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Adaptive Robust Optimization Approach for Energy System Optimization Models

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***Abstract*—Climate policy goals require massive expansion of renewable energy plants as well as transmission capacities and sector-coupling technologies. Although this requires a fundamental transformation, the energy system must be able to reliably supply future energy demand, especially for electricity and gas. In this context, Energy System Optimization Models (ESOMs) provide recommendations on future energy system designs. However, these models rely on deterministic assumptions about future developments. This reduces the robustness and validity of their findings in the context of uncertainty, especially with respect to future energy demands. To address this issue, Robust Optimization methods offer promising approaches to enhance the resilience of the optimized energy system designs by explicitly accounting for uncertainty in model inputs.**

In this context, this paper introduces an Adaptive Robust Optimization framework to consider uncertainty in future energy demands and applies it to a state-of-the art ESOM. The resulting model can be used to identify robust capacity expansions of generation and transmission infrastructures, that protect against the uncertainty across various scenarios.

***Index Terms*—Adaptive Robust Optimization, Energy System Optimization, Uncertainty, Energy Demand**

I. Introduction

Energy-related infrastructure expansions, such as the construction of power plants or the reinforcement of transmission grids, involve significant costs and long investment cycles [1, 2]. Therefore, these decisions must consider long-term developments and uncertainties. However, forecasts on the future vary depending on the underlying assumptions and are therefore highly uncertain. In particular, different transformation paths for the demand structure are conceivable, in which the demand for specific energy carriers varies greatly [1].

Consequently, considering uncertainties in future energy demand within planning frameworks is crucial. In this context, Energy System Optimization Models (ESOMs) provide decision-support tools that evaluate energy system designs under varying assumptions [3]. They provide recommendations for policymakers and planners on which technologies to deploy, where to expand infrastructures, and to which extent sector-coupling technologies should be integrated into the system. Although ESOMs provide recommendations on energy system designs, they typically rely on deterministic assumptions regarding future developments [3, 4]. This can reduce robustness and validity of the findings. To address this, Robust Optimization (RO) offers a method to enhance robustness of the optimized energy system designs by explicitly accounting for uncertainty in the model parameters. RO aims to identify expansions in the energy system that protect against the unknown realization of uncertainties and ensure that energy demands can be supplied in all future scenarios [2, 5].

The original concept of RO assumes that all decision variables must be determined before uncertainty realizes [6]. However, since expansions are determined by future operating conditions, ESOMs include variables for long-term investment decisions as well as variables for short-term operational decisions. This makes the single-stage RO not suitable for ESOMs, as one exact operation for all future scenarios cannot be determined. Adaptive Robust Optimization (ARO) extends the RO to a two-stage framework and allows a subset of decision variables to be determined after the actual realization of uncertainty, thereby reacting to the uncertainty realization and mitigating potentially harmful impacts [5]. Therefore, ARO is suitable for optimizing investment decisions on capacity expansions, which need to be taken today, while allowing different operational decisions to react to uncertainties.

A. Related Work

In the literature, RO and ARO have been applied to optimization problems in energy system analysis, especially in Transmission Expansion Planning problems (see [7]–[10]). Riepin et al. [11] employ ARO to a European gas infrastructure planning problem with long-term uncertainties on the demand and supply side. However, to the best of the authors' knowledge, this paper constitutes the first usage of ARO in Generation and Transmission Expansion Planning within a large-scale ESOM, that considers multiple energy carriers and long-term uncertainties regarding their future demand.

B. Main Contribution and Structure

The objective of this paper is to develop and apply an ARO framework within a large-scale ESOM. The ESOM includes the energy carriers electricity, hydrogen, methane, and synthetic fuels, and optimizes the operation and capacity expansion of their respective generation and transport infrastructures. The novel extension allows for identifying infrastructure expansions, which are robust against future developments of the energy demand and the associated uncertainties. The model is applied to the European energy system to investigate the

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impact of uncertainties and robustness on the energy system design. To ensure the practical relevance of the results, the case study is based on expert-defined future demand scenarios from the German Federal Ministry for Economic Affairs and Energy and therefore considers policy-relevant uncertainties.

