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Originally published as:

[Odenweller, A.](#) (2022): Climate mitigation under S-shaped energy technology diffusion: Leveraging synergies of optimisation and simulation models. - Technological Forecasting and Social Change, 178, 121568.

DOI: <https://doi.org/10.1016/j.techfore.2022.121568>

Climate mitigation under S-shaped energy technology diffusion: Leveraging synergies of optimisation and simulation models

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Abstract

Transforming global energy systems is critical for climate change mitigation and requires overcoming not only techno-economic, but also socio-technical hurdles. The main tools to analyse challenges in these two domains are integrated assessment models (IAMs) and transition theories or models, respectively. Despite a surging interest in integrative research that leverages complementarities in order to include social constraints into IAMs, both approaches are often confined to their own disciplinary background and practical integration studies of existing models are scarce. Here I demonstrate the feasibility of model integration by a bi-directional soft-link that merges the strengths of a neoclassical intertemporally optimising IAM with one global region, and a technologically and regionally highly resolved, evolutionary simulation model of S-shaped technology diffusion in the power sector. The new model iteratively converges to a stable equilibrium via two time-dependent coupling variables: carbon prices and renewable energy shares. The results for a 2 °C scenario show that due to gradual technology diffusion, energy transition challenges are exacerbated and incur higher economic losses. I discuss the potential of coupling existing models as an option to combine insights from different disciplinary perspectives to energy transitions.

Keywords: Integrated assessment modeling, Energy transition, Climate change mitigation, Model coupling, Technology diffusion

1. Introduction

Curbing the confirmed and growing human influence on the climate system in order to abide by the 2015 Paris Agreement (UNFCCC, 2015) will require a profound transformation of the global energy system from fossil fuels to low-carbon energy sources. In order to accelerate technological change and spur innovation, policymakers therefore need to draw on ‘a wide portfolio of mitigation options and a significant upscaling of investments in those options’ (IPCC, 2018, p. 15). This entails phasing out fossil technologies and scaling up renewable technologies, potentially beyond growth rates observed so far (Cherp et al., 2021). Studies of technology diffusion describe the dynamics of these processes on the macro level (Grübler et al., 1999).

Technological change and the diffusion of new technologies are analysed from different vantage points, which may broadly be subsumed into techno-economic and socio-technical perspectives, ranging from technical feasibility to economic viability and social acceptance. In juxtaposition, these two categories help to understand the observed disparities between ambition and action as the ‘disconnect between where we are and where we need to be’ (UNEP, 2019, p. 1) continues to widen. The feasibility of mitigating climate change therefore hinges not only on negotiating techno-economic obstacles, but also on overcoming socio-technical constraints of the energy transition.

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This division of the multi-faceted challenges of technological change into techno-economic and socio-technical aspects of energy transitions resonates with a multitude of meta-theoretical frameworks (Cherp et al., 2018; Grubb et al., 2015) and relates to two disciplinary approaches with distinct theories, contrasting modelling assumptions, and hence complementary strengths. Unlocking these synergies to find solutions to energy and climate challenges, increase realism in models and foster interdisciplinary learning has been the focal point of a new research community (Trutnevyte et al., 2019; Hirt et al., 2020) that is quickly gaining ground alongside calls to ‘embed the social sciences in climate policy’ (Victor, 2015), suggestions that ‘integrated assessment model-based analysis should be complemented with insights from socio-technical transition analysis and practice-based action research’ (Geels et al., 2016), and forthright statements that ‘climate policy models need to get real about people’ (Peng et al., 2021).

Despite a general agreement about the complementary knowledge base of techno-economic and socio-technical approaches to global energy transitions, the discussion on how to best leverage the available synergies has all but converged. Different approaches of operationalising socio-technical transitions range from the development of scenario narratives based on social science insights for usage in techno-economic integrated assessment models (IAMs) (van Sluisveld et al., 2020) to the development of fully new modelling frameworks such as overlapping socio-technical energy transition (STET) models (Li and Strachan, 2017) and agent-based models (ABMs) (Lamperti et al., 2018; Hötte, 2020). These two possibilities either follow in the footsteps of the ‘story and simulation’ approach, iteratively translating qualitative storylines into quantitative scenarios (Alcamo, 2008), or attempt to merge insights from social sciences into completely new models. Meanwhile, practical studies that leverage synergies of two already-existing models from the techno-economic and socio-technical realm remain few and far between (Hirt et al., 2020).

