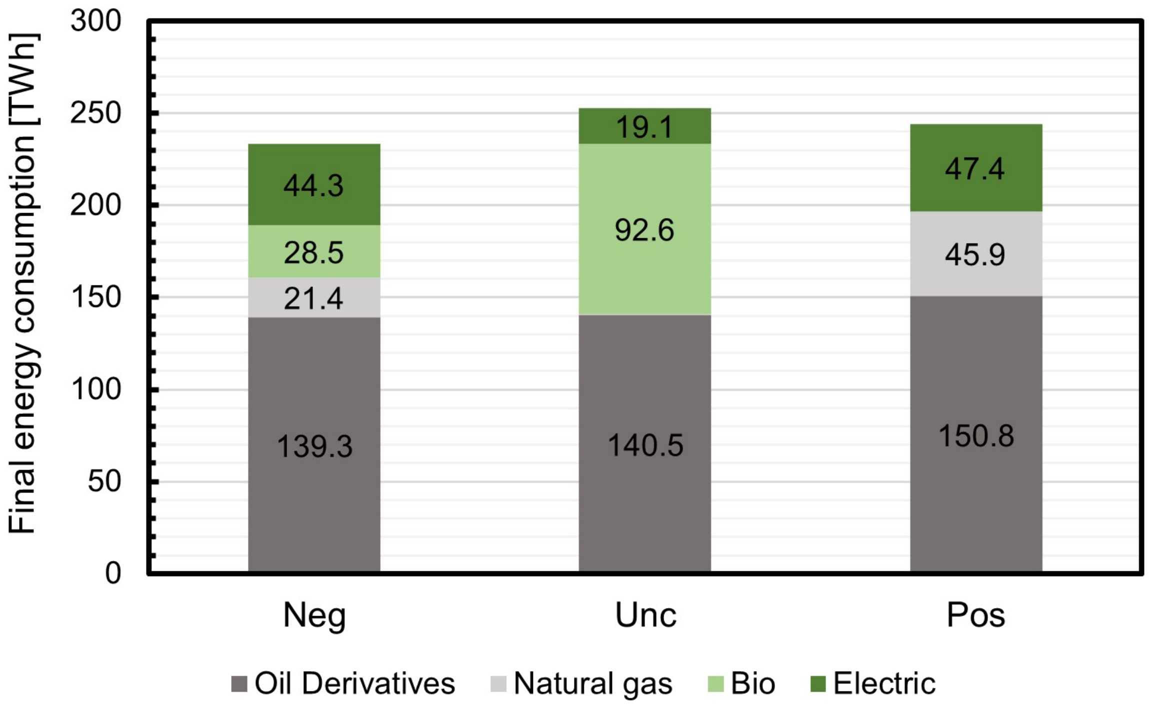

Figure 4.4: Annual consumption of final aggregated energy vectors in the transportation demand sector for 2030 (TWh).

the costs of renewables increase in tandem with them: EVs become more expensive to operate if the renewable electricity mix also becomes costlier, transmitting these costs and giving fossil fuels a competitive advantage. This translates directly to the car fleet, with a preference for PHEVs to electrify part of the mobility and greater use of natural gas in ICEVs. On the contrary, the reliance on biofuels in the uncorrelated baseline scenario represents a clear preference for ICEV.

Renewable energy deployment in this scenario is the lowest, with a combined wind and solar capacity of 94.4 GW, compared to 101.3 GW in the uncorrelated baseline, as observed in Table 4.1. Paradoxically, it accounts for the lowest emissions in the energy generation sector. This can be attributed to the electricity consumption being approximately 45 TWh lower than in the negative correlation scenario, reducing overall emissions despite a lower renewable share. Additionally, a greater share of CCS provides lower-emission electricity backup, especially important given the reduced nuclear capacity and minimal hydropower growth. This adjustment in the electricity sector compensates for higher emissions in the transportation sector, which heavily relies on fossil fuels, thus meeting the 2030 emissions target.

An interesting phenomenon when assuming a positive correlation is the absence of offshore wind, in contrast to the other two scenarios where the maximum allowed capacity of 3 GW is installed, aligned with NECP planning due to licensing constraints (Gobierno de España, 2021). This can be explained by the significant correlation between offshore wind deployment and crude oil prices (Energy, 2020): offshore wind and oil industries compete for vessels, oil majors' investments in offshore wind are negatively driven by the price of oil, and the price of oil influences the cost of transport fuel, steel, and copper. This, again, underscores the importance of considering correlations and their impact on decision-making.

If a **negative correlation** scenario is assumed, the investment strategy contrasts sharply with both the uncorrelated and positive correlation scenarios. It features the highest level of electrification, approaching nearly 300 TWh annually, as observed in Table 4.2. This electrification strategy is strongly complemented by the highest deployment of wind and solar at 134.1 GW aggregated, marking a nearly 40 GW difference compared to the other scenarios, as presented in Table 4.1. However, higher capacity in combined cycle gas turbines enhances firm capacity and supports increased variable installed capacity, resulting in the highest total installed capacity in the electricity sector among the scenarios. This is consistent with the greater electrification of demand in this

Car fleet [Million vehicles]	2030		
	Neg	Unc	Pos
ICEV	11.7	18.1	11.7
PHEV	0.3	0.0	2.3
EV	5.6	0.0	3.5

Table 4.3: Car fleet in 2030 (Millions of Vehicles). The heatmap colors facilitate comparison between the three scenarios (Neg: Negative correlation scenario; Unc: Uncorrelation scenario; Pos: Positive correlation scenario) by highlighting the relative number of vehicles within each row using an orange gradient. Abbreviations: Internal Combustion Engine Vehicle (ICEV), Plug-In Hybrid Electric Vehicle (PHEV), Electric Vehicle (EV).

scenario. Nevertheless, this scenario exhibits the highest emissions in the energy generation sector, primarily due to the lower capacity of CCS for backup and significantly higher electricity consumption: despite having the largest share of renewables in the electricity mix, it is not enough to offset the increased generation.

This electrification, when assuming this negative correlation scenario, primarily occurs in the transportation sector, resulting in a more diversified mix of energy vectors. Specifically, natural gas and biofuels, though less prevalent than in other scenarios, play significant roles. The car fleet predominantly favors EVs over PHEVs. Additionally, ICEVs increase the use of natural gas and biofuels, which is consistent with the overall energy consumption patterns of the transportation sector.

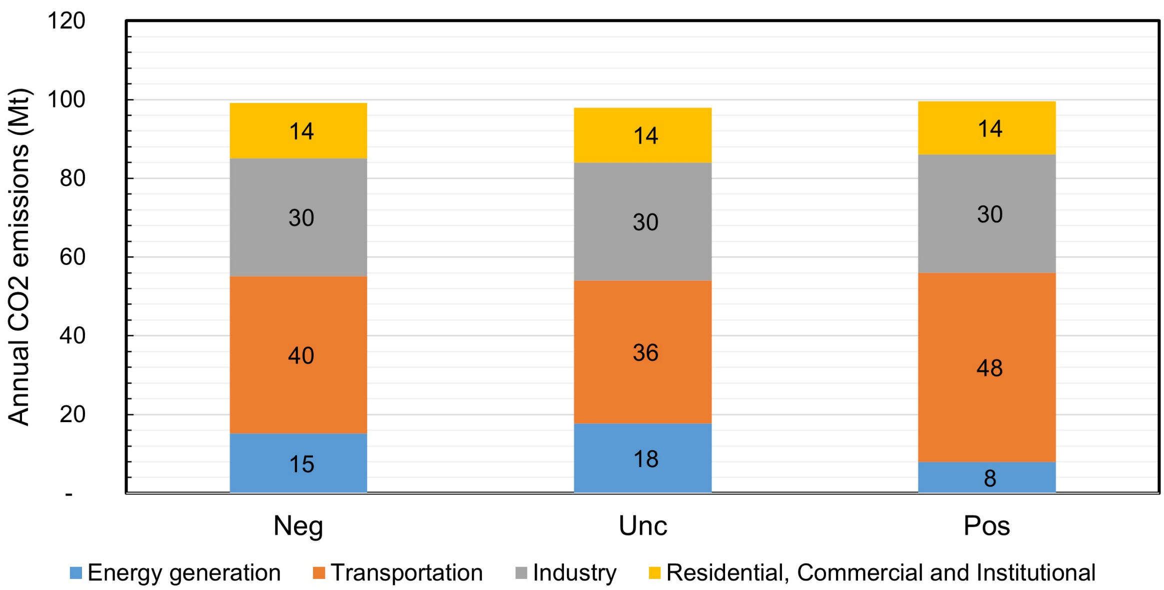

Figure 4.5: Annual sectorial CO_2 emissions for 2030 (Mt).

4.5 Conclusions and future work

This study is the first to incorporate correlations between uncertain parameters into a strategic energy planning model. Using a novel PCA-based methodology, correlations between fuel prices and energy technology investment costs are examined in a case study on the decarbonization of the Spanish energy system, aligned with the 2030 CO_2 emission reduction targets. By developing scenarios with varying levels of correlation between fossil fuel prices and renewable energy costs, the impact on decision-making processes and the deployment of renewable energy technologies is assessed.

The case study results reveal that decarbonization strategies vary significantly with the level of correlation. When assuming an uncorrelated scenario, a key finding is that greater decarbonization in the transportation sector is achieved by heavily investing in biofuels rather than electrification. This outcome can largely be attributed to vehicle fleet inertia, where only vehicles at the end of their life cycle are replaced. Consequently, while electric vehicle adoption is slow by 2030, the existing ICEV fleet can still reduce emissions through biofuels. This underscores the potential role of biofuels in the transitional decarbonization of transportation as EVs gradually replace ICEVs under this assumption.

If the correlation between fossil fuel prices and renewable energy costs is positive, and beyond initial adoption barriers of EVs, such as investment cost, home-based charging, and vehicle range, higher renewable electricity costs make EV operation more expensive, hindering this transition. This finding could be transferable to other electrifiable demands, such as those using heat pumps or electrified industrial processes, which are key contributors to emissions reduction. A particularly sensible technology in this regard is offshore wind energy, which is deeply linked with the fossil fuel industry, and hence subject to its fluctuations.

Our results have significant policy implications for the energy transition. First, it shows the relevance of including these correlations into energy planning and the design of transition strategies. Policymakers, when deciding upon decarbonization strategies, should take into account the correlation between uncertain parameters in order to produce robust and consistent pathways. The energy mix changes markedly across scenarios, suggesting that strategies based on wrong correlation assumptions may lead to inefficient investments and potential lock-ins. Therefore, introducing correlations into energy planning, and accurately understanding the expected sign and value of those correlations, is crucial to produce robust and consistent strategies and to minimize costly mistakes.

Second, policymakers should deploy policies that may help in decoupling unwanted correlations. For example, decoupling renewable energy costs and fossil fuel prices can be done by investing in R&D to reduce the dependence of renewable energy technologies on fossil fuels (e.g., by developing green steel or concrete). Promoting a circular economy for materials can also help achieve the same goal.

Additionally, faster green electrification of the production processes through which transition technologies (renewables, batteries, etc.) are produced can also help decouple their costs from fossil fuel prices. This electrification should then be given priority in the decarbonization of industry. Another policy that would help reduce the unwanted impacts of correlations would be to use alternative fuels, not that dependent on fossil fuels for their manufacturing: biofuels may play an important role in making decarbonization strategies more robust in the presence of uncertain correlations.

Third, our results show that a positive correlation between fossil fuel prices and renewable energy costs makes it more difficult to electrify transportation, residential, or industrial demands. Therefore, support policies may be needed to address this reduced competitiveness (unless this positive correlation has been minimized through other policies, as mentioned above). This may call for a larger use of carbon pricing (which separates further the fossil fuel price and renewable energy cost), or for stronger support systems for low-carbon technologies (such as subsidies for electric vehicles or renewable energy generation).

In this regard, it is worth noting that carbon prices, when determined in emissions markets, are typically set by fossil fuel prices (typically the opportunity cost of shifting to natural gas). Therefore, there is also a correlation between fossil fuel prices and carbon prices in markets, which must be taken into account, and which generally goes against the original sign of the correlation. Emissions markets can, therefore, play an interesting role as "mitigators" of the correlations analyzed in the study.

Finally, the existence of a correlation (positive or negative) between fossil fuel prices and renewable energy costs should be accounted for by designing support systems for renewables which are indexed to fossil fuel prices, as has already been done in some countries (e.g. Germany).

Moreover, this methodology has potential applications beyond the energy sector and can be extended to explore interdependencies in other contexts. For instance, the approach could be adapted to assess correlations in sectors such as water or agriculture, where similar dynamics of resource dependencies exist (X. Cao et al., 2022). Additionally, it could support integrated planning across interdependent systems, such as those with water-energy-food, by capturing cross-sectoral correlations. From a regional perspective, the methodology can provide insights into localized correlation dynamics, informing tailored policies for regions with distinct economic structures, resource dependencies, or decarbonization challenges.

Despite its contributions, the study has limitations that suggest directions for future research. The methodology considers the level of correlation during the data preprocessing phase, using these correlations to generate the necessary parameters, such as eigenvalues and eigenvectors, for constructing the uncertainty set. Consequently, modifying the level of correlation dynamically over time is not directly feasible within the current optimization framework. However, a potential avenue for future research could involve combining this methodology with adaptive optimization techniques. For example, implementing a rolling horizon approach could enable the consecutive optimization of subperiods, where the uncertainty set would be updated to reflect varying levels of correlation over time. Although it would represent a challenge both computationally and methodologically, this could provide a more flexible framework for addressing evolving trends driven by market transformations, policy shifts, and technological innovation, particularly in analyses that extend toward long-term horizons. Furthermore, future work could also explore correlations and interdependencies beyond fuel prices and technology costs, expanding the applicability of the methodology to capture broader interdependencies.

Appendix 4.A: A literature review of studies incorporating correlation between uncertainties in energy-related models

Table 4.4: Literature review of studies incorporating correlation between uncertainties in energy-related models

Authors	**Model**	**Correlation Methodology**	**Correlated Uncertainties**	**Application**
W. Wang et al. (2021)	Energy Hub (EH) Planning Model	Multidimensional parallelepiped interval model. A correlation coefficient is used to describe the correlation between two interval variables	RES (wind speed and light intensity) and demand response, through electricity price	Electric-Heat-Gas coupled energy system planning
Abdalla, Abu Adma, et al. (2020)	GEP Model	Polyhedral uncertainty set based on the estimated correlation matrix	Uncertainty among different RES plants (Onshore wind, offshore wind, PV, CSP and Hydro)	Generation Expansion Planning (GEP). Egyptian electric system
Roldan et al. (2019)	Two-stage adaptive RO model	Ellipsoidal uncertainty set relying on their variance-covariance matrix	Spatial correlations of RES and demand	Transmission network expansion planning. Spanish electric system
Saxena et al. (2018)	IEEE-30 bus system	A correlation matrix is used to apply Cholesky Decomposition to obtain random scenarios with correlation	Spatial correlations of load and generation (wind speed)	Coordinated Generation and Expansion planning

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Table 4.4 – continued from previous page

Authors	Model	Correlation Methodology	Correlated Uncertainties	Application
Dehghan et al. (2016)	Garber 6-bus test system, IEEE 24-bus y IEEE 73-bus reliability test systems (RTS)	Bounded intervals, through a polyhedral uncertainty set	Demand and wind power generation	Expansion planning
Y. Fu et al. (2021)	Two-stage stochastic programming model	Copula function is introduced to get the joint probability distribution function	Energy demand and solar radiation	Integrated Energy Systems (IESs)
Qiu et al. (2019)	-	Scenario generation method through Copula function	Wind farms generation in different locations	Power system with wind/ hydrogen production
Zhu et al. (2020)	Multi-energy complementary power generation system (MECP)	Copula-based interval full-infinite programming (CIFP) method	Wind and solar power generation binary joint distribution function	South China Sea island power system supply
L. Yu et al. (2020)	CFIP-WEN model	Copula-based fuzzy interval-random programming method	Water resources availability and electricity consumption	Water-energy nexus system of Henan Province, China
Mu et al. (2022)	Park-level integrated energy system (PIES) model	Copula function to construct the joint distribution function. Random scenarios considering correlation are generated with Monte Carlo	Natural gas and electricity prices	A grid-connected PIES in the USA

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Table 4.4 – continued from previous page

Authors	**Model**	**Correlation Methodology**	**Correlated Uncertainties**	**Application**
S. Zhang et al. (2018)	CCP-based multi-objective distributed generation planning model. Minimization of both cost and risk.	Pearson correlation coefficient matrix (normal distributed variables). Spearman rank correlation coefficient matrix (non-normal distributed variables)	Wind speed, light intensity and load demand	Distributed generation planning in distribution network
Zeng, Y. Liu, et al. (2021)	Combined heat and power based multi-energy system model	Scenario-based stochastic programming formulation to explicitly capture the correlations among uncertainties	Customers' responsiveness, energy demand and RES generation	Optimal demand response in renewable-based energy systems
H. Yu et al. (2022)	Triangle Splitting (TSA) bi-objective operation optimization model	Cholesky decomposition	Cooling demand, electric demand, and solar radiation	Community integrated energy systems (CIES) in China
Q. Wang et al. (2022)	Bayesian distributionally RO model	Copula function to obtain the joint probability function. Generation of low-dimensional scenario set	Wind and solar generation	Energy storage planning. Storage sizing model.
Abdalla, Smieee, et al. (2020)	Two-stage robust GEP model	Polyhedral uncertainty set based on its variance-covariance matrix	Spatial and temporal correlations among different wind farm sites	Generation Expansion Planning

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Table 4.4 – continued from previous page

Authors	**Model**	**Correlation Methodology**	**Correlated Uncertainties**	**Application**
M. Cao et al. (2019)	Chance-constrained optimization model	Correlation matrix.	Wind farms and load at different buses	Storage sizing model. Isolated grid application.
Lei et al. (2020)	Multi-objective bi-level stochastic model	Multi-dimensional correlated scenario sets (MDCS) generation method. Considers time sequence, autocorrelation y cross-correlation of RES and multi-energy loads.	Renewable energy and multi-energy loads	Expansion Planning. Regional integrated energy system (RIES). Yangzhong City (China).
Xu et al. (2020)	Risk-averse two-stage stochastic optimization model	Ellipsoidal uncertainty sets. Minimum volume enclosing ellipsoid (MVEE) algorithm.	Power outputs of geographically-close wind farms	Integrated energy and reserve dispatch problem.
Patankar et al. (2022)	Temoa	Robust optimization technique based on (Bertsimas et al., 2004), but incorporating temporal auto-correlation	Fuel costs and technology capital cost	U.S. decarbonization pathways

Appendix 4.B: Case study calibration

The time-varying parameters are defined with initial values corresponding to the year 2020 and final values for the year 2030. Intermediate values within this period are determined using linear interpolation. This approach facilitates the modeling of learning curves for emerging technologies and the fluctuations in fuel prices driven by regulatory changes and variations in supply and demand. To account for changes in annual demand, an annual growth rate is applied. Hourly demand is then calculated using a load curve applied to the annual demand. In the following, the most significant parameters for this case study are defined. More information can be found on openMASTER's GitHub webpage and on Chapter 2.