The remainder of the paper is structured as follows: Chapter II presents a brief overview of the theoretical background, beginning with optimizing energy system designs under uncertainties and introducing RO and ARO. The third chapter describes the method in detail, including the mathematical formulation of the ESOM and the practical implementation of ARO. This is followed by exemplary investigations and their results in Chapter IV, where the ARO approach is applied to a case study. Finally, Chapter V summarizes the findings of the paper and outlines possibilities for future research.

II. Theoretical background

A. Optimization under Uncertainties

Optimization problems, including ESOMs, are usually formulated as deterministic problems [4]. However, since predicting future developments is uncertain, reliably parameterizing the objective function and constraint coefficients in ESOMs is challenging. Therefore, deterministic optimization models and their results are subject to parametric uncertainties [4].

Political discussions focus mainly on uncertainties in future energy demand [1]. The demand for different energy carriers depends on several factors, like technological, economic, and social drivers [12]. Since ESOMs are used to identify optimized energy system designs and to support decision-making in politics, society, and science, high standards are imposed on the reliability and validity of their results [4]. To avoid conveying a misleading reliability of the optimized results, uncertainties in the future energy demand and their impacts must be considered. Considering that the energy system should be able to supply energy demand in all possible situations, approaches are needed to derive robust system designs [5].

B. Robust Optimization

The goal of RO is to determine solutions, in our case optimized energy system designs, that remain feasible in their constraints for all uncertainties that may occur [5, 13]. Therefore, RO offers a framework to identify strategies that protect against the worst uncertainty realization within a given uncertainty set [5, 13]. In contrast to stochastic optimization, RO does not rely on probability distributions of the uncertain parameters [4]. This is beneficial as determining probabilities for future demand scenarios is challenging.

In the general concept of RO, uncertain parameters can take values within an uncertainty set $u \in \mathcal{U}$ that characterizes all potential realizations of uncertain coefficients in $\mathbf{c}, \mathbf{b}, \mathbf{A}$ [13]. The objective aims to minimize the worst-case costs over all uncertainty realizations, providing an upper bound for the total system costs [5]. Consequently, the *Robust Counterpart (RC)* for a linear program (LP) which is subject to uncertainty in its coefficients, can be formulated as follows [13, 15]:

$$\begin{aligned} \min_{x} \max_{u} \; & c^\top \mathbf{x} \\ \text{s.t. } & \mathbf{A}\,\mathbf{x} \leq b \\ & (c, A, b) \in \mathcal{U}, \end{aligned} \tag{1}$$

where $\mathcal{U}$ denotes the uncertainty set that contains all possible realizations of the uncertain parameters. A particular realization of the uncertain parameters is referred to as a *scenario*, denoted by s. The RC ensures that the constraints are satisfied for all possible realizations of the uncertain parameters within $\mathcal{U}$, thereby providing a solution that is guaranteed to be feasible under any scenario captured by the uncertainty set. [15]

C. Adaptive Robust Optimization

The original concept of RO assumes that all variables represent decisions that must be made before uncertainty realizes [6]. However, in the majority of real-world optimization problems as well as in energy system planning via ESOMs, only a few variables represent so-called 'here-and-now' decision variables [6]. In ESOMs these correspond to long-term investment decisions. This applies to the expansion of generation and transport capacities. On the other hand, the optimization problem includes 'wait-and-see' variables, which can be adopted after the uncertainty has been realized [6]. These include short-term operational decisions within the energy system, allowing for adjustments based on the investment decisions made. As they represent decisions that can be made after uncertainty realizes, they are also known as recourse decisions. The resulting problem is called a two-stage or adaptive decision making problem [5].