In this paper, I contribute to this growing body of literature by shining a spotlight on an example of practical model integration. Specifically, I present a bi-directional iterative soft-link that merges two models:

- **MIND**: a techno-economic optimisation IAM with one global region that maximises social welfare under a given temperature target, using a neoclassical Ramsey-type growth core and a parsimonious climate model
- **FTT:Power**: a socio-technical simulation model of the power sector based on logistic technology diffusion with 24 technologies in 61 regions, including pronounced path-dependencies and a simplified aggregate representation of actor heterogeneity

The MIND-FTT soft-link addresses the multi-dimensionality of technological change by a numerical scheme that joins insights from two complementary modelling paradigms: neoclassical economics, which provides techno-economic intertemporal optimality, and evolutionary economics, which builds upon the socio-technical notion of behavioural and systemic inertia (Marechal and Lazaric, 2010).

The remainder of this paper is structured as follows. In the upcoming Section 2, I review the literature, juxtapose techno-economic and socio-technical approaches in policy models and identify key complementarities. Drawing on this, in Section 3, I concisely describe and justify the choice of both models. In Section 4, I develop the soft-link procedure. Section 5 shows key results for a global 2 °C scenario. In Section 6, I discuss insights, limitations and prospects against the backdrop of incorporating societal dynamics into models for energy and climate policy. Section 7 concludes.

2. Perspectives on technological change

Technological change of energy system technologies are analysed from different vantage points with complementary research foci and distinct research communities. In the past decade, various meta-theoretical categorisation frameworks have emerged. Following Cherp et al. (2018), a three-fold classification distinguishes the *techno-economic* perspective, the *socio-technical* perspective, and the *political* perspective. This trichotomy loosely resonates with and condenses other classifications such as Grubb et al.’s (2015) ‘three domains’ of energy-climate transitions, Turnheim et al.’s (2015) and Geels et al.’s (2016) ‘three analytical approaches’ for sustainability transitions, and Grübler’s (2012) ‘insights and cautionary tales’ on energy transitions research.

As variables within the politico-institutional domain are often understood as the solution space of IAMs and because complex political processes defy easy quantification, they are usually not modelled endogenously, but rather analysed with model intercomparison projects that explore second-best non-idealised scenarios under fragmented action (e.g. Edenhofer et al., 2012). I follow this practice and limit myself to the techno-economic and socio-technical perspective, which are now briefly summarised.

2.1. *Techno-economic approaches*

Techno-economic considerations focus on a process-oriented representation of markets, energy flows, energy conversion processes, and capital stocks and thus feature predominantly in quantitative systems modelling (Cherp et al., 2018). This includes energy system models and IAMs, which are best known for providing the backbone of the policy recommendations of the IPCC (2007, 2014, 2018) reports. Many IAMs have disciplinary roots in neoclassical economics, which due to its well-established axiomatic foundations lends itself easily to the analysis of quantitative variables in forward-looking models.

The techno-economic perspective of technological change focusses on quantifiable industrial dynamics such as depreciation of capital stocks, resource scarcity effects, and technological turnover rates. A prominent debate in this context revolves around the threat of a carbon lock-in as a special case of path dependency particularly prone to entrenchment due to the large associated capital costs and the longevity of infrastructure investments (Unruh, 2000; Bertram et al., 2015; Seto et al., 2016). This has recently aroused heightened interest as committed emissions from existing energy infrastructure were found to jeopardise the 1.5 °C target (Tong et al., 2019), which necessitates to strand fossil fuel assets (Pfeiffer et al., 2018), potentially putting financial stability at risk due to severe economy-wide macroeconomic impacts (Mercure et al., 2018).