Primary energy	**Fuel price** [EUR/MWh]
Nuclear	2.88
Imported Coal	8
Natural Gas	18.4
Liquefied Natural Gas	37
Crude Oil	40
Hydro Run off the River	0
Hydro with Reservoir Capacity	0
Mihi Hydro	0
Wind Onshore	0
Wind Offshore	0
Solar Photovoltaic	0
Solar Thermoelectric	0
Solar Thermal	0
Biomass Energy Crops	21
Biomass Agriculture Waste	17
Biomass Forestry Waste	8
Solid Waste	21
Bioethanol Production Inputs	54
Biodiesel Production Inputs	46
Biogas	104

Table 4.5: Fuel prices for primary energy vectors in EUR per MWh.

Energy Technologies	**Investment Cost** [EUR/kW]
Nuclear Power	4800
Imported Coal Traditional	1450
Imported Coal Integrated Gasification Combined Cycle	1950
Imported Coal Super-critical Pulverised Coal	1650
Imported Coal Super-critical Pulverised Coal with CCS	3400
Combined Cycle Gas Turbine Traditional	550
Combined Cycle Gas Turbine with CCS	1750
Open Cycle Gas Turbine Traditional	450
Open Cycle Gas Turbine with CCS	900
Fuel Oil Traditional	784
Hydro Run off the River	1715
Hydro with Reservoir Capacity	2100
Hydro with Pumping Storage	3804
Mini Hydro	1715
Wind Onshore	1300
Wind Offshore	2800
Solar Photovoltaic Centralised with Tracking	463
Solar PV Distributed w/o Tracking (Industrial Sector)	645
Solar PV Distributed w/o Tracking (Other Uses Sector)	645
Solar Thermoelectric Centralised	3000
Solar Thermal Distributed Industry	848
Solar Thermal Distributed Other Uses	848
Biomass Electricity Centralised	2517
Solid Waste	5503
Cogeneration in Industry (Natural Gas)	1425
Cogeneration in Other Uses (Natural Gas)	2093
Cogeneration in Industry (Biomass)	2137.5
Cogeneration in Other Uses (Biomass)	3139.5
Refinery Low Complexity	114
Refinery High Complexity	330
Refinery Very High Complexity	653
Bioethanol Production Plant	1040
Biodiesel Production Plant	510
Regasification Terminal	35

Table 4.6: Investment costs for energy technologies in EUR per kW.

Table 4.7: Previous installed capacity and conversion losses for different energy technologies.

Energy Technologies	**Previous Installed Capacity** [GW]	**Conversion Losses** [%]
Nuclear Power	7.4	0.62
Imported Coal Traditional	3.0	0.58
Imported Coal Integrated Gasification Combined Cycle	3.0	0.52
Imported Coal Super-critical Pulverised Coal	1.0	0.55
Imported Coal Super-critical Pulverised Coal with CCS	0.5	0.64
Combined Cycle Gas Turbine Traditional	26.6	0.42
Combined Cycle Gas Turbine with CCS	0.0	0.54
Open Cycle Gas Turbine Traditional	0.0	0.55
Open Cycle Gas Turbine with CCS	0.0	0.65
Fuel Oil Traditional	3.7	0.62
Hydro Run off the River	2.15	0.0
Hydro with Reservoir Capacity	12.0	0.0
Hydro with Pumping Storage	3.3	0.30
Mini Hydro	0.0	0.0
Wind Onshore	28.0	0.0
Wind Offshore	0.0	0.0
Solar Photovoltaic Centralised with Tracking	8.4	0.0
Solar Photovoltaic Distributed without Tracking (Industrial Sector)	0.0	0.0
Solar Photovoltaic Distributed without Tracking (Other Uses Sector)	0.0	0.0
Solar Thermoelectric Centralised	2.3	0.0
Solar Thermal Distributed Industry	0.0	0.0
Solar Thermal Distributed Other Uses	0.0	0.0
Biomass Energy Crops Centralised	0.32	0.61
Biomass Agriculture Waste Centralised	0.68	0.61
Biomass Forestry Waste Centralised	0.0	0.61
Solid Waste	0.7	0.61
Cogeneration in Industry (Natural Gas)	2.4	0.26
Cogeneration in Other Uses (Natural Gas)	2.4	0.27
Cogeneration in Industry (Biomass)	0.0	0.26
Cogeneration in Other Uses (Biomass)	0.0	0.27
Refinery Low Complexity	62.2	0.07
Refinery High Complexity	24.3	0.09
Refinery Very High Complexity	0.4	0.17
Bioethanol Production Plant	0.4	0.0
Biodiesel Production Plant	6.7	0.01
Regasification Terminal	76.0	0.01

Appendix 4.C: Correlation matrix for the case study

The correlation matrices utilized are presented in the following tables. These correlations have been calculated based on historical data from various sources and normalized using the z-score technique.

These sources include (i) BloombergNEF: investment costs of non-renewable energy technologies (nuclear, CHP, coal and gas-fired power plants), onshore and offshore wind, solar PV, and biomass power plants; (ii) IRENA renewable power generation costs 2022 report (IRENA, 2023): investment costs of hydroelectric technologies; (iii) ESA Atomic (European Commission, 2024): natural uranium price; (iv) MIBGAS (MIBGAS, 2024): natural gas and LNG prices; (v) Brent market (Nasdaq, 2024): crude oil price; (vi) AVEBIOM (AVEBIOM, 2024): biomass price.

The data from BloombergNEF is subscription-based and not publicly available, so it is not shown in this work. The remaining sources can be consulted in the references provided.

Regarding the correlation levels between fossil fuel prices and renewable energy technology investment costs, the values of L in Table 4.10 are adjusted by 0.5 for the positive correlation scenario and -0.5 for the negative correlation scenario.

It is important to note that the objective of this study is not to empirically determine the actual level of correlation between uncertain parameters, but rather to explore how different correlation structures—positive, zero, or negative—influence the design of robust energy strategies. To this end, the analysis explicitly considers multiple scenarios for the correlation level parameter L. Although the PCA method is grounded in historical data, its primary role in this context is to enable the construction of internally consistent uncertainty sets under varying structural assumptions. Future research could complement this approach by statistically validating the relevance of specific correlation patterns across different empirical datasets.

Table 4.8: Correlations between primary energy prices

	NUCL	IMPCO	NAGAS	LNGAS	CROIL	HYDRR	HYDRC	MNHY	WINON	WINOF	SOLPV	SOLTE	SOLTH	BIOMEC	BIOMAW	BIOMFW	SWAST	BIOETHPI	BIODIEPI	BIOGAS
NUCL	1	0.62	0.6	0.62	0.59	0	0	0	0	0	0	0	0	0.85	0.85	0.85	0.85	0	0	0
IMPCO	0.62	1	0.96	0.95	0.83	0	0	0	0	0	0	0	0	0.7	0.7	0.7	0.7	0	0	0
NAGAS	0.6	0.96	1	0.99	0.84	0	0	0	0	0	0	0	0	0.61	0.61	0.61	0.61	0	0	0
LNGAS	0.62	0.95	0.99	1	0.83	0	0	0	0	0	0	0	0	0.64	0.64	0.64	0.64	0	0	0
CROIL	0.59	0.83	0.84	0.83	1	0	0	0	0	0	0	0	0	0.73	0.73	0.73	0.73	0	0	0
HYDRR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HYDRC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MNHY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WINON	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WINOF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOLPV	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOLTE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOLTH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIOMEC	0.85	0.7	0.61	0.64	0.73	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
BIOMAW	0.85	0.70	0.61	0.64	0.73	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
BIOMFW	0.85	0.7	0.61	0.64	0.73	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
SWAST	0.85	0.7	0.61	0.64	0.73	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
BIOETHPI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIODIEPI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIOGAS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4.9: Correlations between the investment cost of energy technologies

	NUCLEAR	IMCOTRA	sIMCOIGCC	IMCOSCPC	IMCOSCCCS	CCGTTRA	CCGTCCS	OCGTTRA	OCGTCCS	FUOITRA	HYRURIV	HYRSCAP	HYPSTOR	MINIHYDR	WINDON	WINDOFF	SOPHVCEWT	SOPHVDIWOTIND	SOPHVDIWOTOTH	SOTELCE	SOLTHDIIND	SOLTHDIOTH	BIOELECE	SLDWAST	COGENINDNG	COGENOTHNG	COGENINDBIO	COGENOTHBIO	REFINLOWC	REFINHIGC	REFINVHIC	BIOETHPP	BIODIEPP	REGASIF
NUCLEAR	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IMCOTRA	0	1	1	1	1	0.82	0.82	0.62	0.62	0	0	0	0	0	0	0	0	0	0	0	0	0	0.71	0.71	0.98	0.98	0.98	0.98	0	0	0	0	0	0
IMCOIGCC	0	1	1	1	1	0.82	0.82	0.62	0.62	0	0	0	0	0	0	0	0	0	0	0	0	0	0.71	0.71	0.98	0.98	0.98	0.98	0	0	0	0	0	0
IMCOSCPC	0	1	1	1	1	0.82	0.82	0.62	0.62	0	0	0	0	0	0	0	0	0	0	0	0	0	0.71	0.71	0.98	0.98	0.98	0.98	0	0	0	0	0	0
IMCOSCCCS	0	1	1	1	1	0.82	0.82	0.62	0.62	0	0	0	0	0	0	0	0	0	0	0	0	0	0.71	0.71	0.98	0.98	0.98	0.98	0	0	0	0	0	0
CCGTTRA	0	0.82	0.82	0.82	0.82	1	1	0.63	0.63	0	0	0	0	0	0	0	0	0	0	0	0	0	0.75	0.75	0.74	0.74	0.74	0.74	0	0	0	0	0	0
CCGTCCS	0	0.82	0.82	0.82	0.82	1	1	0.63	0.63	0	0	0	0	0	0	0	0	0	0	0	0	0	0.75	0.75	0.74	0.74	0.74	0.74	0	0	0	0	0	0
OCGTTRA	0	0.62	0.62	0.62	0.62	0.63	0.63	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0.5	0.5	0.5	0.5	0	0	0	0	0	0
OCGTCCS	0	0.62	0.62	0.62	0.62	0.63	0.63	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0.5	0.5	0.5	0.5	0	0	0	0	0	0
FUOITRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HYRURIV	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HYRSCAP	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HYPSTOR	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MINIHYDR	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WINDON	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0.74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WINDOFF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.74	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOPHVCEWT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0.98	0.98	0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOPHVDIWOTIND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.98	1	1	0.19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOPHVDIWOTOTH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.98	1	1	0.19	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOTELCE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.14	0.19	0.19	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOLTHDIIND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOLTHDIOTH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIOELECE	0	0.71	0.71	0.71	0.71	0.75	0.75	0.2	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0.7	0.7	0.7	0.7	0	0	0	0	0	0
SLDWAST	0	0.71	0.71	0.71	0.71	0.75	0.75	0.2	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0.7	0.7	0.7	0.7	0	0	0	0	0	0
COGENINDNG	0	0.98	0.98	0.98	0.98	0.74	0.74	0.5	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0.7	0.7	1	1	1	1	0	0	0	0	0	0
COGENOTHNG	0	0.98	0.98	0.98	0.98	0.74	0.74	0.5	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0.7	0.7	1	1	1	1	0	0	0	0	0	0
COGENINDBIO	0	0.98	0.98	0.98	0.98	0.74	0.74	0.5	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0.7	0.7	1	1	1	1	0	0	0	0	0	0
COGENOTHBIO	0	0.98	0.98	0.98	0.98	0.74	0.74	0.5	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0.7	0.7	1	1	1	1	0	0	0	0	0	0
REFINLOWC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REFINHIGC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REFINVHIC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIOETHPP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIODIEPP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REGASIF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4.10: Cross-correlations between primary energy prices and investment cost of energy technologies

	NUCLE	IMPCO	NAGAS	LNGAS	CROIL	HYDRR	HYDRC	MNHY	WINON	WINOF	SOLPV	SOLTE	SOLTH	BIOMEC	BIOMAW	BIOMFW	SWAST	BIOETHPI	BIODIEPI	BIOGAS
NUCLEAR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IMCOTRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IMCOIGCC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IMCOSCPC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IMCOSCCCS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CCGTTRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CCGTCCS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OCGTTRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OCGTCCS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FUOITRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HYRURIV	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HYRSCAP	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HYPSTOR	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MINIHYDR	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WINDON	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
WINDOFF	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOPHVCEWT	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOPHVDIWOTIND	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOPHVDIWOTOTH	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOTELCE	0	L	L	L	L	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOLTHDIIND	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SOLTHDIOTH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIOELECE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SLDWAST	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
COGENINDNG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
COGENOTHNG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
COGENINDBIO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
COGENOTHBIO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REFINLOWC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REFINHIGC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REFINVHIC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIOETHPP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BIODIEPP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
REGASIF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

5 Designing robust energy policy packages under deep uncertainty: A multi-metric decision support framework

This chapter is based on the article entitled *"Designing robust energy policy packages under deep uncertainty: A multi-metric decision support framework"*, authored by Antonio F. Rodriguez-Matas, Thomas B. Wild, Pedro Linares, Jonathan R. Lamontagne, and David Dominguez-Barbero. The manuscript is currently under review in *Energy Policy*, Elsevier, at the time of submission of this thesis.

The work presented in this chapter was developed during international research stays at the Pacific Northwest National Laboratory (PNNL) and Tufts University, in collaboration with Earth Scientist Thomas B. Wild and Associate Professor Jonathan R. Lamontagne, respectively.

5.1 Introduction

The energy transition is a pivotal process in addressing some of the most pressing global challenges, including climate change, energy security, public health, and energy affordability. This transition involves shifting from fossil fuel-based energy systems to more sustainable and renewable energy sources, through changes in both supply and demand. The importance of this shift is multifaceted: it aims to reduce greenhouse gas emissions, decrease dependency on imported fossil fuels, improve air quality to enhance public health, and ensure affordable energy access for all.

Given the complexity of energy transitions and the long-term nature of infrastructure investments, policies play a fundamental role in shaping the direction and pace of change. Policymakers must design and implement effective policy packages that balance environmental, economic, and social objectives while ensuring a resilient energy system. Different policy levers—such as carbon pricing, renewable energy incentives, or energy efficiency standards—can significantly influence investment decisions, technology deployment, and consumer behavior, ultimately determining the success or failure of transition strategies.

However, the effectiveness of these policies is heavily influenced by the uncertainties inherent in the energy transition itself. Technological advancements, socio-economic changes, and climate impacts introduce profound uncertainty—often so deep that assigning probabilities becomes infeasible (Knight, 1921; Walker et al., 2003). These uncertainties shape not only how the system evolves but also how policies perform; promising strategies that seem effective under certain assumptions may fail when conditions change.

Long-term energy planning models play a crucial role in navigating this uncertainty. These models—ranging from energy system optimization models like TIMES to simulation-optimization frameworks such as GCAM and agent-based models (Fodstad et al., 2022)—serve as essential tools for designing and assessing policies aimed at effectively guiding this transition. They enable the anticipation of economic, technical, and environmental effects of specific policy levers, offering insights into emissions, costs, and system resilience.

Yet, traditional modeling approaches often fall short when facing deep uncertainty because they rely on a limited set of predefined scenarios. Addressing this challenge requires exploratory modeling techniques capable of systematically sampling a wide range of plausible futures to uncover key drivers, interactions, and vulnerabilities. Scenario discovery is one such approach, offering valuable tools for identifying the combinations of uncertainties and policy levers that critically shape outcomes (Bryant et al., 2010; Lamontagne et al., 2018; Lempert, 2002).