Adaptive or adjustable robust optimization was first introduced by Ben-Tal et al. [6] and extends the traditional RO approach by accounting not only for static here-and-now decisions, but also for wait-and-see decisions as recourse decisions [6]. The optimization is then composed of an outer minimization of the investment costs and a coupled inner max-min problem of the operational costs. After solving the outer investment optimization problem with respect to the decision variables $\mathbf{y}$ and their investment costs C_I, the worst-case realization of the uncertainty in terms of costs is determined. Subsequently, the recourse problem is solved for this realization by optimizing the corresponding operational decision variables $\mathbf{x}$. As described in [11], the resulting three-stage optimization problem is then formulated as

$$\begin{aligned} \min_{y} \;\; & C_I^\top\, \mathbf{y} + \max_{u} \min_{x} \left[C_O^\top\, \mathbf{x} \right] \\ \text{s.t. } \; & h(\mathbf{y}) = 0, \\ & g(\mathbf{y}) \leq 0, \\ & \mathbf{y} \in \mathcal{Y}^n, \; u \in \mathcal{U}, \; \mathbf{x} \in \Xi(\mathbf{y}, u) \end{aligned} \tag{2}$$

where $h(\mathbf{y})$ and $g(\mathbf{y})$ denote constraints that only affect $\mathbf{y}$. The feasibility set $\Xi(\mathbf{y}, u)$ of the inner minimization (operational

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decisions) depends on the investment decisions of the first stage $\mathbf{y}$ and the uncertainty realization u. [2, 5, 11]

The approach to solve the ARO problem described in (2) depends on the structure of the uncertainty set $\mathcal{U}$ and the underlying optimization problem. When the uncertainty set is continuous, an infinite number of uncertainty realizations must be considered, making the ARO problem typically computationally intractable (NP-hard) [6, 16]. In contrast, scenario-based approaches like in [17], [18] and [19] can be applied, where the uncertainty set consists of discrete scenarios. The scenario-based approach introduces new operational variables x^s for each scenario $s \in S$ to represent the uncertainty realizations [18]. This reformulation increases the number of variables but still remains tractable when the uncertainty set consists of a limited number of discrete scenarios. For an uncertainty set consisting of r discrete scenarios, i.e., $\mathcal{U} = \{s_1, s_2, \ldots, s_r\}$, this results in the model in (3). The condition $G\,\mathbf{y} + E\,\mathbf{x}^s \leq \mathbf{e}$ ensures that a single set of investment decisions remains feasible for all scenarios.

To solve ARO problems with discrete uncertainty sets, the inner maximation problem can be reformulated via its epigraph as introduced in [20]. The epigraph reformulation introduces a new variable z, which acts as an upper bound of the inner maximization problem. This allows to move the inner problem to the constraints, so that only a deterministic objective function remains [5, 7]. A graphical illustration of an epigraph for a generic function is provided in Fig. 1. Since z must be greater than or equal to $f(x)$ for all $x \in \mathcal{X}$, maximizing $f(x)$ is equivalent to minimizing z subject to $z \geq f(x)$ [20].

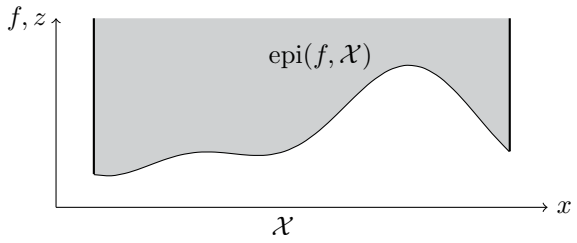


Fig. 1. Epigraph of a function f on $\mathcal{X}$ [20]