For their strong points of a rigorous, formalised and systematic analysis, techno-economic policy models are routinely used to produce cost-optimal scenario results under exogenous emissions reduction constraints. In this context, optimality refers to a single or compound metric (e.g. aggregated welfare, abatement costs), which includes quantifiable trade-offs and interactions between different sectors (Geels et al., 2016). However, while ensuing results are *possible* from a purely techno-economic viewpoint, they may not be *plausible* from a wider societal stance once further frictions stemming from behavioural effects, gradual innovation processes, and path-dependent technology diffusion are accounted for (Cherp et al., 2018; Mercure et al., 2019; Trutnevyte et al., 2019). For example, a recent report argued that ‘limiting global surface warming below about 1.7 °C by 2100 is currently not plausible’ due to such constraints (Stammer et al., 2021). Scenarios that explore non-idealised emission pathways are therefore often informed by narratives about societal developments such as the shared socio-economic pathways (SSPs) (O’Neill et al., 2014), yet seldom endogenised. Expanding the scope of primarily techno-economic models to incorporate additional socio-technical constraints thus continues to be challenging.

2.2. *Socio-technical approaches*

Socio-technical analyses, on the other hand, are often concerned with less tangible, yet equally important, processes. With respect to energy transitions, the focus lies on more nuanced and fine-grained aspects of technological change, most notably the emergence and diffusion of new technologies (Cherp et al., 2018). This encompasses a wide spectrum of studies, ranging from ‘technological innovation systems’ with roots in evolutionary economics and a focus on temporal transformation dynamics (Markard et al., 2012; Mercure et al., 2019) to ‘socio-technical transition analysis’ with closer disciplinary connections to the social sciences (Turnheim et al., 2015; Geels et al., 2016), including the prominent multi-level perspective (Geels, 2002; Geels and Schot, 2007).

The socio-technical perspective of technological change revolves around technology diffusion and technological lock-ins, which are however portrayed in the wider co-evolutionary understanding of society and technology. Notable aspects that go beyond the techno-economic scope include agent heterogeneity (Li and Strachan, 2019; Mercure et al., 2016), a broader notion of path dependence as structural resilience (Turnheim et al., 2015), and behavioural effects (Knobloch and Mercure, 2016). Both qualitative frameworks and quantitative modelling may be used, of which the latter requires a substantial degree of simplification to cast complex societal dynamics into model equations (Trutnevyte et al., 2019). The socio-technical perspective

goes beyond the techno-economic notion of inertia of technological change by covering additional frictions at both the behavioural and systemic level (Marechal and Lazaric, 2010; Li et al., 2015).

The main strength of socio-technical analyses therefore lies in its contextualised fine-grained perspective of innovation and technology diffusion due to multiple actors that interact on different levels, leading to an enhanced ‘attention to inertia of existing systems’ (Geels et al., 2016, p. 580). While this enables a more holistic view of the path-dependent nature of technology transitions (Marechal and Lazaric, 2010), it also bears the risk of overlooking the important techno-economic bedrock of energy transitions (Cherp et al., 2018). Furthermore, socio-technical analyses often focus on descriptive qualitative case studies, which complicates integration into forward-looking quantitative models that require generalisable context-independent patterns. Despite these pitfalls, the two complementary approaches are not incommensurable as recent research has outlined benefits and strategies for a mutually enriching, structured dialogue.

2.3. *Benefits and strategies of linking both approaches*

During the past years, a new strand of research has emerged that aims to leverage the synergies of the techno-economic and socio-technical perspective by linking quantitative modelling with transition theories (review in Hirt et al., 2020). This encompasses studies that embrace quantitative modelling in transitions research with varying degrees of integration (e.g. van Sluisveld et al., 2020; Li and Strachan, 2017; Geels et al., 2020; Hötte, 2020) as well as more conceptual roadmaps that highlight complementarities, outline exchange possibilities, and thus point the way ahead for future research (Otto et al., 2020; Trutnevyte et al., 2019; Geels et al., 2016; Victor, 2015; Hof et al., 2020; Li et al., 2015; Turnheim et al., 2015; De Cian et al., 2020; Marechal and Lazaric, 2010).