The literature[a] applying exploratory modeling techniques to energy systems has primarily focused on characterizing system behavior under uncertainty and identifying critical drivers of transition dynamics. Early work by McJeon et al. (2011) applied Patient Rule Induction Method (PRIM) analysis to the GCAM model after threshold identification to understand high-cost scenarios in global emission stabilization pathways. Subsequent studies have developed more sophisticated methodological combinations: hierarchical clustering with Classification and Regression Trees (CART) in agent-based models (Gerst et al., 2013), Gaussian mixture models with PRIM for regional energy planning (Moksnes et al., 2019), and recently, the integration of Modeling to Generate Alternatives with tree-based ensemble methods and marginal effects analysis (Sasse et al., 2023). The evolution of methods shows increasing sophistication in handling complex energy system dynamics.

These studies have progressively expanded the scope of uncertain parameters and metrics considered. From early focuses on specific technology parameters (McJeon et al., 2011) to comprehensive analyses incorporating numerous uncertainties: Woodard et al. (2023) examined 12 socioeconomic factors, Wessel et al. (2024) analyzed 11 transition-related parameters, and Campigotto et al. (2024) incorporated 107 parameters in their analysis. The metrics evaluated have also broadened from single objectives like costs (McJeon et al., 2011) to multiple criteria including emissions, economic impacts, and social factors (Campigotto et al., 2024; Wessel et al., 2024).

While this body of work has been instrumental in characterizing system behavior under uncertainty and identifying key drivers, it has generally not aimed to support the explicit design of robust policy packages. In particular, few approaches systematically explore how combinations of policy levers can be designed to prevent unacceptable outcomes and manage trade-offs across multiple objectives under deep uncertainty.

Within the broader Decision Making under Deep Uncertainty (DMDU) literature, Robust Decision Making (RDM) has emerged as an iterative framework to identify decisions that remain effective across a wide range of plausible futures, typically through vulnerability and trade-off analyses (Paredes-Vergara et al., 2024). RDM has been extensively applied in water and transport planning, with fewer applications to energy systems. For instance, Groves et al. (2020) applied RDM to assess Costa Rica's decarbonization strategy, Benavides et al. (2021) evaluated carbon neutrality pathways in Chile, and Sridharan et al. (2019) studied the resilience of Eastern Africa's electricity sector. Earlier examples include Isley et al. (2013) exploring the political sustainability of emission control policies and Popper et al. (2009) analyzing natural gas strategies for Israel. These studies illustrate the potential of RDM to inform energy policy, yet they typically focus on testing the vulnerability of predefined strategies rather than systematically identifying policy combinations that maximize robustness across multiple objectives.

Another prominent DMDU approach is Dynamic Adaptive Policy Pathways (DAPP), focusing on the design of adaptive roadmaps and sequences of actions that evolve over time in response to observed conditions (Haasnoot et al., 2013). DAPP has proven particularly effective in long-term infrastructure and climate adaptation planning, where the timing of interventions and the identification of adaptation tipping points are central. Nonetheless, its application to macro-energy system transitions remains limited. This may be partly attributed to the methodological challenges of embedding complex techno-economic system representations and large combinatorial policy spaces—common in macro-energy systems—into flexible decision-making frameworks. These characteristics complicate the construction of adaptive pathways in the energy domain, particularly when the goal is to design robust policy packages rather than time-staged sequences of contingent actions. Moreover, our approach also differs from DAPP in its conceptualization of robustness, focusing specifically on protection against worst-case outcomes rather than adaptive flexibility.

At this point, it is important to clarify that robustness can be understood in different ways, each reflecting a distinct approach to decision-making under uncertainty. As discussed in recent literature, three main interpretations can be distinguished (Rodriguez-Matas, Linares, et al., 2024): Wald robustness, which seeks the best-performing solution under the worst-case scenario (aligned with the Wald pessimistic criterion); sensitivity robustness, which focuses on finding the solution that is least affected by changes in uncertain parameters; and Savage robustness, which aims to minimize regret across possible realizations of uncertainty (following the Savage criterion). These interpretations are often confused in the literature, yet they imply different analytical choices and policy priorities. In this study, we adopt a satisficing robustness perspective, specifically grounded in Wald's maximin criterion: our objective is to identify policy packages that prevent worst-case out-

[a] A comprehensive review of the literature is provided in detail in Appendix 5.A.

comes across multiple objectives, prioritizing the ability of energy transition policies to remain acceptable even under the most adverse conditions.

Another important gap lies in the type of modeling frameworks used to analyze policy effects. Previous studies—relying on macroeconomic models (Campigotto et al., 2024) and integrated assessment models (IAM) like GCAM (Wessel et al., 2024; Woodard et al., 2023)—offer valuable insights but differ substantially from energy system optimization models in their analytical capabilities. Macroeconomic models focus on broader economic impacts and social indicators, while IAMs provide aggregate representations of energy-economy-climate interactions. Our approach, based on openMASTER (Rodriguez-Matas, Perez-Bravo, et al., 2024), a detailed energy system optimization model, enables a granular analysis of the technology-specific implications of policy choices. This comprehensive technological representation across the entire energy value chain allows us to evaluate how policy packages shape the energy mix and associated technology pathways. This detailed insight is critical for understanding the real-world consequences that policy choices could have on the evolution of the energy system. For decision-makers, mapping these pathways is valuable not only to anticipate potential trade-offs and synergies but also as a monitoring tool to track whether the system is following the expected transition trajectory or deviating in ways that may require additional actions. While our framework focuses on the design of robust policy packages rather than adaptive sequencing, this pathway-based analysis offers relevant information that could support future policy adaptation—contributing to broader decision-support processes inspired by approaches such as Dynamic Adaptive Policy Pathways (DAPP). Such insights are generally not accessible through more aggregate modeling approaches. Compared to previous applications of exploratory modeling with energy optimization models—such as Moksnes et al. (2019), which focused on electricity infrastructure and two cost metrics—our approach leverages the full granularity of the model to map policy decisions to detailed energy and technological transitions.

To address these gaps, this study makes the following contributions:

- We develop a systematic framework for designing robust policy packages across multiple energy transition objectives under uncertainty. The framework combines exploratory modeling with an iterative Robust Decision Making (RDM) approach to systematically identify the combinations of policy levers that offer balanced robustness across competing objectives. Exploratory modeling is used to explore the space of uncertainties and policy options, informing the iterative selection of robust policy packages. The framework introduces a novel multi-metric robustness measure that guides decision-making towards policies that prevent worst-case performance across a wide range of futures.

- We leverage the technological detail of energy system optimization models not simply to understand policy effects but to operationalize the monitoring and management of energy transitions. By producing explicit energy system pathways associated with robust policy packages, our framework enables decision-makers to anticipate required infrastructure investments, detect deviations from planned trajectories, and identify when adaptive interventions may be necessary. This practical forward-looking capability supports active governance of the energy transition process.

- We demonstrate the application of this framework using openMASTER, an open-source energy system optimization model, analyzing four key policy levers across six critical uncertainties affecting the energy transition. Our results provide practical guidance for policymakers by identifying a robust policy package and its associated technological pathways for achieving multiple energy transition objectives.

Through these contributions, our work advances both the methodological approaches for analyzing energy transition policies under uncertainty and the practical understanding of how to design robust policy portfolios that effectively manage uncertainties while balancing multiple objectives.

The remainder of this chapter is structured as follows. Section 5.2 presents our novel decision support method, detailing the systematic approach for designing robust policy portfolios that maximize protection across multiple objectives under uncertainty. Section 5.3 applies this methodology to an illustrative case study of the Spanish energy system, demonstrating how the framework can be used to evaluate and select robust policy combinations, and analyzes the technological and energy pathways that emerge from implementing the identified robust policies, providing detailed insights into the mechanisms through which these policies achieve their objectives. Finally, Section 5.4 discusses the broader implications of our findings for energy transition policy design and suggests directions for future research.

5.2 A novel decision support method

We propose a systematic decision support method for designing robust policy portfolios that maximize robustness across multiple objectives under uncertainty. This approach integrates energy system optimization with an indicator-based decision method leveraging scenario discovery techniques to identify policy combinations that mitigate adverse outcomes while revealing their underlying energy and technological mechanisms. The method consists of four key steps, presented in Figure 5.1. The rationale, assumptions, and technical implementation of each step—as well as the key concepts used—are detailed in the subsections that follow.

5.2.1 Experimental Design

Our method is based on generating a diverse set of scenarios to systematically explore how uncertainties and policy interventions shape energy transition outcomes. This large ensemble of scenarios provides the foundation for identifying robust policy packages by assessing policy performance across a wide range of plausible futures.

We follow the XLRM framework (Lempert et al., 2003) which structures the analysis around four key components: Uncertainties (X), Policy Levers (L), Relationships (R), and Metrics (M).

- Uncertainties (X) represent external factors beyond the control of decision-makers that influence the system, such as technological developments, fuel prices, or demand growth.

- Policy Levers (L) are the decisions available to shape system outcomes, including instruments like carbon pricing, energy efficiency standards, or public transit promotion.

- Relationships (R) describe how uncertainties and policy levers interact within the system to influence results. These relationships are modeled using an energy system optimization framework.

- Metrics (M) define the performance criteria used to assess outcomes, such as emissions, costs, or energy dependency.

Typically, the definition of Uncertainties (X) and Policy Levers (L) in XLRM analysis is informed by expert judgment, literature insights, and stakeholder engagement to ensure relevance and completeness. Using a full factorial design, we generate a large ensemble of scenarios representing all possible combinations of the uncertainties and policies interventions under consideration.. This enables a comprehensive exploration of potential futures and their implications for system performance, providing a solid foundation for assessing the robustness of alternative policy packages.

The Relationships (R) component is operationalized through an energy system optimization model, which computes least-cost system configurations for each scenario while satisfying technical and policy constraints. The optimization problem is formulated as a cost minimization—including social costs such as emissions—but it is not a multi-objective formulation. In our illustrative case study (described in Section 5.3), we use openMASTER (Rodriguez-Matas, Perez-Bravo, et al., 2024), an open-source energy system optimization model designed for long-term strategic planning. Nevertheless, the proposed method remains compatible with other optimization tools that offer comparable levels of technological detail and support large-scale scenario exploration.

Metrics (M) are calculated ex-post based on the endogenous decision variables of the optimization model, even if they are not directly included in the objective function. This allows the assessment of trade-offs and the evaluation of policy robustness across multiple dimensions such as emissions, costs, and energy dependency. Further details on the optimization model are provided in the illustrative case study section.

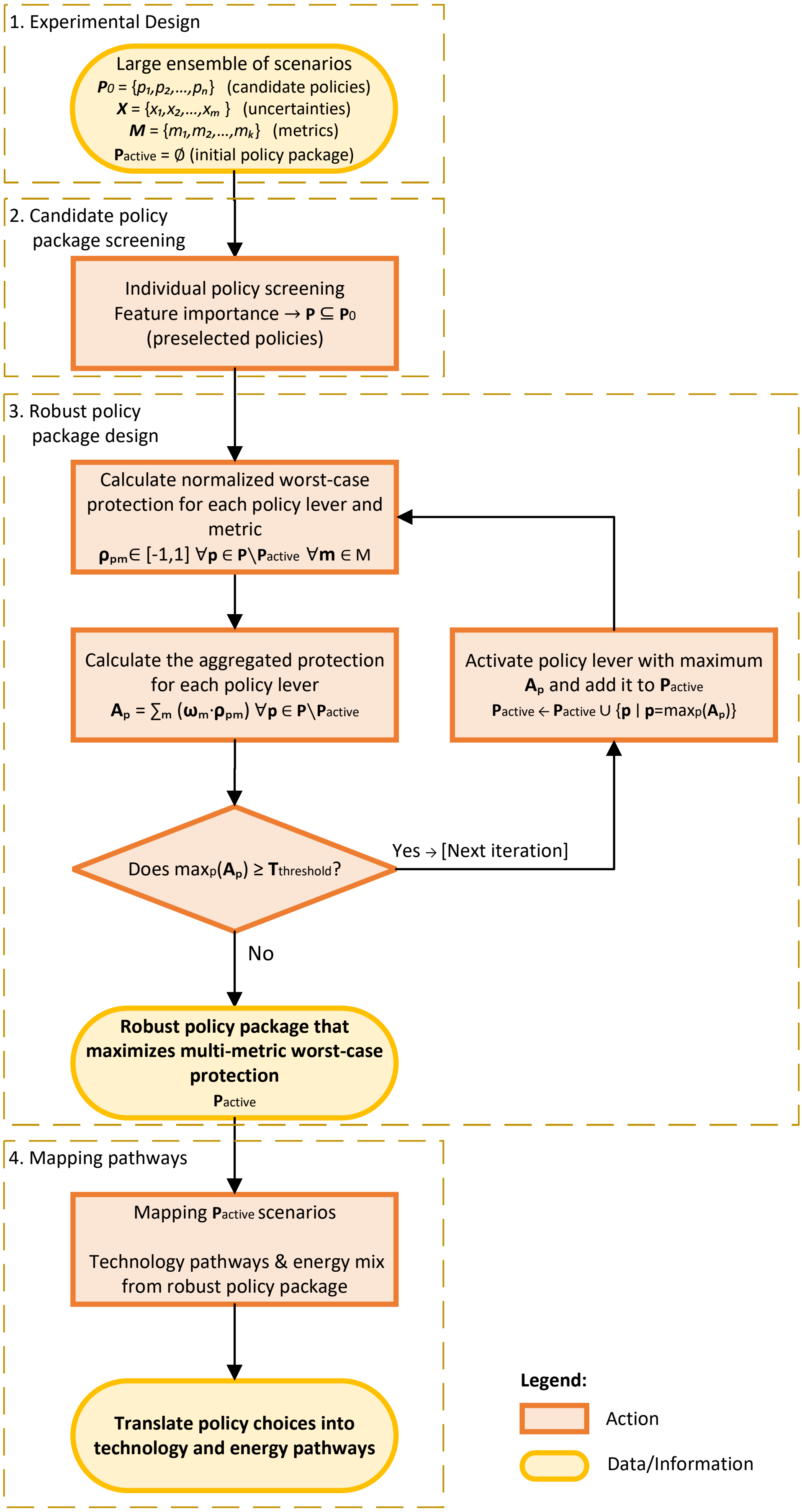

Figure 5.1: Flowchart of the proposed decision support method.

5.2.2 Candidate policy package screening

The first analytical step involves identifying the most influential policy levers P from an initial set P_o, in order to reduce the policy space and focus the robustness assessment on those levers most relevant for shaping transition outcomes.

To achieve this, we perform a feature importance analysis to quantify how individual factors—both policy levers and external uncertainties—contribute to variations in key system performance metrics. Building on the approach described by Wessel et al. (2024), we adopt a Random Forest model (Breiman, 2001) combined with normalized SHAP (Shapley Additive Explanations) values. SHAP values are chosen for their solid theoretical foundation in cooperative game theory, allowing a fair allocation of the marginal contribution of each feature to model predictions. Normalization ensures consistent comparison across features, enabling evaluation on a common scale despite differing units or ranges.

Our use of Random Forest and SHAP values aligns with the broader exploratory modeling and scenario discovery literature, as it leverages a large ensemble of scenarios to systematically explore how uncertainties and policy levers shape system performance. While this differs from traditional scenario discovery methods focused on extracting decision rules or vulnerability regions (e.g., PRIM), it serves a similar purpose: identifying the most influential drivers of system outcomes and guiding the selection of candidate policies for robustness assessment.

In this context, feature importance provides a first indication of each policy lever's potential contribution to robustness. By quantifying how strongly a policy influences performance metrics across the entire outcome space, we identify levers that have a consistent and significant impact on key objectives. Policies with low feature importance are unlikely to substantially improve system performance or prevent extreme outcomes, and can therefore be deprioritized. Conversely, policies with high importance are retained as candidates because their ability to shape system behavior suggests greater potential to enhance robustness in subsequent worst-case analysis.

This screening step is critical to our framework. It improves computational efficiency by narrowing down the policy space and ensures that the iterative robustness assessment focuses on levers with real potential to contribute to robust policy packages. Additionally, this step creates an opportunity for refining the experimental design in future iterations, based on the identified key drivers.

5.2.3 Robust policy package design

In deep uncertainty contexts, such as the energy transition, policy evaluation must go beyond average impacts to assess their ability to mitigate adverse outcomes. This becomes even more critical when pursuing objectives across multiple dimensions. While the feature importance analysis conducted during the screening phase provides a first indication of effectiveness—by identifying policy levers that consistently influence system performance across the outcome space—this is only a preliminary step. Assessing the worst-case robustness of policies remains essential to designing robust policy packages.

Within this framework, policy levers are modeled as binary decisions, meaning that each policy is represented by two discrete states. This binary structure does not necessarily refer to the mere existence or absence of a policy but can also capture choices between two predefined levels of ambition (e.g., a higher versus lower carbon price).