The epigraph-based reformulation allows the ARO problem in (2) to be expressed as a single minimization problem:

$$\begin{aligned} \min_{\mathbf{y},\mathbf{x},\mathbf{z}} \; & C_C^\top\,\mathbf{y} + \mathbf{z} \\ \text{s.t.} \; & z \geq c_O^\top \mathbf{x}^s, \quad s = 1, \ldots, r, \\ & h(\mathbf{y}) = 0, \\ & g(\mathbf{y}) \leq 0, \\ & G\,\mathbf{y} + E\,\mathbf{x}^s \leq \mathbf{e}, \quad s = 1, \ldots, r, \\ & \mathbf{y} \in \mathcal{Y}^n. \end{aligned} \tag{3}$$

In this formulation, while z is minimized, the solver must ensure that it remains no smaller than the worst-case realization of the inner minimization problem across all scenarios. Thus, problem (3) implicitly performs a maximization over the discrete elements of $\mathcal{U}$ [19].

III. Methodology

A. Energy System Optimization Model

An existing ESOM introduced by [21] and [22] serves as basis for this paper. The model is formulated as a large-scale LP to represent the European energy systems, containing only linearized formulations and no binary expansion variables. It is classified as a Generation and Transmission Expansion Planning problem, since it optimizes the expansion and operation of generation and transmission infrastructures [21]. The ESOM represents infrastructures for electricity, hydrogen, methane, and synthetic fuels, including sector-coupling technologies that enable energy conversion between energy carriers.

The model minimizes the total annual energy system costs to identify optimized energy system designs. To this end, the objective function includes annuity investment costs for expansions as well as operating costs. Operating costs include electricity, gas, or fuel generation costs as well as import and storage costs. The demand for the different energy carriers must be supplied at each node and time step, otherwise penalty costs for unserved energy demand occur.

In addition to the objective, the model comprises various constraints. Since ARO differentiates between investment and operational variables, the constraints linking these variables are of special interest. The linking constraints are given by

$$x_{i,n,q,t} \leq Y_{i,n}^{\text{init}} + y_{i,n} \quad \forall\, i \in I,\ n \in N,\ q \in Q,\ t \in T \tag{4}$$

and are defined for all generation or conversion technologies $i \in I$ for the represented energy carriers $q \in Q$. This includes non-dispatchable renewable energy resources (RES) plants or thermal power plants, electrolysers, methanation, or synthetic fuel generation plants. The conditions in (4) restrict the maximum power, gas, or fuel injection or withdrawal $x_{i,n,q,t}$ possible at a given node $n \in N$ for all timesteps $t \in T$, based on the sum of the initial capacity $Y_{i,n}^{init}$ and additional capacity expansion $y_{i,n}$.

The same conditions are formulated for the transport infrastructures of the respective energy carriers $q \in Q$. For each power or gas transmission connection $e \in E$ between two nodes $(n, m) \in N$ the flow $f_{e,q,t}$ is restricted by the initial capacity F_e^{init} and the expanded capacities f_e^+:

$$|f_{e,t}| \leq F_e + f_e^+ \qquad \forall\, e \in E(q),\ q \in Q,\ t \in T \tag{5}$$

Additional model restrictions impose limits on greenhouse gas emissions (GHG) to account for climate policy goals and limits on locally available potentials for RES plants. Other constraints model the conversion between energy carriers via sector-coupling plants and energy storages or enable import possibilities. The model further comprises constraints for balancing net-injections (generation) and withdrawals (demand) at each node, as well as enforcing network flow conservation for each energy carrier in its respective transport network.

B. Adaptive Robust Optimization Framework

This paper focuses on uncertainties in the future energy demand, i.e., only on parameters of the right hand side of the

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optimization problem. Discrete scenarios form the uncertainty set. Scenarios are commonly used to describe potential future developments and are based on comprehensive analysis and models to capture the factors influencing future demand. Therefore, they provide a consistent description of future developments and their uncertainties. Uncertainties in other parameters, like objective coefficients, are not considered.