Acknowledging complementary strengths, the *linking benefits* largely correspond with the shortcomings of techno-economic models. Following Trutnevyte et al. (2019), IAMs could benefit the most from interdisciplinary exchange in three interrelated areas. The first area is related to behavioural effects such as changes of consumption patterns (Grubler et al., 2018), individual preferences (Engels et al., 2013), but also wider questions related to society’s adaptive capacity and willingness to transform (Andrijevic et al., 2020). The second major area concerns temporal transformation dynamics, for example regarding lock-ins (Bertram et al., 2015; Seto et al., 2016), path dependencies (Turnheim et al., 2015), and the pace of transformations due to inertia in the energy system (Grubb et al., 2021) as also reported in Keppo et al. (2021). The third area includes heterogeneity on multiple scales such as contextual factors (Li and Strachan, 2017), distributional impacts (Mercure et al., 2018), and incumbent industries (McDowall, 2014). Enabling exchange in these key areas leads to three distinct benefits with increasing levels of difficulty: interdisciplinary learning, enhancing realism of models, and identifying practical solutions to energy and climate challenges (Trutnevyte et al., 2019; Hirt et al., 2020).

Trutnevyte et al. (2019) identify three main *strategies* for linking models with insights from social sciences with increasing degrees of integration: *bridging*, *iterating*, and *merging*. The *bridging* strategy relies on models and storylines that proceed in parallel and only exchange information at pre-specified moments, briefly building so-called bridges between shared concepts (Geels et al., 2016; Turnheim et al., 2015; van Sluisveld et al., 2020; Geels et al., 2020). The *iterating* strategy is akin to the story and simulation approach (Alcamo, 2008), which translates broad narratives about societal development into quantitative assumptions such as the SSPs (O’Neill et al., 2014) that are used to constrain models whose output is subsequently used to revise the storyline assumption in an iterative process (Trutnevyte et al., 2014; McDowall, 2014; Robertson et al., 2017).

At the upper end of the integration spectrum, the *merging* strategy aims at an in-depth consolidation of the two approaches in a mathematical formalism, which implicitly assumes that the key dynamical properties of the underlying socio-technical systems can be cast into model equations (Hirt et al., 2020; Li and Strachan, 2017, 2019; Mercure et al., 2016; McCollum et al., 2017; Hötte, 2020). While the merging strategy comes at the expense of simplifying complex contextual insights from the social sciences into generic quantifiable patterns, it also bears the chance to realise all three linking benefits mentioned above. Not daring to venture towards this last step of integration risks biasing policy recommendations in favour of mitigation pathways that are merely easy to model, yet perhaps not easy to achieve (Trutnevyte et al., 2019).

Trutnevyte et al. (2019) also propose three steps for future research on the merging strategy. The first step involves mapping assumptions on societal transformations of existing models, going beyond general model properties. This step directly connects to the benefit of interdisciplinary learning. The second step suggests to conduct empirical research on generalisable patterns, which may enhance realism of models. S-shaped technology diffusion curves are a prime example of such patterns. However, incorporating S-curves into models is only one option to harness their insights as the theory has also been used to compare IAM scenarios to historical growth rates for example (Cherp et al., 2021). The third and final step relates to modifying or building new models, which contributes to the last benefit of finding practical solutions to energy and climate challenges.

The merging strategy therefore encompasses different approaches to integrate social science insights into quantitative models. It is important to note that merging models is only one among many options of merging knowledge from different disciplines. Further possibilities to enrich models with empirical insights abound (van Sluisveld et al., 2020; Geels et al., 2020; Hötte, 2020). However, in this work I focus on the option of merging models as one possibility of merging insights. I use the term model *coupling* when referring to methodological soft-coupling, which leaves the underlying models largely unaltered and therefore forms a subset of model *merging*, which could also mean developing fully new models. The terms soft-link and soft-coupling are used interchangeably throughout.