To formalize this evaluation, we propose a Normalized Worst-Case Protection Indicator $\rho_{p,m}$, which quantifies how much a policy lever improves the worst possible outcome for a given metric m. Here, protection is defined as the extent to which activating a policy lever mitigates extreme negative outcomes compared to when the policy is inactive. This measure focuses specifically on worst-case conditions rather than average performance, ensuring that policies enhance system resilience under the most adverse scenarios. The Normalized Worst-Case Protection Indicator $\rho_{p,m}$ is computed as:

$$\rho_{p,m} = \frac{\max\limits_{p' \in P,\, p' \neq p} v_{m,p_{\text{inactive}},p'_{\text{all}}} - \max\limits_{p' \in P,\, p' \neq p} v_{m,p_{\text{active}},p'_{\text{all}}}}{\max\limits_{p' \in P} v_{m,p'_{\text{all}}}} \quad \text{such that } \rho_{p,m} \in [-1, 1] \tag{5.1}$$

where:

- $\max\limits_{p' \in P,\ p' \neq p} v_{m,p_{\text{inactive}},p'_{\text{all}}}$ is the worst-case outcome for metric m when policy p is inactive, considering all possible combinations of other policies p'.

- $\max\limits_{p' \in P,\ p' \neq p} v_{m,p_{\text{active}},p'_{\text{all}}}$ is the worst-case outcome for metric m when policy p is active, considering all possible combinations of other policies p'.

- The denominator term $\max\limits_{p' \in P} v_{m,p'_{\text{all}}}$ is the worst-case outcome for metric m when policy p is active, considering all possible combinations of other policies p'.

Since this metric is normalized, it takes values in the range $[-1, 1]$:

- $\rho_{p,m} > 0 \rightarrow$ The policy reduces worst-case risks (**protective** effect).

- $\rho_{p,m} < 0 \rightarrow$ The policy increases worst-case risks (**vulnerability-inducing** effect).

This normalization acknowledges the complex reality that activating a policy lever can have multidirectional effects. A policy intervention might simultaneously mitigate worst-case outcomes in some metrics while potentially introducing new vulnerabilities in others.

It is important to note that our conceptual approach is grounded in the worst-case criterion, consistent with Wald's robustness principle, as it directly focuses on minimizing extreme negative outcomes under deep uncertainty. However, we acknowledge that relying strictly on worst-case values may introduce noise or instability, especially in cases where extreme outcomes are driven by outliers or specific modeling assumptions. For such situations, a practical alternative could be to compute protection based on high-percentile values (e.g., the 95^{th} percentile) instead of absolute worst-case outcomes. This would provide a more stable estimate of adverse impacts while still capturing the tail behavior of the outcome distribution.

Assessing the normalized worst-case protection indicator for each policy lever and metric provides a preliminary identification of trade-offs, which is crucial for designing a robust package of policy levers. However, the analytical complexity increases exponentially as additional policy levers and metrics are incorporated or as more ambiguous trade-offs emerge. Furthermore, policymakers' preferences regarding the relative importance of different metrics introduce an additional layer of complexity, as these preferences directly influence the prioritization of policy measures in worst-case scenarios.

Given these challenges, the development of a comprehensive protection indicator becomes essential for a decision-support framework aimed at designing robust policy configurations. Such an indicator would enable a systematic comparison of policy effectiveness across multiple dimensions, facilitating the selection of policy packages that offer strong performance under adverse conditions while balancing competing objectives.

To this end, we define an Aggregated Protection Indicator A_p for each policy lever, which integrates its performance across all relevant metrics:

$$A_p = \sum_{m \in M} \left(\omega_m \cdot \rho_{p,m} \right) \quad \forall p \in P \setminus P_{\text{active}},\ \forall m \in M \tag{5.2}$$

where $\rho_{p,m}$ represents the worst-case protection of policy p for metric m, and ω_m is the weight reflecting the policymaker's preference for each metric, with $\sum_m \omega_m = 1$. It is important to note that vulnerabilities (negative contributions) reduce the overall protection value. The Aggregated Protection Indicator A_p provides a single, weighted protection score for each policy lever, enabling a unified assessment of its performance across multiple metrics.

The assignment of these weights depends on the policymakers' priorities for protecting against worst-case outcomes across different metrics. It is also important to consider the range and variability of each metric, particularly when normalizing results prior to aggregation. For example, a metric with the potential to exceed critical thresholds may justifiably receive a higher weight. Additionally, normalization can interact with weighting: metrics with narrower ranges may exhibit proportionally larger normalized variations, potentially amplifying their influence relative to metrics with wider ranges. While our framework allows for flexible weighting to reflect policy priorities, it also makes this interaction transparent, enabling users to adjust weights accordingly if needed.

While weighting provides a structured approach to incorporating stakeholder preferences for metric importance, our approach also enables the visualization of trade-offs between policy levers and performance metrics. In particular, radar plots, as presented in the illustrative case study in the following section (Figures 5.5, 5.6, and 5.7), provide a complementary means of examining the multidimensional effects of different policy configurations, offering a more transparent representation of potential trade-offs.

Following this, the iterative selection process continues. The policy lever with the highest aggregated protection is added to the active policy package if its aggregated protection A_p meets a minimum required threshold:

$$\max_p A_p \geq T_{\text{Threshold}} \tag{5.3}$$

The threshold $T_{\text{Threshold}}$ serves as a lower bound for the additional protection a new policy must provide to justify its inclusion. By default, we suggest setting $T_{\text{Threshold}} = 0$, which implies that any policy offering net positive protection is selected. Higher threshold values can reflect more demanding criteria, indicating that only policies with a sufficiently strong marginal contribution to worst-case protection are included. This threshold can be qualitatively interpreted as a proxy for the minimum acceptable improvement in system resilience under worst-case conditions.

If a policy meets this criterion, it is activated, and a new iteration begins. In each iteration, the policy lever with the highest aggregated protection A_p is selected first, provided it exceeds the threshold $T_{\text{Threshold}}$. Once a policy is added to the active package, the robustness evaluation is updated to reflect its fixed state. The remaining policies are then reassessed based on the updated package of active policies, requiring a recalculation of their normalized worst-case protection indicators. At this stage, only scenarios where the already activated policies remain fixed in their active state are considered, reducing the number of scenarios from 2^P to $2^{P-P_{\text{active}}}$ as policies are activated and fixed in the package, where P_{active} is the number of activated policies and 2 represents the binary state (active/inactive) of each policy lever. The iteration stops once no remaining policy meets the threshold requirement, yielding a robust policy package that maximizes aggregate protection across all selected metrics.

It is important to note that worst-case protection indicators are normalized using the original range of all policy levers to maintain a consistent reference scale across iterations. This approach preserves the magnitude of protection effects relative to the initial policy space, where all policy lever states were considered. Consequently, protection values in subsequent iterations may exceed the $[-1, 1]$ range, as they could reflect greater (de)protection relative to this fixed reference. By maintaining this reference scale, we can meaningfully compare the incremental protection offered by each policy lever across iterations and identify interaction effects that may be overlooked in isolated policy analysis.

5.2.4 Mapping technology and energy pathways

The final step of our methodology focuses on understanding how robust policy packages translate into specific energy system transformations. By leveraging the detailed technological representation of the energy optimization model, this analysis provides insight into how policy choices shape the energy mix, technology deployment, and sectoral dynamics.

While the robustness assessment identifies which policy combinations prevent worst-case outcomes under uncertainty, this step helps policymakers understand the mechanisms through which robustness is achieved. Specifically, it allows us to trace how the robust policy package influences the deployment of key technologies, shifts in energy carriers, and structural changes in the energy system. For example, the analysis can reveal whether robustness is primarily delivered through increased electrification, the diversification of energy sources, or the adoption of specific technologies.

This pathway mapping is relevant for decision-makers because it helps anticipate system-level consequences of policy packages, identify potential implementation challenges, and monitor whether the energy system is evolving as expected. By tracking how the energy sector changes over time, policymakers can assess whether the transition aligns with strategic objectives and design adaptive mechanisms if deviations occur. Additionally, the analysis highlights possible barriers or synergies between technologies, offering guidance on complementary policies needed to support the robust package's effective implementation.

Rather than serving purely as an illustration, this step enhances the decision-support process by translating abstract policy combinations into concrete system-level changes, providing valuable information for monitoring, adjustment, and strategic planning during the energy transition.

5.3 An illustrative case study

In this section, we present an illustrative case study to showcase the practical application of the decision support method outlined in this chapter. By applying the steps of our approach, we demonstrate how the method can be used to evaluate and design robust policy portfolios under uncertainty. This case study serves to highlight the effectiveness of the method in a real-world context, providing insights into its utility for policymakers aiming to navigate complex decision-making processes in energy system planning and policy design.

5.3.1 Experimental Design

The experimental design for this illustrative case study explores the interaction between four key policy interventions and six critical external uncertainties affecting the energy transition. In this study, since the focus is on methodological development and the case study is illustrative, uncertainties and policy levers were defined by the research team based on expert knowledge and existing literature. The policy levers represent distinct policy options currently under debate or implementation in many energy systems:

- Carbon pricing policy – Moderate versus high carbon price level applied to energy-related emissions.
- Urban mobility transition policy – Compares a limited intervention versus a strong modal shift toward public and active transport, combined with measures to reduce urban mobility demand (e.g., remote working programs, last-mile logistics solutions, and delivery optimization).
- Building energy efficiency policy – Contrasts moderate retrofitting programs with ambitious large-scale building renovation strategies aimed at improving energy efficiency.
- Industrial decarbonization pathway policy – Compares pathways prioritizing electrification of industrial processes versus those favoring the deployment of renewable gases as decarbonization vectors. For this policy, a preference for higher electrification over renewable gas adoption will be considered as the "active" level.

These policies are combined with uncertainties related to future energy demand patterns, technology costs, and fuel prices:

- Residential and Service demand – Uncertainty in building stock and commercial space by climatic zone, driven by urbanization and demographic trends.
- Transport demand – Uncertainty in passenger and freight volumes due to population shifts and economic activity.
- Industrial growth – Uncertainty in industrial output influenced by economic trends, automation, and trade.
- Fossil fuel prices – Market-driven fluctuations in coal, oil, and gas prices.
- Electrification technology costs – Uncertainty in EVs and heat pump costs due to learning curves and material constraints.
- Renewable technology costs – Uncertainty in wind, solar, and storage costs driven by technological progress, material availability, and social acceptance.

A full factorial design is applied, resulting in 1,024 scenarios (2^{10}) representing all possible combinations of binary levels for policy levers and uncertainties[b].

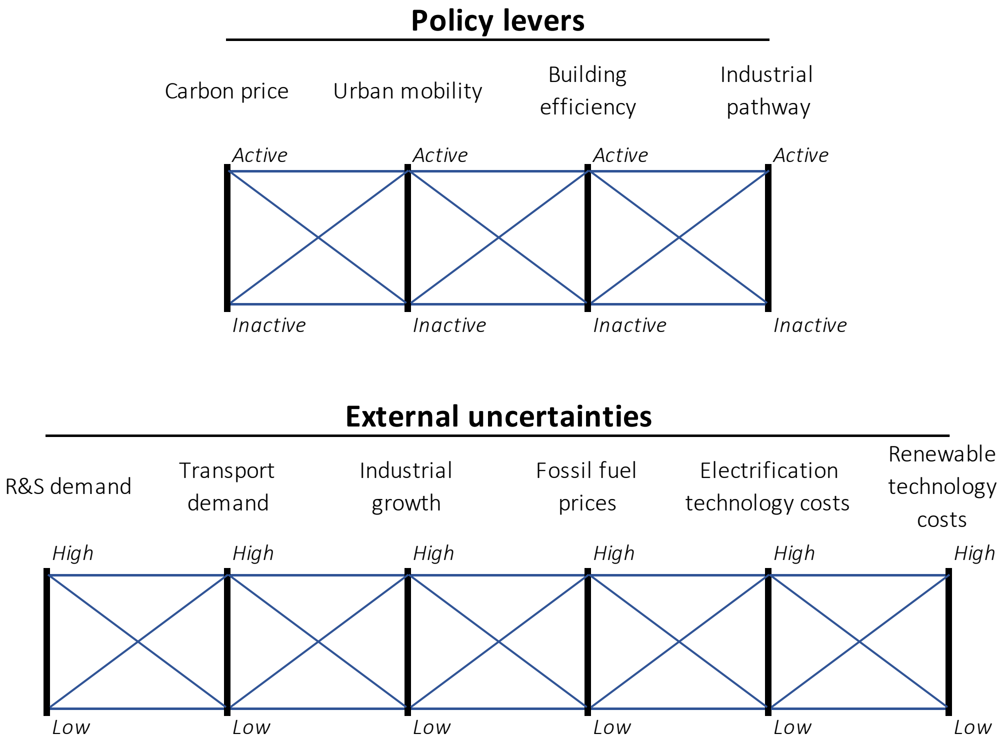

Figure 5.2: Summary of Policy Lever (L) and External Uncertainty (X) levels explored in the 2^{10}=1,024 scenarios.

It is important to note that this exploratory modeling exercise is designed to assess the robustness of different policy combinations under uncertainty, rather than to evaluate their direct cost-effectiveness. Therefore, the direct costs of implementing specific policy measures—such as subsidies for building retrofitting or investments in public transport infrastructure—are not explicitly included in the model. These costs are considered exogenous to the energy system optimization, which focuses instead on the endogenous system responses to the presence or absence of each policy lever under multiple uncertain futures. The aim is to understand how different strategies perform across a wide range of plausible conditions, rather than to determine their financial feasibility or prioritize them based on implementation cost.

The Spanish national energy system serves as our case study, offering an ideal testing ground due to its diverse energy mix, abundant renewable resources, and ambitious decarbonization policies. While specific to Spain, the qualitative insights from this analysis may inform similar energy systems facing complex transitions under uncertainty. Generalizing results to other contexts should, however, consider structural differences in energy systems and policy environments.

The analysis employs openMASTER, an open-source strategic energy planning model (Rodriguez-Matas, Perez-Bravo, et al., 2024), to evaluate system performance across multiple metrics:

- Cumulative CO_2 emissions (2020-2050) – Cumulative carbon dioxide emissions from energy use over the study period, expressed in $MtCO_2$.
- Air quality impacts (2020-2050) – Cumulative emissions of regulated air pollutants (NO_x, SO_x, and $PM_{2.5}$).
- Cumulative energy transition costs (2020-2050) – Total system costs including investments, fuel expenditures, and operation and maintenance costs, expressed in net present value using a social discount rate

[b] A detailed description of the experimental design is provided in Appendix 5.B.

- Energy dependency in 2050 – Defined as the share of primary energy supply met through imports from outside the national territory.

While not exhaustive, these metrics represent a balanced mix of environmental, economic, and energy security objectives commonly considered in energy transition planning. They provide a suitable set for demonstrating the method's capacity to navigate trade-offs and support robust policy design.

It is important to clarify that, while security of supply is not included as an explicit output metric in this set, it is nonetheless accounted for within the optimization framework. In particular, the model penalizes unserved energy—representing situations where supply cannot meet demand—through the inclusion of an *Energy Not Supplied* (ENS) variable with a very high cost. This penalty reflects the substantial social and economic impacts associated with supply shortages, in line with standard practices in power system planning. By doing so, the model strongly discourages solutions that result in supply interruptions, thereby ensuring that energy security considerations are embedded within the optimization process. Although this approach does not generate an output indicator such as "loss of load expectation" or "hours of supply shortage," it implicitly enforces a high level of supply adequacy across scenarios.

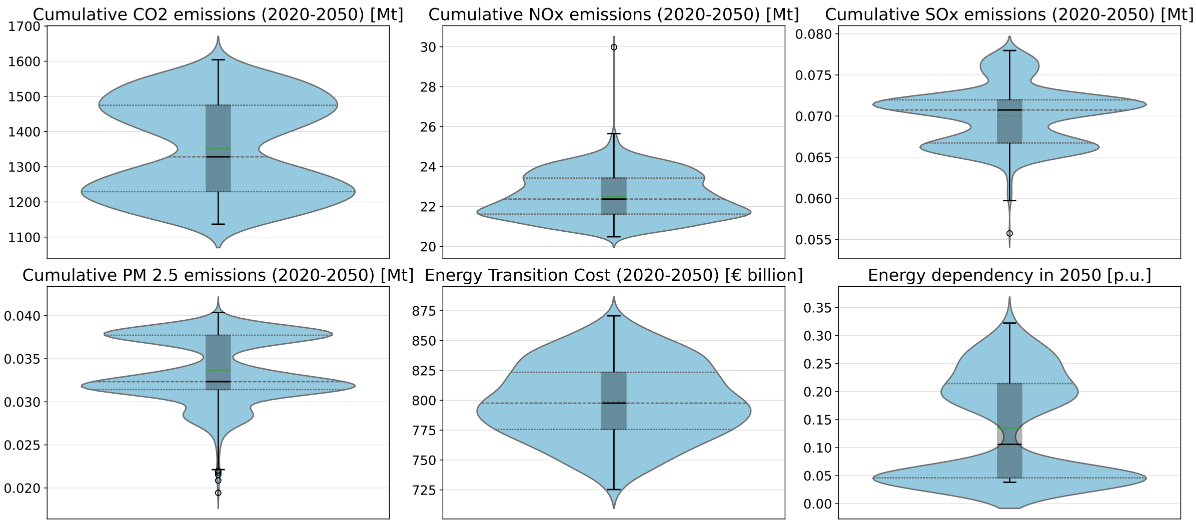

Figure 5.3: Distribution of metrics across the 1024 scenarios: Violin plots with percentile ranges. Each subplot shows the distribution of a specific metric, with quartile and mean values as depicted by the boxplot.