To apply the ARO from (3) to the objective function of the ESOM, the expansion variables are separated from the operational variables. The objective function only includes the capacity expansion variables ($y_{i,n}$ and f_e^+), and the variable z from the epigraph formulation, which replaces the worst-case maximization problem. All remaining variables are operational decisions that are moved to the constraints via z.

For constraints, the epigraph reformulation shown in (3) introduces additional constraints for each scenario. This ensures that the auxiliary variable z is greater than or equal to the operational costs of each respective scenario. In doing so, the objective function accounts for the worst-case scenario and its costs via z. In addition, a single set of investment decisions must remain feasible for all scenarios $s_1, s_2, \ldots, s_r$. For this, the constraints enforce the feasibility for all operational decisions $\mathbf{x}^s$ in all scenarios. The linking constraints (4) and (5) are therefore formulated for each scenario individually, containing the respective operational decisions $\mathbf{x}^s$, but the same set of expansion decisions $\mathbf{y}$. Furthermore, all constraints that contain only operational deciscions must be formulated for each scenario.

IV. Results and Discussion

A. Use Case

The *Langfristszenarien* (LFS, *Long-term Scenarios*) from the German *Federal Ministry for Economic Affairs and Energy* form the basis for the scenarios of the uncertainty set $\mathcal{U}$ [1]. In particular, this paper investigates three alternative scenario pathways to a GHG-neutral German energy system by 2045 using the 'T45'-scenarios released in 2022. The scenarios focus on different technological demand trajectories, especially high electrification (*T45-Electricity*), extensive usage of green hydrogen (*T45-H2*), or an increased use of synthetic methane and synthetic fuels (*T45-PtX*). Each LFS quantifies sectoral energy demands and therefore represents the relevant uncertainties from an energy supply perspective. [1]

The spatial scope of the investigations includes the EU member states, the UK, Norway, Switzerland, and the Balkan states at country-level. Germany represents the focus area with a spatial resolution of NUTS-2. The temporal scope is the year 2045 with an hourly temporal resolution. Data for regionalization and the generation of time series for the demand scenarios is described in [12]. Other input data assumptions are described in [22].

B. Results

This section investigates the application of the ARO framework. First, we apply the original ESOM described in section III.A deterministically to the three scenarios to optimize the respective energy system expansion. Subsequently, the ARO model presented in section II.B and III.B is applied to the uncertainty set of the three scenarios as a whole. Afterwards, the infrastructure expansions of the four runs are compared to examine the impact of uncertainties and robustness.

Fig. 2 shows the installed capacities for the RES plants (left) and the sector-coupling technologies (right) in Germany for the LFS in 2045. The first three bars represent the deterministic optimizations of the scenarios *T45-Electricity*, *T45-H2*, and *T45-PtX*, while the fourth bar represents the ARO results.

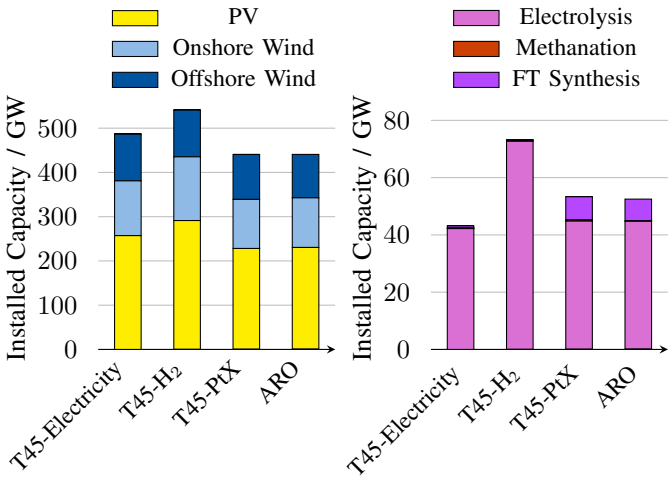


Fig. 2. Installed capacities of RES (left) and sector-coupling plants (right) in Germany for the deterministic and ARO runs.