2.4. Contribution of this paper

In this paper, I provide an example of the merging strategy in a methodologically literal sense by coupling two models. In contrast to previous research, which either combined quantitative models with qualitative storylines (*bridging* or *iterating*) or developed entirely new models (*merging*), I here demonstrate the feasibility of soft-linking two existing models from the techno-economic and socio-technical sphere as another promising possibility. Specifically, I couple a welfare-maximising global IAM (the MIND model by Edenhofer et al. (2005)) with a fine-grained simulation model of S-shaped technology diffusion in the power sector (FTT:Power by Mercure (2012)).

This methodologically novel approach is worthwhile for three reasons. Firstly, it contributes to filling the research gap between the lack of practical model integration studies on the one hand (Hirt et al., 2020) and a plethora of theoretical propositions on how to achieve such model integration on the other hand (Holtz et al., 2015; Victor, 2015; Geels et al., 2016; Trutnevyte et al., 2019; Peng et al., 2021). Secondly, it seizes upon a suggestion of Trutnevyte et al. (2019), who cite S-curves as ‘potentially quantifiable patterns [...] for modeling technology adoption’ in IAMs, similar to the successful and widespread adoption of experience curves (Samadi, 2018). Thirdly, this approach touches upon the representation of temporal transformation dynamics in IAMs, an element recently identified as critical (Keppo et al., 2021).

The upcoming sections correspond with the three-step approach for future research on the merging strategy suggested in Trutnevyte et al. (2019). I firstly describe the two models and their opposing, yet complementary, theoretical underpinnings, secondly outline the promising potential of S-shaped logistic technology diffusion, and thirdly soft-link both to create the MIND-FTT model.

3. Methods

This section introduces both models and their complementarities.

3.1. MIND

The Model of Investment and Technological Development (MIND) by Edenhofer et al. (2005) is a global one-region optimisation IAM, which maximises intertemporally aggregated social welfare by assigning investment streams that observe certain climatological constraints. With roots in neoclassical economics, it rests on an idealised social planner perspective and consists of a Ramsey-type economic growth module, an explicit energy module and a parsimonious climate model. MIND is the predecessor of the regionally and technologically disaggregated REMIND model (Baumstark et al., 2021).

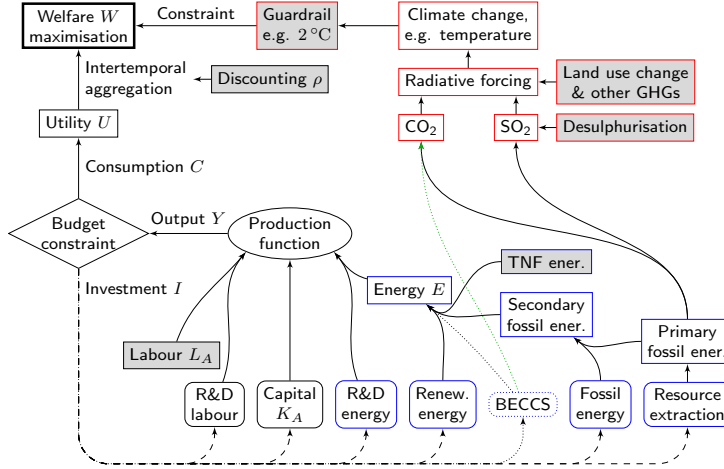


Figure 1: Model structure of MIND in a CEA setting, observing a deterministic guardrail. Black boxes indicate standard components of a Ramsey-type macroeconomic growth module, blue boxes the energy module, and red boxes the climate module. The diamond box illustrates the point of decision. Solid arrows indicate flows, while dashed arrows refer to control variables, i.e. investments. Exogenous variables are marked by grey boxes. BECCS is an optional technology not explored herein as illustrated by dotted lines.

Figure 1 shows the general model structure of MIND in a standard cost-effectiveness analysis (CEA) setting. The model solves for optimal investment streams given various economic and energy options, allocating the residual output of each period to consumption, which in turn increases utility and thus intertemporally aggregated welfare. The extracted amount of carbon from the fossil energy sector translates into CO_2 and coupled SO_2 emissions with a positive and negative climate forcing, respectively. These are processed within a parsimonious impulse-response climate model based on Petschel-Held et al. (1999) and Kriegler and Bruckner (2004). The ensuing temperature anomaly is subsequently used as a guardrail to constrain the optimisation, thereby initiating a shift of investment into renewable energies and energy efficiency measures.