Figure 5.3 illustrates the distribution of performance metrics across all scenarios, revealing the considerable variability in potential outcomes. The violin plots, enhanced with percentile ranges, demonstrate how different combinations of policy levers and uncertainties shape key transition metrics. This visualization underscores the importance of robust policy design, as it shows how different policy combinations can lead to significantly different outcomes. Notably, the distribution of energy dependency in 2050 displays a near-binary pattern, indicating that certain policy combinations shift the system between two distinct regimes—either a high reliance on imported energy or a predominantly domestic energy supply. This highlights the system's sensitivity to specific levers and the potential for policies to fundamentally alter long-term strategic dependencies.

5.3.2 Candidate policy package screening

The analysis of the 1,024 scenarios reveals distinct patterns in how policy levers and uncertainties influence key energy transition metrics. Figure 5.4 presents the feature importance analysis based on SHAP values, providing a quantitative assessment of the relative contribution of each policy lever to the outcomes.

Carbon pricing emerges as the dominant driver across multiple dimensions, being the highest influence on CO_2 and NO_x emissions, transition costs, and energy dependency. This finding underscores its central role in shaping system-wide decarbonization dynamics. Notably, for air quality indicators such as SO_x and $PM_{2.5}$ emissions, while carbon pricing remains a significant determinant, industrial growth emerges as the primary driver, highlighting the sector-specific nature of certain environmental impacts.

Urban mobility policies also play a critical role, particularly in determining transition costs and CO_2 and SO_x emissions. Their strong feature importance suggests that interventions in the transportation sector significantly shape both economic and environmental outcomes.

Among the policy levers analyzed, Building energy efficiency and Industrial decarbonization pathways exhibit limited influence on achieving the modeled objectives. Their low feature importance suggests that, within the current scenario framework, they contribute minimally to shaping transition outcomes on average. Based on this preliminary screening, these policy levers could be excluded from further analysis to streamline the selection of a robust policy package. However, for this illustrative case study, we retain them to ensure a broader policy space for robustness evaluation, allowing a more comprehensive assessment of potential synergies and interactions among policies.

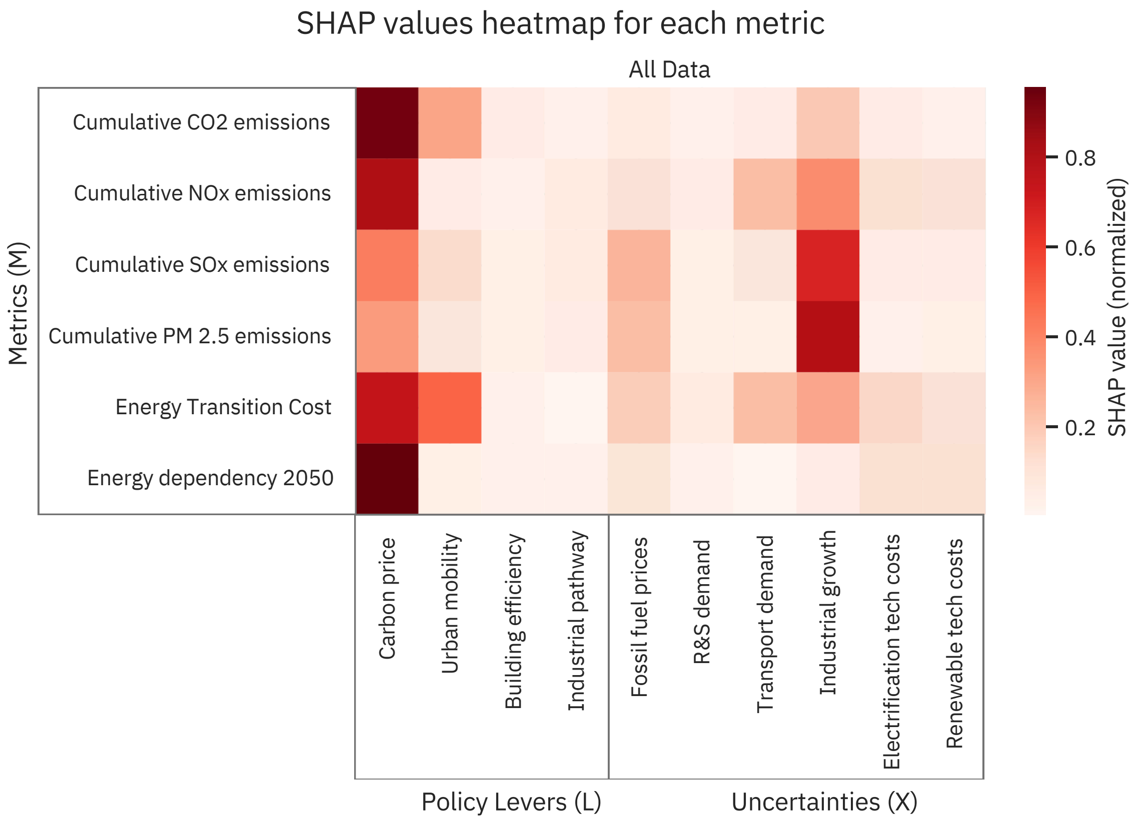

Figure 5.4: Heatmap of normalized SHAP values for each metric. The heatmap visualizes the normalized SHAP values, which represent the relative importance of each feature in predicting the outcome for each metric. The color intensity reflects the magnitude of the impact each feature has on the Random Forest model's predictions, with higher values indicating greater importance.

5.3.3 Robust policy package design

To assess the robustness of policy options, we begin by calculating the normalized worst-case protection $\rho_{p,m}$ for each policy lever and corresponding metric in the first iteration. Figure 5.5 provides a comprehensive visualization of these measures, illustrating the trade-offs involved in applying the four policy levers across the different metrics.

Carbon pricing emerges as a highly influential individual policy lever, providing robust protection, particularly for emissions-related metrics, including CO_2, NO_x, and SO_x, and energy dependency. However, under worst-case conditions, this intervention can lead to the highest levels of system costs and particulate matter ($PM_{2.5}$) emissions. This increase in $PM_{2.5}$ emissions could occur primarily due to the carbon pricing mechanism incentivizing a scenario with a significant shift towards biomass—while biomass is carbon-neutral, its combustion typically generates higher particulate matter emissions compared to alternatives like natural gas.

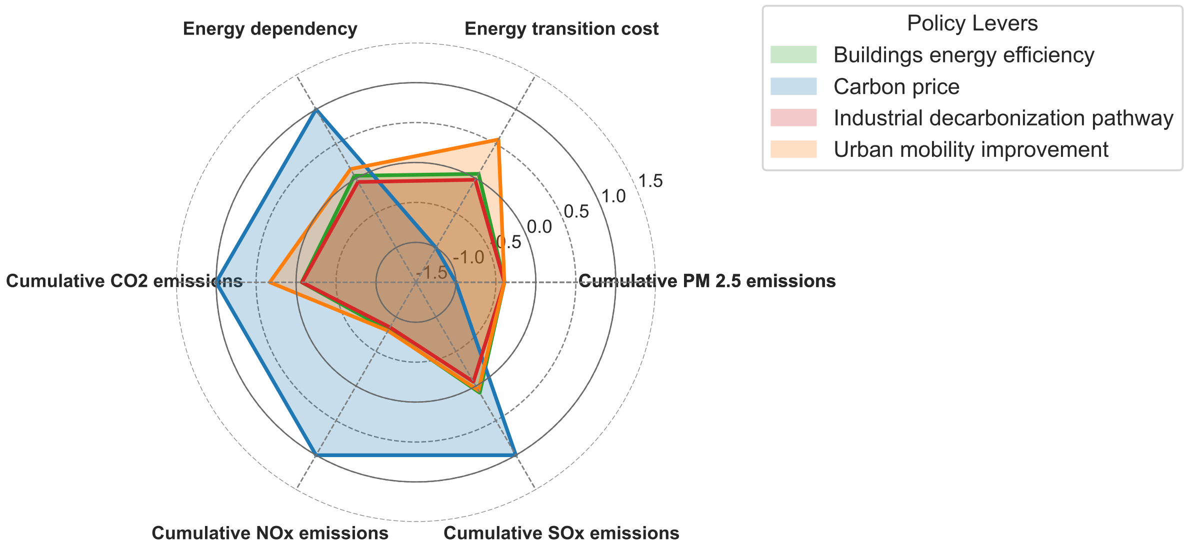

Figure 5.5: Normalized worst-case protection of policy levers on metrics for the first iteration. Higher values indicate greater protection across all metrics.

This unintended consequence reveals the potential of a single policy to introduce new vulnerabilities, highlighting the critical importance of a multi-metric analytical approach.

Similarly, higher system costs under worst-case conditions reflect the significant economic effort required to decarbonize the energy system in adverse scenarios. This cost increase is primarily associated with the rapid deployment of low-carbon technologies and infrastructure adjustments necessary to comply with carbon pricing constraints, as well as the explicit accounting for higher social costs of carbon emissions.

Urban mobility improvement shows a more balanced protective effect across metrics. This policy lever provides safeguarding capabilities for transition costs, CO_2 emissions, and energy dependency. Its ability to enhance the worst-case affordability of the transition underscores its strategic versatility, making it a potential complement to carbon pricing strategies.

Building energy efficiency and industrial pathway policies exhibit similar protection patterns, characterized by moderate protective intensity across most metrics. A nuanced observation emerges from the analysis: while carbon pricing and urban mobility improvements show some complementary effects in mitigating worst-case scenarios, the protective coverage of building efficiency and industrial policies is encompassed within the protective range of urban mobility. This suggests urban mobility is the dominant policy lever among these three in terms of worst-case protection, with the potential to enhance carbon pricing effectiveness.

To calculate the Aggregated Protection for each policy lever, we first define the weights that reflect policymakers' relative priorities for protecting against worst-case scenarios across different metrics. For this case study, the distribution of metrics, as shown in Figure 5.3, would be analyzed to identify which metrics may exceed undesirable thresholds or exhibit high variability. However, since these weights ultimately depend on the policymakers' preferences and the specific context of each case study, we have decided to assign equal importance to the four groups of metrics—cost, dependency, CO_2 emissions, and air quality—for this illustrative case study.

Given that air quality is represented by three distinct metrics (NO_x, SO_x, and $PM_{2.5}$ emissions), we allocate the total weight for air quality equally across these three metrics by adjusting the weight for air quality to one-third for each type of emission. Consequently, the relative weights for each group of metrics are as follows: $\frac{1}{4}$ for cost, $\frac{1}{4}$ for dependency, $\frac{1}{4}$ for CO_2 emissions, and $\frac{1}{4}$ for air quality (with each air quality metric receiving $\frac{1}{3}$ of the air quality weight), as presented in Table 5.1.

Table 5.1: Metric weights used for the protection evaluation.

	Cost	Dependency	CO_2	NO_x	SO_x	$PM_{2.5}$
Weights	0.25	0.25	0.25	0.083	0.083	0.083

According to these weights, the aggregated protection indicators for each policy lever are:

Table 5.2: Aggregated protection indicators for each policy lever in iteration 1.

Policy Lever	**Aggregated Protection**
Buildings energy efficiency	−0.082 920
Carbon pricing	0.333 333
Industrial decarbonization pathway	−0.144 359
Urban mobility improvement	0.163 007

According to Table 5.2, negative values of the aggregated protection indicator for Building energy efficiency and Industrial decarbonization pathway indicate that, under worst-case conditions, activating these policy levers increases the system's exposure to adverse outcomes rather than reducing it. This occurs when the negative contributions of the policy—i.e., increased worst-case outcomes in one or more metrics—outweigh its protective effects in the aggregated calculation, considering the weights assigned to each metric.

Meanwhile, the policy lever offering the highest aggregated protection in Table 5.2 is Carbon pricing, and since its value exceeds the threshold $T_{\text{Threshold}} > 0$, it is selected as part of the active policy package.

Following the decision algorithm illustrated in Figure 5.1, the process enters the second iteration. In this iteration, we recalculate the worst-case protection parameters (presented in Figure 5.6), considering only the subset of 512 scenarios where Carbon pricing is active.

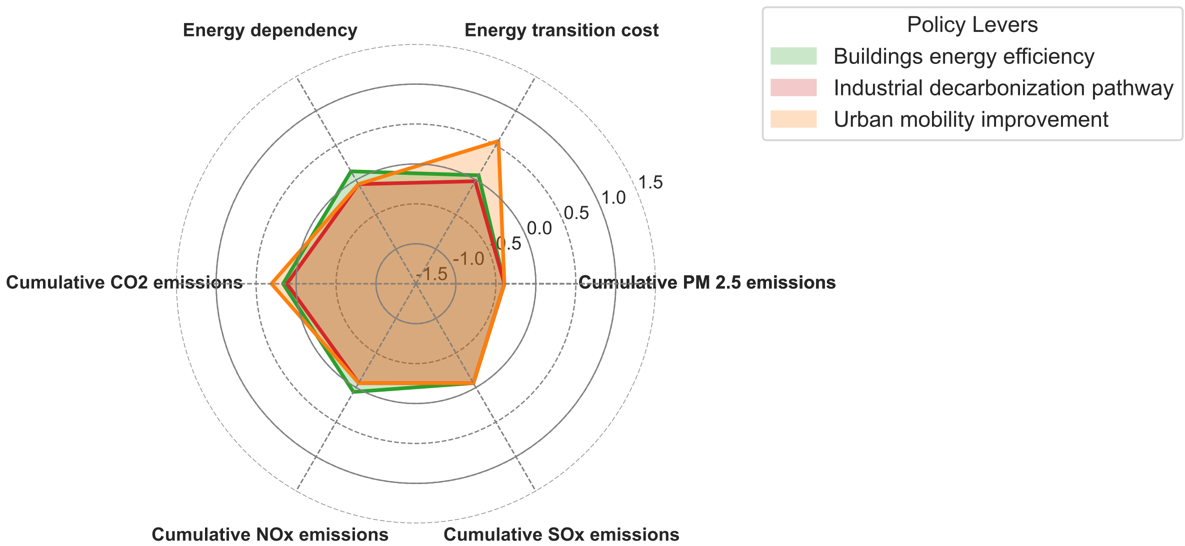

Figure 5.6: Normalized worst-case protection of policy levers on metrics for the second iteration. Higher values indicate greater protection across all metrics.

It is worth highlighting how the additional protection provided by policy levers changes when we consider them as additional candidates for a policy package where policy levers are already active. Compared to the worst-case protection presented in Figure 5.5, where Buildings energy efficiency and Industrial decarbonization pathways were both completely contained within the area of Urban mobility improvement—suggesting the latter was dominant in providing worst-case protection—we now see that Building energy efficiency provides greater protection in certain metrics (energy dependency and NO_x emissions) than Urban mobility improvement when these policies are considered in combination with Carbon pricing. This reveals the importance of considering policy lever combinations when evaluating their impacts, rather than considering them individually, as their behavior may not be linear when combined, potentially presenting effects that amplify or reduce individual impacts.

Calculating the aggregated protection of each policy lever for the second iteration:

Table 5.3: Aggregated protection indicators for each policy lever in iteration 2.

Policy Lever	**Aggregated Protection**
Buildings energy efficiency	0.056 117
Industrial decarbonization pathway	−0.034 362
Urban mobility improvement	0.159 531

Results from the second iteration reveal a notable shift in policy robustness, as presented in Table 5.3. Building energy efficiency, when combined with Carbon pricing, demonstrates positive additional protection—a reversal from its negative aggregated protection in the first iteration (Table 5.2).

This result highlights the importance of analyzing policies in combination, as some may only provide protection when implemented alongside complementary interventions. The iterative structure of the method captures these dynamics, showing that policies initially performing poorly in isolation can contribute positively once certain robust policies are in place—or, conversely, that some policies may lose protective value depending on the evolving policy package.

In this iteration, Urban Mobility Improvement emerges as the policy lever with the highest aggregated protection, exceeding the threshold value of 0, and is consequently incorporated into the active policy package alongside Carbon price.

Following the algorithm described in Figure 5.1, the process proceeds to the third iteration. In this step, worst-case protection indicators are recalculated for the remaining policy levers and metrics, as presented in Figure 5.7. As previously discussed, normalized worst-case protection values may extend beyond the $[-1, 1]$ range, since normalization is referenced to first-iteration worst-case protection to maintain a consistent scale for comparative analysis. This is evidenced in $PM_{2.5}$ emissions, where protection values fall below -1, indicating that policy combinations generate effects that amplify vulnerability beyond individual policy impacts. Such outcomes highlight significant interaction effects that are not discernible when policies are analyzed in isolation.