The installed RES capacities vary only slightly between the scenarios, as electricity is needed in all scenarios. Besides the scenario with high electrification, this also applies to the scenarios with high demands for hydrogen or synthetic energy carriers, since their production relies on electricity. Consequently, the *T45-H2* scenario indeed shows the highest installed RES capacity for Germany. As Fig. 2 shows, the optimization prefers hydrogen production via domestic electrolysis over hydrogen imports in this scenario. Significant capacities for Fischer-Tropsch (FT) synthesis to produce synthetic fuels are only expanded in the *T45-PtX* scenario.

Analyzing the total costs for the entire European energy system, the *T45-PtX* scenario turns out to be the most expensive. The total system costs are 5% higher than in the cheapest, the *T45-Electricity* scenario. In the *T45-PtX* scenario, especially the imports of synthetic energy carriers from non-European countries, represent the main cost drivers. The up to 2.4 times higher import volumes compared to the other scenarios imply that the significantly higher methane and liquid demands in the *T45-PtX* cannot be cost-effectively supplied by domestic production. This leads to overall higher system costs, despite having lower installed capacities than in the *T45-Electricity* and *T45-H2* scenario.

Since it is the most expansive scenario, the ARO identifies the *T45-PtX* as worst-case. This results in similar optimized capacity expansions in the *ARO* run and *T45-PtX* (see Fig. 2). At the same time, the expanded infrastructure capacities

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of *T45-PtX* / *ARO* are sufficient to supply the energy demand in the other scenarios. This indicates that the *T45-PtX* scenario remains the most expansive, even when the *T45-Electricity* or *T45-H2* scenario realizes within this energy system design. In this specific case, choosing the most expensive energy system design provides flexibility to adapt to varying scenarios. Consequently, the cost of robustness for one scenario pathway corresponds to the cost difference to the most expensive, deterministic scenario, i.e. at most 5%.

Although the overall system costs remain lower than in the *T45-PtX* scenario, using this worst-case energy system design implies higher import quantities in the other scenarios. Especially in the *T45-H2* scenario, large amounts of hydrogen imports from outside of Europe become necessary. These imports were not part of the optimized solutions of the deterministic *T45-PtX* or *T45-H2* scenarios. Consequently, significant increases in imports allow operating the energy system in all possible scenarios. However, it remains questionable whether low-cost import options can be used in such a flexible way. Therefore, further investigations might be necessary that restrict the import options more strictly.

V. Conclusion

In this paper, we have developed and applied an ARO model within a large-scale ESOM to consider long-term uncertainties in future energy demand. In contrast to the traditional concept of RO, ARO provides a two-stage optimization framework that allows some decision variables to be determined after uncertainty realization. This makes ARO particularly suitable for ESOMs, where capacity expansions and operational decisions are being optimized. Within the paper, the ARO problem was reformulated using an epigraph formulation and adapted to a discrete uncertainty set consisting of expert-defined scenarios.

The ARO model was applied to the European energy system to investigate the impact of uncertainties and robustness. The results identify the *T45-PtX* scenario as the most expensive due to high synthetic energy carrier imports. This makes it the worst-case uncertainty realization for the ARO. Since this scenario remains the most expensive even within other uncertainty realizations (*T45-Electricity* or *T45-H2*), it becomes the decisive scenario for the ARO algorithm. With regard to long-term uncertainties in energy demand, it therefore provides a robust energy system design. However, large import quantities are needed in case other scenarios occur.

While the investigations focus on demand uncertainties, broader robustness requires the consideration of further uncertainties. These include RES and fuel import availability or cost parameters. Although the presented model can be applied to these uncertainties as well, the number of simultaneously optimized scenarios remains limited. Therefore, further developments are necessary here. Moreover, ARO still remains a conservative approach, since it protects against the worst-case scenario. This results in high system costs and a overly conservative design. Therefore, less-conservative robustness concepts should be examined.

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