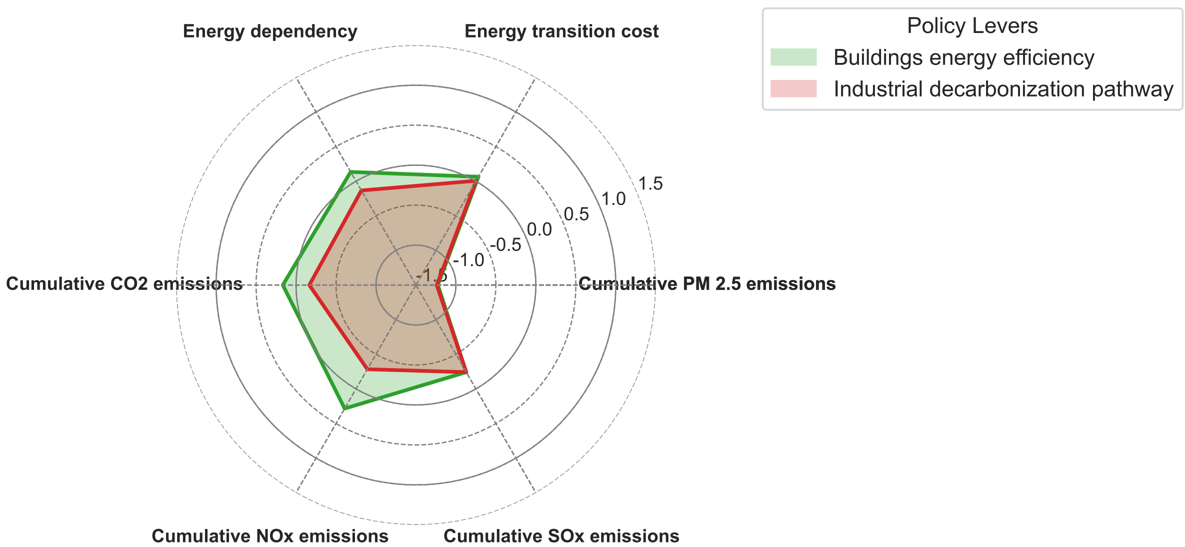

Figure 5.7: Normalized worst-case protection of policy levers on metrics for the third iteration. Higher values indicate greater protection across all metrics.

The aggregated protection results shown in Table 5.4 indicate that neither of the remaining policy levers provides positive additional protection. Consequently, the policy package that maximizes protection against worst-case outcomes consists of the combination of Carbon pricing and Urban mobility improvement.

Table 5.4: Aggregated protection indicators for each policy lever in iteration 3.

Policy Lever	Aggregated Protection
Buildings energy efficiency	−0.007 660
Industrial decarbonization pathway	−0.220 368

5.3.4 Mapping technology and energy pathways

This final step analyzes how the robust policy package—carbon pricing and urban mobility improvement—translates into specific technological and energy system transformations. While the previous steps focused on identifying which policy combinations prevent worst-case outcomes across multiple objectives, this analysis shifts the focus toward understanding how those robust outcomes are achieved in terms of system-level changes. Specifically, we examine the technological pathways associated with scenarios in which the robust policy package is active.

It is important to clarify that the analysis here does not assess the robustness of individual technologies across alternative policy combinations. Instead, it evaluates the system's technological response to residual uncertainty—that is, the uncertainty that remains after fixing the robust policy package. This residual uncertainty stems from unresolved external factors (e.g., fuel prices, demand levels, technology costs) and from endogenous interactions not fully controlled by the policy levers. By exploring the variability in outcomes across these scenarios, we assess whether key decarbonization trends—such as electrification or renewable penetration—emerge consistently under the robust policy package, or whether certain technological dimensions remain highly sensitive to external conditions.

The analysis of primary energy consumption (Fig. 5.8) shows a consistent shift towards renewable energy sources across scenarios. Both solar and wind expand significantly, with both technologies exhibiting high variability—close to 200 TWh—by 2050 across scenarios. This level of variability may reflect the system's flexibility to meet decarbonization targets through different renewable mixes and could indicate potential complementarity between solar and wind, as the system adjusts their deployment in response to how uncertainties unfold.

Biomass consumption remains remarkably stable around 200 TWh by 2050, indicating that its role is structurally robust within the transition, likely reflecting its importance in hard-to-electrify sectors. In contrast, natural gas exhibits significant variability in the medium term but declines sharply by 2050, reflecting the consistent long-term pressure the policy package exerts on phasing out fossil fuels.

Final energy consumption (Fig. 5.9) patterns reveal electrification as a stable and robust outcome of the policy package, characterized by consistent growth and low variability across scenarios and years. Hydrogen demand increases notably from 2040 onwards, suggesting that while not explicitly targeted by the policies, hydrogen emerges organically as a robust component of the decarbonization pathway in later stages.

The analysis of energy conversion technologies (Fig. 5.10) further confirms the system's flexibility observed in the primary energy mix, with renewable capacity deployment—particularly solar and wind—showing high variability by 2050, reflecting the ability to adapt to different scenario conditions. Notably, bioenergy infrastructure—such as biogas and biomethane upgrading facilities—exceeds 50 TWh by 2050 in most scenarios. This indicates that the robust policy package creates conditions that naturally support alternative fuels where direct electrification may be challenging.

End-use technology adoption (Fig. 5.11) shows distinct patterns emerging from our policy package. Electric vehicles (EV) follow an S-curve pattern, with rapid growth in the 2030s (from approximately 40% to 80% adoption) reaching near-complete penetration by 2050. In contrast, heat pump adoption shows greater variability, particularly in 2040, ultimately reaching around 60% penetration by 2050. This more moderate and variable adoption rate suggests that the transformation of the building sector responds differently to our core policies compared to transport electrification. The larger deployment of electric vehicles compared to heat pumps is

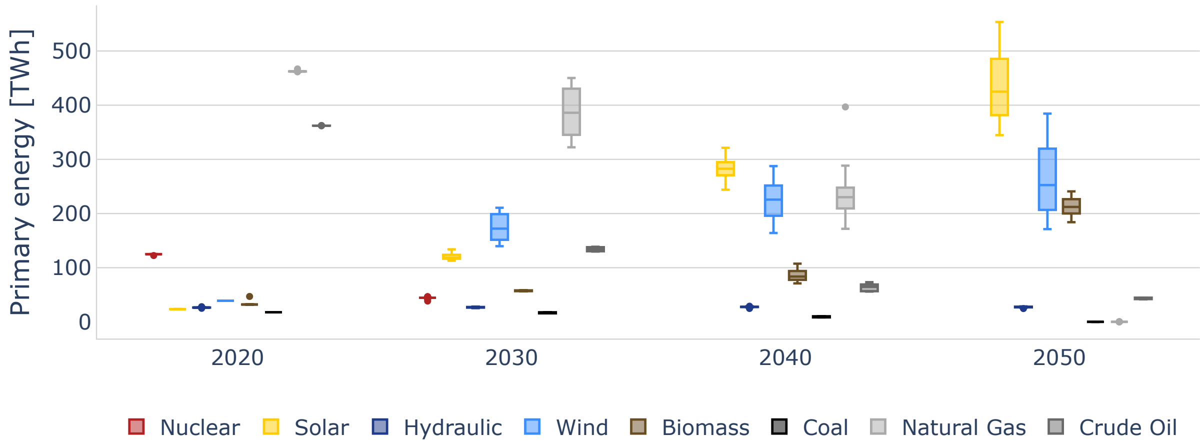

Figure 5.8: Temporal evolution of the distribution of primary energy consumption results in scenarios corresponding to the active package of robust policies.

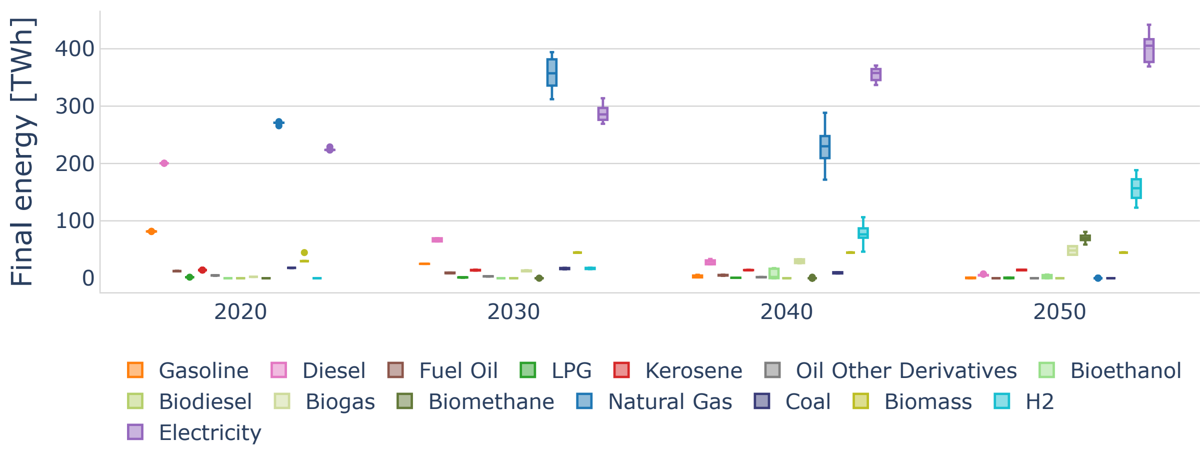

Figure 5.9: Temporal evolution of the distribution of final energy consumption results in scenarios corresponding to the active package of robust policies.

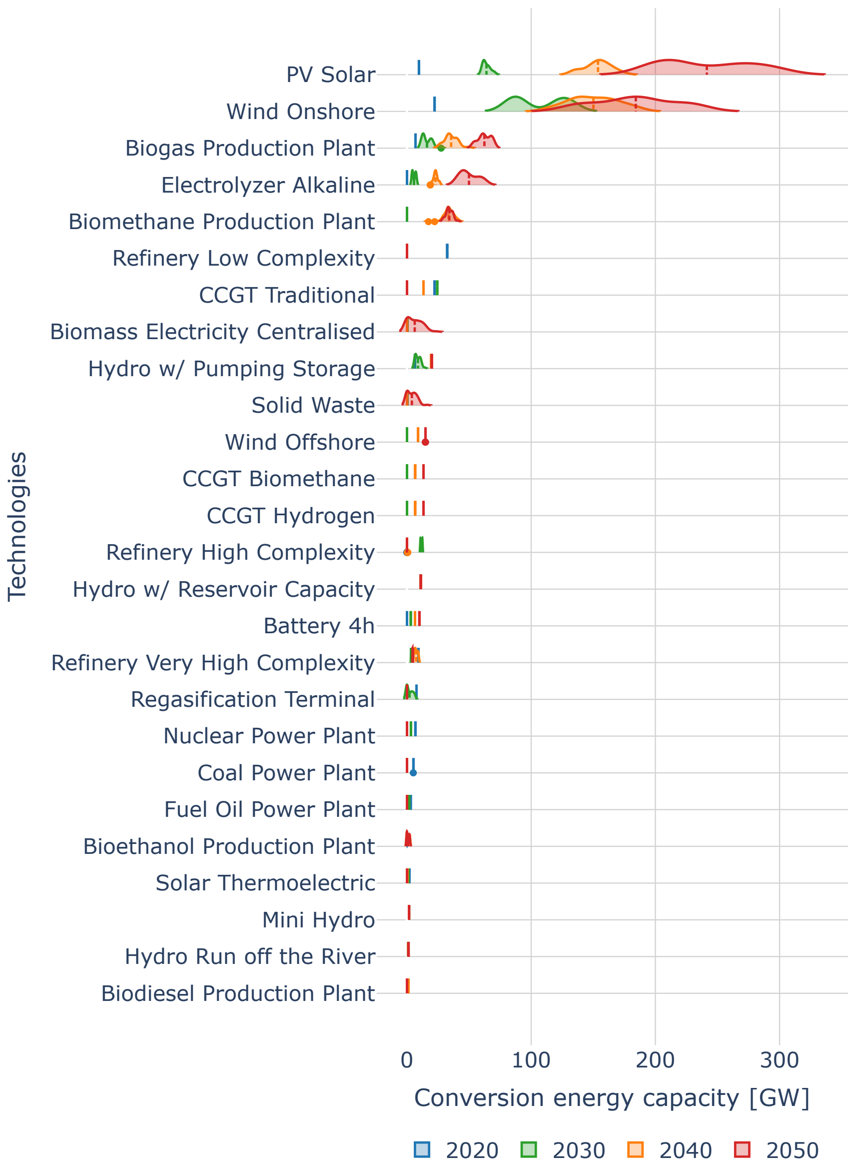

Figure 5.10: Temporal evolution of the distribution of conversion energy capacity results in scenarios corresponding to the active package of robust policies.

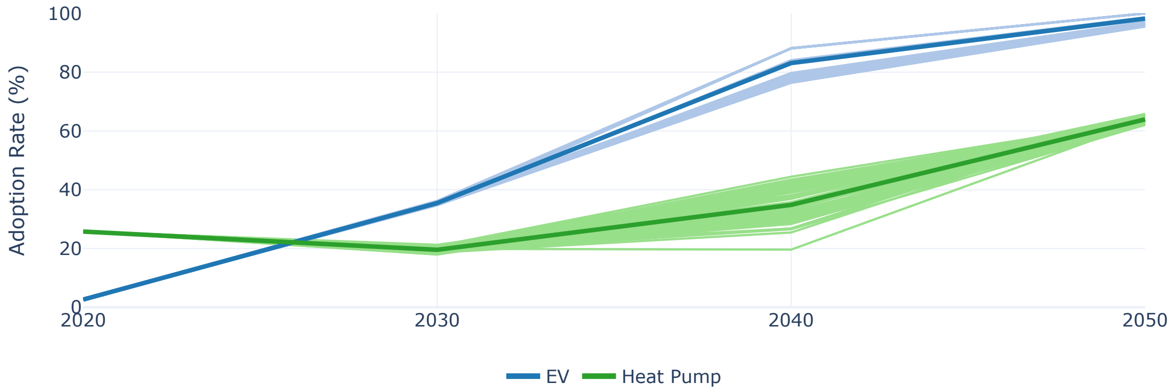

Figure 5.11: Temporal evolution of the adoption of electric vehicles (EVs) and heat pumps in scenarios corresponding to the active package of robust policies. Each line represents a scenario, with the dark-colored line representing the mean across scenarios.

likely influenced by the Urban mobility improvement policy, which has a direct impact on the transportation sector.

This pathway analysis provides valuable information for policymakers by:

- **Confirming which system-level transformations are robust and where residual uncertainties generate variability**: Large-scale electrification of final energy demand emerges as a robust outcome of the combined carbon pricing and urban mobility policies, consistently observed across scenarios despite uncertainty. This reinforces electrification—particularly in the transport sector—as a cornerstone of Spain's energy transition. In contrast, significant residual variability remains in the balance between solar and wind capacity by 2050, indicating that both technologies will expand, but their relative shares may depend on how specific uncertainties unfold.

- **Identifying critical sectors or technologies that may require additional policy support**: The residential sector stands out as an area where electrification outcomes are more sensitive to uncertainty. While electric vehicle adoption follows a consistent and robust trajectory across scenarios, heat pump deployment—critical for decarbonizing buildings—exhibits greater variability. This suggests that, under the current policy package, residential electrification may not be sufficiently robust, highlighting the potential value of exploring complementary or more targeted measures to reinforce outcomes in this sector.

- **Enabling monitoring of transition pathways to ensure alignment with strategic goals**: Particular attention should be given to the phasing out of natural gas and the evolving role of biomass and hydrogen. Monitoring these elements over time will be essential to assess whether the energy system is progressing as expected or if adaptive policy adjustments are needed to stay on track with long-term decarbonization objectives. This use of pathway information complements elements of the Dynamic Adaptive Policy Pathways (DAPP) framework, particularly its emphasis on monitoring system evolution and identifying conditions under which additional actions may be required.

Rather than serving merely as an illustration, this analysis enhances the decision-support process by translating the robust policy package into concrete and monitorable energy system pathways.

5.4 Conclusions

This study presents a systematic decision support framework for designing robust energy transition policy packages under deep uncertainty. The approach complements existing uncertainty-informed decision support methods by aligning with core principles of Robust Decision Making (RDM)—multi-objective evaluation, iterative refinement, and explicit consideration of deep uncertainties.

The framework advances robustness analysis by quantifying how policy packages protect against extreme adverse outcomes across multiple metrics. This enables decision-makers to identify not only which policies are robust individually but also how they interact, generate trade-offs, or reinforce each other when confronted with uncertainty. The iterative algorithm progressively builds the robust policy package by selecting policy levers based on their marginal contribution to worst-case protection.

A key strength of the framework is its ability to translate abstract policy combinations into concrete technological and sectoral pathways, providing insight into the mechanisms through which robustness is achieved. By leveraging detailed energy system optimization models, the method supports strategic planning, implementation monitoring, and adaptive management by mapping technology deployment, energy mix evolution, and sector-specific transitions.

The illustrative application to the Spanish energy system demonstrates the practical value of the framework. Spain provides a relevant test case due to its diverse energy mix, ambitious decarbonization targets, and significant renewable resource potential—characteristics shared by many countries undergoing similar transitions. The case study shows how the method identifies robust policy packages—specifically, a combination of carbon pricing and urban mobility improvements—and reveals their technological implications. While the primary contribution of this chapter is methodological, the qualitative insights from the Spanish case may be transferable to other energy systems facing comparable challenges.

Several promising avenues for future research emerge. First, while the framework focuses on worst-case protection, exploring alternative robustness criteria—such as percentile-based approaches—could enhance its flexibility. Second, extending the method to incorporate multi-level policy levers would enable analysis of how varying levels of policy ambition affect robustness, moving beyond binary formulations. Third, explicitly modeling policy sequencing and timing could improve implementation strategies. In this regard, future extensions could explore synergies with the Dynamic Adaptive Policy Pathways (DAPP) framework, particularly by leveraging our method's ability to monitor energy system trajectories under uncertainty as a basis for designing dynamic policy sequences. Fourth, incorporating additional metrics—such as social impacts, distributional effects, and just transition considerations—would broaden the assessment scope. Finally, future applications could integrate stakeholder engagement to co-define objectives, policy options, and uncertainties, while refining trade-offs and enhancing policy relevance.

In conclusion, this chapter provides a practical, transparent, and systematic framework for designing robust energy transition policies under deep uncertainty. By combining multi-metric robustness assessment with detailed technological representation, the method offers actionable insights for policymakers tasked with managing complex energy system transformations. Beyond energy, the framework holds potential for application in other domains where uncertainty, complexity, and multi-objective decision-making converge.

Appendix 5.A: Literature review application of exploratory modeling methods to energy-related models

Table 5.5: Review of application of Scenario Discovery methods to Energy Planning models

Authors	Model	Method	Uncertain parameters	Application	Metrics
Gerst et al. (2013)	ENGAGE (Agent-based model)	Multidimensional scenario discovery first uses hierarchical clustering of model simulations to identify groups with similar outcomes over multiple attributes. These serve as candidate scenarios that, in a second step, are further refined using classification and regression tree (CART) analysis to identify common scenario drivers.	200 simulations representing stochastic realizations. Predictor variables: relative efficacy of R&D, technology innovation, technology experience	4 scenarios (baseline and carbon tax w/ different policies)	Annual household consumption and levelized annual carbon emissions per household
Moksnes et al. (2019)	OSeMOSYS South America Base (SAMBA)	Clustered into groups using a Gaussian mixture model (GMM). Then, what key determinants best explain the cost parameters of each group, by using the Patient Rule Induction Method (PRIM)	324 scenarios: (1) electricity demand, (2) fossil fuel price, (3) renewable technology learning curves, (4) discount rate (cost of capital), (5) CO_2-emission cap and (6) the effects of climate change on hydropower (water availability). Between 2 and 3 levels	South American electricity infrastructure. 2013–2063 period	Two cost dimensions (capital and variable costs)

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Table 5.5 – continued from previous page

Authors	**Model**	**Method**	**Uncertain parameters**	**Application**	**Metrics**
Sahlberg et al. (2021)	OnSSET, the Open Source Spatial Electrification Tool. GIS-based	1. Generate data from a simulation model 2. Use Patient Rule Induction Method (PRIM) to identify candidate scenarios: 3. Choose the scenario or set of scenarios with high quality measures	1944 electrification simulations were constructed for Burkina Faso from a combination of seven input levers: 1. Solar PV cost; 2. Grid electricity generation cost; 3. Short-term grid expansion limit; 4. Discount rate (cost of capital); 5. Mini-grid policy environment; 6. Demand levels; 7. Grid-extension strategy	Electrification of Burkina Faso	Average electricity LCOE
Woodard et al. (2023)	GCAM	CART analysis	4,096 scenarios by varying 12 different socioeconomic factors at high and low levels: Fossil fuel costs, Emissions, Bioenergy constraint, Nuclear costs, Carbon capture and storage (CCS), Wind & solar backups, Wind storage costs, Wind tech costs, Solar storage costs, Solar tech costs, Energy demand, Electrification	Global decarbonization	Solar and wind generation in 2050

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Table 5.5 – continued from previous page

Authors	**Model**	**Method**	**Uncertain parameters**	**Application**	**Metrics**
Campigotto et al. (2024)	Eurogreen model: Post-Keynesian economic theory; combines system dynamics and stock-flow consistent methods	Sensitivity analysis and Random Forests	16,000 simulation runs. In each simulation, 107 parameters are randomly drawn from a wide range of possible values (given distribution): warming scenarios, carbon tax, output constraints, depreciation rate of fixed capital, working hours per year, pension-to-wage, etc.	Just transition applied to France: What policy combinations can reduce carbon emissions while promoting income equality	4 criteria: (1) reducing greenhouse gas emissions; (2) reducing income inequality (Gini coefficient of net income); (3) reducing emissions and inequality; (4) reducing emissions and inequality while increasing GDP
McJeon et al. (2011)	GCAM	First, set a threshold (cost exceeds 80th percentile), and then PRIM	768 runs, based on 384 different combinations of assumptions about the future performance of technologies (solar, wind, CCS, nuclear, buildings, transportation and industry) and two CO_2 stabilization goals.	Global	Searches for a combination of a small number of technology assumptions that best explain these high-cost cases

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Table 5.5 – continued from previous page

Authors	**Model**	**Method**	**Uncertain parameters**	**Application**	**Metrics**
de Wildt et al. (2020)	(Not specified) Agent-based model	First, EMA (Exploratory Modelling and Analysis). Second, Patient Rule Induction Method (PRIM)	Resource level of the entire population, education, suitable housing for decentralised energy production.	Development of decentralised energy systems. Potential occurrence of energy capability conflicts (life and bodily integrity, emotions, senses, trust, etc.) between households in one type of neighbourhood	Conflict between Trust and Thought
Wessel et al. (2024)	GCAM	Random Forest	5,760 scenarios: emissions constraint; land use change emissions sinks; population and GDP; institutional factors; wind and solar capital costs; direct air capture cost; advanced hydrogen; industry energy efficiency; buildings energy efficiency; transport electrification; climate impacts on demand.	Global energy transition under national emissions pledges	Electricity price; electricity share in final energy; stranded assets; capacity investments; energy burden; level CO_2 removal; land use change emissions

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Table 5.5 – continued from previous page

Authors	**Model**	**Method**	**Uncertain parameters**	**Application**	**Metrics**
Sasse et al. (2023)	EXPANSE electricity system model	Modeling to Generate Alternatives (MGA), tree-based ensemble method. ExtraTrees, a method to quantify the interactions of inputs in models (assess the relative importance of individual regional and EU targets toward the variance of regional electricity system infrastructure, emissions, and costs). PRIM to quantify specific ranges of regional electricity system infrastructure capacities, GHG emissions, and total system costs associated with specific regional targets. Marginal effects: quantify the marginal effect of individual regional and EU targets on regional electricity system infrastructure, GHG emissions, and total system costs	5,090 alternative cost-effective scenarios representing a narrow range of cost-optimal and nearly cost-optimal scenarios, with alternative implementations of electricity system infrastructures and targets	European regional interdependencies of cost-effectively implementing European electricity sector targets for renewable electricity and GHG emissions in 2035	Regional electricity system infrastructure capacities, greenhouse gas emissions, and total system costs

Appendix 5.B: Experimental Design

We designed a comprehensive methodological framework that combines energy system optimization modeling with scenario discovery techniques. This section describes our experimental design using the XLRM framework, which offers a systematic way to evaluate the interplay between key elements that shape the outcomes of policy decisions, especially under conditions of deep uncertainty. It is particularly suited for studying the complexities of energy systems, where numerous factors, ranging from market dynamics to socioeconomic changes and technological innovation, interact over extended time horizons.

The specific data used to construct the experimental design are provided in the Excel file *Experimental_Design.xlsx*, provided as an electronic supplementary file of the published manuscript on which this chapter is based. This file contains the precise values used to define the binary states—active/inactive for policy levers and high/low for uncertainties—as well as the detailed values of all parameters involved in the analysis. The table specifies the parameter name, values by year (e.g., y2020, y2025, …, y2050), or a constant value labeled as y0000 in the case of time-invariant parameters. The Excel file also documents sources, references, and assumptions used to define parameter values, where applicable.

Uncertainties (X)

These represent external factors beyond the control of policymakers but which have significant impacts on the system. In our analysis, these uncertainties span various domains:

Residential and Service demand (R&S): Measured by the number of dwellings (for residential) and commercial surface (for service) by climatic zone (Mediterranean, Atlantic, and Continental). For residential, further disaggregated by dwelling type (single-house and block). This uncertainty arises from urbanization patterns, population shifts, housing type preferences, and evolving commercial trends.

Transport demand: Number of passengers (in millions) in urban and rural areas, and freight demand (in millions of tons). Mobility demand reflects shifts in population distribution, economic activity, and freight logistics.

Industrial growth: Industrial growth for all subsectors. Industrial activity is influenced by global and regional economic trends, advancements in automation, and shifting trade patterns.

Fossil fuel prices: Correlated fluctuations in coal, oil, and gas prices caused by market dynamics and geopolitical factors.

Electrification technology costs: Capital costs for electrification technologies such as electric vehicles (EVs) and heat pumps are influenced by learning curves, material availability, and geopolitical factors.

Renewable technology costs: Capital costs for wind (onshore and offshore), photovoltaics (PV), and battery storage technologies are driven by technological advancements and maturity, influenced by material constraints, geopolitical issues, land use policies, and societal acceptance of infrastructure projects.

Levers (L)

These are policy instruments and interventions that decision-makers can deploy to shape outcomes. For this study the following are considered:

Carbon price policy: Changes in CO_2 emissions prices are driven by policies such as raising (or reducing) the price or cap of emissions in carbon markets.

Urban mobility transition: Changes in passenger demand across urban and rural environments for urban (short-)distance and the maximum allowed annual modal shift (e.g., from private vehicles to buses or metros). Policies like low-emission zones (LEZs), work-from-home (WFH) programs, and investments in public transport redefine these mobility patterns.

Building energy efficiency: Improvements in the number of energy-efficient dwellings by type (single-house and block) and climatic zone (Mediterranean, Atlantic, and Continental), driven by policies such as building retrofit incentives, energy performance standards, and subsidies for energy-efficient renovations.

Industrial decarbonization pathway: Decision-makers face trade-offs between electrification and hydrogen adoption for industrial processes. Support mechanisms such as production tax credits for green hydrogen or incentives for electrification technologies can tip the balance toward one pathway or another, with scenarios representing varying levels of electrification and hydrogen penetration across industrial subsectors. For this policy, a preference for higher electrification over hydrogen adoption will be considered as the "active" level.

Relationships (R)

These are the interconnections within the system that translate the impacts of uncertainties and levers into measurable outcomes. This study has been conducted within openMASTER, an open-source strategic energy planning model.

openMASTER is a dynamic (multi-stage), linear programming (LP) model that operates on a bottom-up, partial equilibrium basis. Its primary aim is to enable comprehensive analysis of sustainable energy policies. The model addresses exogenous energy service demands across all sectors while adhering to technical and policy constraints, such as greenhouse gas emission reduction targets. Its central objective is to minimize a defined cost function representing the aggregate private economic costs associated with energy supply. Implemented using Pyomo and solved with the Gurobi optimization solver, openMASTER provides a robust framework to explore the relationships between uncertainties and policy levers in shaping energy system outcomes. For further details on openMASTER, readers are encouraged to consult Chapter 2.

Metrics (M)

These capture the system's performance in achieving the desired outcomes:

Cumulative CO_2 emissions: This metric represents the total CO_2 emissions accumulated over the period from 2020 to 2050. It is closely tied to the concept of the carbon budget, which defines the allowable emissions to meet global climate targets (e.g., 1.5°C or 2°C).

Air quality impacts: These metrics measure the cumulative emissions of key pollutants (NO_x, SO_x, and $PM_{2.5}$) during the period 2020-2050. They are important due to their direct link to human health, particularly through respiratory and cardiovascular diseases caused by these pollutants.

Energy transition cost: The cumulative cost of the energy transition from 2020 to 2050, encompassing investments in infrastructure, technology, and operating expenses. This metric is critical for assessing financial feasibility and energy affordability during the energy transition.

Energy dependency in 2050: The share of primary energy demand that must be imported in 2050. This metric assesses energy security, self-sufficiency, and the effectiveness of domestic renewable energy deployment.

By integrating these components, the XLRM framework provides a robust foundation for assessing how different policies interact with uncertainties to shape the energy transition's outcomes. This approach enables the identification of robust strategies that perform well across a wide range of future scenarios.

The case study

To systematically explore the combined effects of policy levers and external uncertainties, we constructed a set of 1024 scenarios using a full factorial design (see Fig. 5.2). Each scenario results from a unique combination of four policy levers, which can be either active or inactive, and six uncertainties, each taking a high or low value. This leads to a total of $2^{10} = 1024$ scenarios, covering a broad spectrum of possible futures for the energy transition. The scenario set was then evaluated using multiple performance metrics to assess key dimensions of energy system outcomes.

6 Conclusions, Limitations and Future Work

This final chapter summarizes the main findings of the thesis, discusses their implications for policy and practice, and outlines limitations and directions for future research. The central goal of the thesis was to improve how long-term energy planning can support robust decision-making under deep uncertainty, by developing novel methods and tools within energy system optimization models. The thesis has addressed this goal through four research questions.

6.1 Conclusions

6.1.1 How can robustness be addressed in energy system optimization models to reflect differentiated decision-making preferences across distinct sources of uncertainty?

This thesis demonstrates that differentiated treatment of uncertainties within energy system optimization is not only conceptually justified but also practically implementable without compromising tractability. By integrating robust optimization for feasibility-related uncertainties and minimax regret for performance-related uncertainties into a single coherent framework, the hybrid method developed in Chapter 3 introduces a new level of flexibility and realism into strategic energy planning.

The results show that treating uncertainties differently—according to whether they endanger system feasibility or merely affect costs—leads to more balanced and decision-relevant strategies. In particular, the hybrid framework avoids the main drawback of conventional robust optimization: the excessive conservatism when all uncertainties are treated alike. Instead, it allows planners to protect critical system functions while maintaining flexibility where appropriate.

Moreover, the empirical results from the illustrative case study reveal that differentiated robustness influences not just the cost or emissions outcomes, but the very structure of transition pathways. Investment patterns, technology choices, and sectoral strategies differ substantially when decision criteria are aligned with the nature of uncertainty. This demonstrates that improving robustness is not simply a technical refinement, but has profound implications for how energy strategies unfold under deep uncertainty. This implies that planners can prioritize safeguarding essential system functions while remaining adaptable where uncertainties are not critical, leading to more efficient and realistic investment decisions.

Thus, beyond proposing a novel algorithm, this work lays methodological foundations for developing more realistic, interpretable, and decision-relevant energy models in contexts where the future cannot be credibly characterized by probability distributions. In practical terms, this enhances the strategic value of energy planning tools by enabling more targeted and robust responses to uncertainty.

6.1.2 How can correlations between uncertain parameters be systematically integrated into energy system models, and what is their impact on energy transition pathways?

Chapter 4 shows that explicitly incorporating empirical correlations among uncertain parameters transforms the design of robust energy strategies. Using a PCA-based approach to build tractable, data-driven uncertainty sets, this thesis provides the first national-scale demonstration of how correlation structures—not just the magnitude of uncertainty—can fundamentally shape transition outcomes.

The findings reveal that neglecting correlations leads to systematically distorted planning recommendations. Strategies that appear robust when uncertainties are assumed independent may fail under plausible joint evolutions of key drivers. Correlations influence not only technological competitiveness—such as the trade-offs between electrification and carbon capture pathways—but also the diversification and timing of investments.

By demonstrating how empirical structures among uncertainties affect robust strategies, this work extends robust energy planning beyond the conventional focus on scenario analysis toward a more rigorous treatment of internal consistency. It shows that credible robustness analysis requires not only exploring a wide range of futures but ensuring that these futures reflect the structural realities of uncertainty dynamics. This has critical implications for policy, as overlooking structural relationships such as the co-evolution of fuel prices and technology costs can result in plans that appear feasible on paper but are fragile in practice.

The application of the PCA-based method offers a practical pathway to enhance the realism of uncertainty modeling without sacrificing computational tractability. It contributes a new tool for improving the credibility, coherence, and policy relevance of robust energy system planning under deep epistemic uncertainty.

6.1.3 How can combinations of energy policy instruments be designed to protect against adverse futures across multiple energy transition objectives?

Chapter 5 develops a multi-metric, scenario-based decision support framework that systematically designs robust policy packages under deep uncertainty. By integrating exploratory modeling, SHAP-based feature importance analysis, and normalized worst-case robustness indicators, the framework enables identifying not just effective individual policies, but coherent combinations that complement each other in mitigating vulnerabilities—understood here as the exposure to worst-case outcomes across key transition metrics such as cost, emissions, or energy security—across multiple objectives.

The application to the Spanish energy system demonstrates its capacity to uncover policy synergies that would not emerge from traditional approaches. For instance, the joint implementation of high carbon pricing and ambitious urban mobility interventions outperforms isolated policies by ensuring robustness across emissions, cost, and energy security metrics.

This offers a powerful tool for policy-making: instead of selecting predefined policy combinations, decision-makers can generate and evaluate coherent portfolios that reinforce each other and maintain performance even under adverse conditions. This improves the resilience of strategies, reduces the risk of policy failure, and supports prioritization when resources are limited.

Beyond this case study, the framework offers a versatile and transparent methodology adaptable to different sectors, scales, and transition objectives. Its modular design allows tailoring metric selection and weighting to diverse policy contexts or stakeholder priorities, and its scenario-based structure facilitates extension to integrated multi-system transitions, such as water-energy-food planning.

Moreover, the framework can serve as a foundation for participatory decision processes, linking exploratory modeling with policy co-design through transparent evaluation of trade-offs. By bridging analytical rigor with actionable guidance, it contributes a practical tool for designing transition strategies that are robust, adaptive, and sensitive to real-world decision complexities.

6.1.4 The development of an open, extensible, and transparent energy system optimization model that enables robustness-oriented planning under deep uncertainty

The development of openMASTER represents a foundational contribution of this thesis, building upon and substantially extending the earlier MASTER model. Originally implemented in GAMS, MASTER has been re-engineered into a fully open-source Python-based platform, enabling broader accessibility and extensibility. In addition to this technological shift, openMASTER introduces significant methodological advances, providing a structurally practical and flexible platform to support robust energy transition planning under deep uncertainty. The model integrates features essential for capturing the complexity of real-world energy systems, including demand formulations based on energy services, endogenous behavioral adaptations, technological vintages and decommissioning processes, and raw material flows.

These structural capabilities are not directly aimed at implementing uncertainty treatments, but are crucial for characterizing how energy systems evolve and respond to profound, interdependent uncertainties. By incorporating key features often neglected in traditional models, openMASTER enhances the credibility and relevance of scenario exploration and robustness analyses, allowing energy transitions to be assessed in a way that more accurately reflects the structural complexity of real-world energy systems.

Importantly, openMASTER was designed from its conception with a modular and extensible architecture, explicitly intended to enable the incorporation of methodological innovations in uncertainty modeling. Its formulation supports the integration of robustness criteria, correlated uncertainty structures, and exploratory scenario frameworks without requiring structural simplifications.

In doing so, openMASTER bridges a critical gap in the energy modeling landscape: providing a transparent, reproducible, and adaptable platform that can serve both as a decision support tool for robust long-term planning and as a foundation for further methodological developments. As energy transitions confront increasing complexity and uncertainty, openMASTER offers a contribution to the scientific community, equipping researchers and policymakers with an open-source tool capable of addressing the strategic challenges ahead.

Although each methodological proposal developed in this thesis addresses a distinct and independent aspect of robust energy planning under deep uncertainty, together they define a complementary set of tools for improving the robustness of long-term decision support. The differentiated treatment of uncertainties, the integration of uncertainty correlations, and the design of robust policy packages each respond to specific gaps in existing modeling practices, and can be applied separately depending on the decision context and available information. While the thesis has not proposed an integrated application of these approaches, their conceptual compatibility and structural alignment within a flexible modeling framework suggest opportunities for future research to explore their combined potential. As a whole, the thesis advances a modular and extensible vision for robust energy system modeling, capable of adapting to the complexity and epistemic uncertainty that characterize contemporary energy transitions.

6.1.5 Summary of main contributions

This thesis has proposed and tested novel methodological approaches to address key challenges in energy planning under deep uncertainty. Specifically, it has produced three independent and complementary methodological contributions:

1. **Differentiated robustness treatments:** A hybrid optimization framework combining robust optimization with minimax regret to support decision-making under epistemic uncertainty. This approach enables the planner to identify strategies that are not only cost-effective on average but also minimize regret under adverse futures.

2. **Correlation-aware uncertainty modeling:** The application of a novel method to incorporate correlations between uncertain parameters, improving the internal consistency of uncertainty representations.

3. **Robust policy package design:** A framework for constructing and evaluating packages of policy instruments that perform well across a large ensemble of scenarios. This method reveals trade-offs, synergies, and potential conflicts between multiple policy objectives under uncertainty.

These contributions have been developed and validated independently using the open-source energy system optimization model openMASTER, which has been extended to support each methodological innovation.

6.1.6 Scientific Outputs and Publications

The research has led to the following scientific outputs, which consolidate and disseminate the contributions of the thesis:

- A.F. Rodríguez-Matas, C. Ruiz, P. Linares, M. Perez-Bravo. *How energy strategies are shaped by the correlation of uncertainties*. **Applied Energy**. Vol. 382, p. 125257, Mar. 2025. [Online: January 2025]

- A.F. Rodríguez-Matas, M. Pérez-Bravo, P. Linares, J.C. Romero. *openMASTER: the open source model for the analysis of sustainable energy roadmaps*. **Energy Strategy Reviews**. Vol. 54, pp. 101456-1 - 101456-12, July 2024. [Online: July 2024]

- A.F. Rodríguez-Matas, P. Linares, M. Pérez-Bravo, J.C. Romero. *Improving robustness in strategic energy planning: a novel decision support method to deal with epistemic uncertainties*. **Energy**. Vol. 292, pp. 130463-1 - 130463-12, April 2024. [Online: January 2024]

- A.F. Rodríguez-Matas, T. Wild, P. Linares, J. Lamontagne, David Dominguez-Barbero. *Designing robust energy policy packages under deep uncertainty: A multi-metric decision support framework*. Under Review in **Energy Policy** at the time of thesis submission.

- A.F. Rodríguez-Matas, J.C. Romero, M. Pérez-Bravo. *El tratamiento de incertidumbres en modelos de planificación energética: un caso de estudio sobre el presupuesto de carbono español para el objetivo climático de 1,5 ºC* (Managing uncertainties in energy planning models: A case study on the Spanish carbon budget for the 1.5ºC climate target). **Papeles de Energía**. Nº. 19, pp. 7 - 50, December 2022.

- A.F. Rodríguez-Matas, P. Linares. *Análisis de escenarios energéticos para España* (Scenario analysis for Spain). **Papeles de Economía Española**. Nº. 174, pp. 2 - 21, December 2022.

6.2 Limitations and Future research directions

While the methodologies developed in this thesis advance the capacity to support robust energy transition planning under deep uncertainty, several limitations and future research directions must be acknowledged:

6.2.1 Integrating the three methodological contributions

While the three contributions have been developed independently, they are not mutually exclusive. In fact, their integration holds significant potential to strengthen the analytical coherence and policy relevance of robust planning frameworks.

- **Correlation-aware uncertainty in robust optimization:** The correlation structures developed can be integrated into the uncertainty sets used in the hybrid minimax regret-robust optimization algorithm. This would enhance the realism and internal coherence of robustness assessments by explicitly capturing interdependencies between uncertain parameters. It is important to note, however, that these correlated uncertainty sets are only applicable to uncertainties treated within the robust optimization framework—i.e., those that affect model constraints. Incorporating correlations among uncertainties that affect the objective function, particularly under the minimax regret criterion, would require solving a non-trivial mathematical challenge and remains an open question for future research.

- **Correlation-aware scenario generation for policy design:** The large scenario ensembles used in robust policy package design could benefit significantly from incorporating correlation structures among uncertain parameters. Doing so would improve the credibility and interpretability of the exploratory scenario space by avoiding implausible combinations of extremes that may distort the assessment of policy robustness. Moreover, modeling joint dynamics across key drivers (e.g., energy prices, demand levels, technology diffusion) enables the identification of structural vulnerabilities and cross-sectoral dependencies that may otherwise be overlooked. However, the integration of correlations into scenario generation raises methodological and computational challenges. It requires selecting appropriate statistical or expert-derived correlation structures, ensuring that the resulting ensembles span a sufficiently diverse but plausible space, and maintaining tractability when evaluating large numbers of scenario-policy combinations.

- **Sequential combination of the hybrid algorithm and policy design:** The process of designing robust policy packages could build upon the results obtained from the hybrid optimization approach. For instance, the investment strategies identified as robust under the minimax regret-robust optimization criterion can serve as a starting point to define policy-relevant constraints—such as investment ranges, technology targets, or sectoral priorities—in the scenario exploration phase. This would help ensure that the exploratory analysis remains grounded in strategies that are already known to perform well under uncertainty. Combining these two approaches could have several advantages. It links two complementary perspectives: the hybrid algorithm provides clear guidance on which strategies minimize risks across futures, while policy package design allows for broader exploration of combinations of instruments and institutional settings. Together, they can support more realistic and actionable transition planning. However, this combination also brings some challenges. It requires careful coordination: the outputs of the hybrid algorithm must be translated into a form that is usable for the exploratory phase, without becoming overly rigid or limiting the space of possible policies. Moreover, the assumptions made in each stage (e.g., which uncertainties are included, what time horizons are considered) need to be aligned to avoid inconsistencies. Despite these challenges, this kind of sequential integration is a promising path for real-world robust policy design.

Future research could systematize these integrations and develop formalized architectures to combine them dynamically within unified planning frameworks.

6.2.2 Computational tractability

Computational tractability remains a relevant constraint, particularly when aiming to scale robust formulations and policy package design frameworks toward applications with greater geographical or temporal detail. Extending the current approaches to more disaggregated models—e.g., including finer spatial or temporal resolution—would require methodological innovations such as decomposition algorithms or high-performance computing to ensure practical feasibility.

In its current implementation, the openMASTER model comprises over 2 million variables and 3 million constraints for a national-scale case study covering a 50-year horizon with 5-year time steps and 96 representative time slices per year. Including additional layers of structural realism—such as explicit representation of power and gas networks, or unit commitment constraints—would significantly increase both the number of variables and the mathematical complexity of the problem, likely requiring a shift from linear to mixed-integer programming.

While such extensions are technically feasible and conceptually desirable, they would entail non-trivial trade-offs between structural detail and computational burden. Future work could explore strategies to enable such enhancements, including model aggregation-disaggregation schemes, Benders decomposition, or parallel solution strategies. These developments would broaden the applicability of openMASTER to multi-scale problems and operational planning tasks, while preserving the ability to conduct robust and policy-relevant long-term energy analyses.

6.2.3 Geographical disaggregation and integrated multi-model frameworks

In terms of modeling capabilities, openMASTER currently operates as a single-node, national-scale energy system model. Incorporating higher geographical disaggregation—allowing explicit modeling of infrastructures and regional network constraints—would significantly enhance its applicability to real-world planning exercises, especially where spatial factors and transmission systems play a critical role. However, the computational burden of such disaggregation is substantial. A promising strategy to address this challenge is model coupling: linking openMASTER with specialized models through soft or tighter integrations.

To date, an initial experience of soft-linking openMASTER with the power system expansion model SPLODER has been tested in a real-world application for a private company. However, this exercise was conducted in a deterministic setting, without incorporating any formal treatment of uncertainty. The models exchanged investment trajectories and operational constraints derived under nominal conditions, which provided useful coordination but lacked robustness to adverse conditions.

Looking ahead, model coupling under uncertainty requires more than sequential runs: it demands consistency in how uncertainty is represented and propagated across models. This implies defining clear interfacing functions—such as policy-induced investment envelopes, technology cost trajectories, or regional reliability targets—that preserve the logic of the uncertainty treatment, whether robust, stochastic, or scenario-based. For example, if openMASTER applies a minimax regret criterion to evaluate investment plans under deep uncertainty, the corresponding input to a power system model must retain this structure, for instance by passing cost-regret profiles or sets of constrained futures rather than single-point estimates.

Future developments could expand this coupling not only for finer spatial resolution but also for integrating macroeconomic models (Rodrigues et al., 2014), Integrated Assessment Models (IAMs) (Henke et al., 2024), or sector-specific models (Tattini et al., 2018), enabling complementary analyses across energy, economy, and climate domains. In all these cases, the ability to represent uncertainty coherently across models is essential for producing meaningful and decision-relevant outcomes. Ultimately, this type of multi-model interoperability could support the development of next-generation planning frameworks—modular, uncertainty-aware, and grounded in the structural complexities of real-world transitions.

6.2.4 Perfect foresight assumption

Another structural characteristic of openMASTER is its assumption of perfect foresight over the planning horizon. Although preliminary tests using a rolling horizon approach to introduce decision-maker myopia have been successfully conducted, a fully stable version of the model incorporating this capability has not yet been developed. Advancing this functionality would allow the model to represent more realistically how planning decisions are made under deep uncertainty, by limiting the information available to decision-makers and enabling the simulation of adaptive, staged strategies. In particular, it would provide a natural framework to explore how path dependencies, investment lock-ins, and sequential responses emerge as uncertainties are progressively revealed over time.

6.2.5 Flexibility in decision-making

Building on this, a critical area for future research is enhancing the flexibility of decision-making frameworks themselves. While the robust methods developed in this thesis provide protection across a wide range of futures, they do not yet systematically account for the opportunity to adapt decisions as new information emerges. Extending the frameworks to explicitly introduce decision flexibility—through mechanisms such as wait-and-see variables, sequential decision pathways, or embedded options for future adjustment—would allow planning processes to preserve optionality, avoid premature lock-ins, and better accommodate the evolving nature of uncertainties. Such developments would move beyond static robustness toward dynamic and adaptive robustness, better aligned with the realities of long-term transition governance under deep uncertainty.

6.2.6 Wald and Savage criteria limitations

While robustness criteria such as Wald and Savage are commonly used in energy planning under deep uncertainty, they have been criticized from the perspective of utility theory and behavioral decision-making. For example, regret-based methods may violate the independence of irrelevant alternatives axiom. Although these criteria are valuable from a normative standpoint, future research could explore their empirical validity by comparing model-based decisions with observed preferences or stakeholder behavior. This would help assess whether such criteria align with actual decision-making under uncertainty in energy policy contexts.

6.2.7 Role of correlation assumptions in the PCA-based method

A relevant clarification regarding the PCA-based robust optimization method presented in Chapter 4 concerns the role of correlation assumptions in the construction of uncertainty sets. The objective of this analysis is not to empirically identify the "true" correlation structure among uncertain parameters such as fuel prices or technology investment costs. Instead, the primary aim is to explore how different structural assumptions—positive, zero, or negative correlations— can be incorporated to energy modeling exercises and how they shape the resulting robust energy strategies.

To this end, the study introduces multiple correlation scenarios by varying the parameter L, which determines the directionality of the assumed relationships. This scenario-based design enables a systematic investigation of how correlation structures affect model outcomes and policy recommendations. While the PCA procedure is informed by historical data, its role in this context is methodological: it supports the construction of internally consistent, lower-dimensional uncertainty sets that reflect a given correlation structure, rather than aiming to replicate historical co-movements.

It is also worth noting that some of the historical data used to inform the PCA were obtained from subscription-based commercial databases. As a result, the raw datasets cannot be published openly, which limits the transparency and reproducibility of the specific empirical inputs used in this case study. However, the methodological framework itself is generalizable, and all the computational procedures are openly documented and available for replication with alternative datasets.

Future research could extend this approach in two directions. First, by expanding the dataset and applying formal statistical tests, researchers could assess which correlation patterns are most representative of empirical energy-economic dynamics. Second, visualizations and empirical diagnostics (e.g., pairwise scatter plots, eigenvalue distributions) could be developed to improve the interpretability and transparency of PCA-based uncertainty representations for decision-makers.

6.2.8 Behavioral measures and the representation of intangible costs

The model includes a set of behavioral measures that are endogenously optimized within the system-level cost minimization framework. These measures entail both tangible costs—such as investments in building retrofits—and intangible costs, such as the discomfort associated with reducing indoor temperatures, shifting travel behavior, or altering daily routines. These costs are incorporated directly into the objective function, enabling the model to explore trade-offs across a broad range of policy options.

The goal of this formulation is not to simulate behavioral dynamics through an agent-based or microeconomic framework, but rather to allow the model to compare behavioral-policy instruments (e.g., subsidies for retrofitting, public awareness campaigns, incentive schemes) with more conventional energy policy interventions. By assigning a cost to behavioral shifts, the model can endogenously determine whether and under what conditions these measures become cost-effective components of a robust transition strategy.

However, a key challenge of this approach lies in the calibration of the associated behavioral costs—particularly the intangible components, which are inherently difficult to quantify and highly sensitive to modeling assumptions. Future research could focus on estimating the perceived burden of specific behavioral changes, developing income-dependent or group-specific discomfort functions, or validating these assumptions against survey or experimental data. Moreover, a dedicated case study could be developed to systematically analyze the role, opportunities, and limitations of behavior-oriented policy instruments in long-term energy planning under uncertainty.

6.2.9 Limited expansion of storage technologies in openMASTER

A relevant outcome of the empirical applications is the limited deployment of electricity storage technologies, despite their prominence in current Spanish energy transition scenarios. This apparent inconsistency can be attributed to several factors:

- **Modeling objective:** The robust optimization criteria (especially minimax regret) emphasize avoiding worst-case outcomes across scenarios. In many cases, robust strategies rely more on overbuilding renewables or backup generation than on storage, particularly if the latter is expensive or underperforms in certain futures.

- **Temporal resolution:** Although the model currently represents seasonal and daily variability, the temporal granularity may not fully capture the balancing needs where storage technologies play a crucial role. Hence, the value of storage may be underestimated.

These results highlight the need for caution in interpreting storage expansion as universally optimal, and emphasize the importance of modeling uncertainty, system interactions, and behavioral dynamics when assessing technology roles.

6.2.10 Application to emerging high-impact challenges

The methodologies developed in this thesis can support the design of resilient strategies for several critical domains:

- **Industrial decarbonization**: Planning robust transition pathways for sectors like steel, cement, or chemicals, under high technology and resource uncertainty.
- **Transport-energy systems**: Assessing strategies that jointly address electrification, modal shifts, infrastructure interdependencies, and behavioral change, as explored in recent resilience assessments (Yeh et al., 2024; Perez-Bravo et al., 2025).
- **Critical material supply chains**: Designing robust strategies to manage disruptions in supply chains for key materials, incorporating inter-sectoral correlations and geopolitical uncertainties.
- **Shock resilience**: Evaluating system robustness to systemic shocks, including market crises, extreme weather, or cascading infrastructure failures.

These directions would extend the methodological frontier and reinforce the policy relevance of robust planning approaches.

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