On the macroeconomic part, MIND maximises the intertemporally aggregated welfare function

$$W = \int_{t_1}^{t_2} e^{-\rho(t-t_1)} U(t) dt, \quad (1)$$

with exponential discounting at rate $\rho = 0.01 \text{ yr}^{-1}$ and an isoelastic utility function

$$U(t) = L(t) \frac{1}{1-\eta} \left(\frac{C(t)}{L(t)} \right)^{1-\eta}, \quad (2)$$

defined via per-capita consumption with L denoting the exogenously given labour force, assuming a stabilising population of 9.5 billion by 2100 according to the CPI baseline (van Vuuren et al., 2003), and a coefficient of constant relative risk aversion $\eta = 2$ in accordance with previous studies (Roshan et al., 2019; Roth et al., 2020). The maximisation satisfies a macroeconomic budget constraint, in which the generic output Y of a production function with constant elasticity of substitution between the three production factors labour L , capital K , and energy E is either re-invested or consumed. Details are documented in Appendix A.1.

The energy module of MIND, which will be linked with FTT:Power in the further course, resolves four different investment options, renewable energy, fossil energy, resource extraction, and energy efficiency improvements through research and development (R&D). Total energy is simply the sum of secondary fossil energy, renewable energy, and traditional non-fossil (TNF) energy,

$$E = E_{\text{fos}} + E_{\text{ren}} + E_{\text{TNF}}, \quad (3)$$

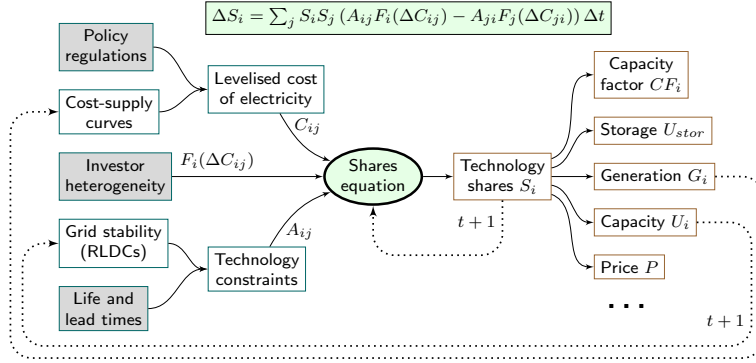


Figure 2: Model structure of FTT:Power with the central shares equation reprinted for convenience. The left part displays input variables within one time step, while the right part only displays some of the manifold output variables. Dotted arrows denote dynamic relations between variables of two adjacent time steps.

the last of which encompasses traditional biomass, nuclear and hydro power (Edenhofer et al., 2005) and follows an exogenous scenario.¹ In order to keep this prototypical work as simple as possible, negative emission technologies are not included. MIND is calibrated to the observed temperature anomaly of 2015, while economic and energy variables are calibrated in line with recent studies (Roshan et al., 2019; Li et al., 2020) and updated to 2020 values for primary energy consumption (BP, 2021).

So far, MIND includes an exogenous constraint on relative emission changes of $-13\%/yr$ in order to account for unobserved socio-technical and political processes (Lorenz et al., 2012). Under a delayed climate policy setting, this constraint is binding for decades and leads to an undesirable corner solution (Roth et al., 2020). The MIND-FTT soft-link addresses this issue by improving the representation of inertia in technology transitions.

In summary, MIND represents a prototype of a neoclassical, techno-economic IAM with a substantial degree of regional and technological aggregation, thereby capturing key interactions between the climate, the energy system, and the economy on a global scale. Due to its social planner perspective, it provides an idealised first-best solution that maximises social welfare under an exogenous climate guardrail, yet without incorporating any socio-technical frictions.

3.2. FTT:Power

The Future Technology Transformations (FTT) model family forms a group of technology transition models built on sector-specific adaptations of the competitive Lotka-Volterra differential equations (Lotka, 1910; Volterra, 1926). Because the energy transition requires widespread electrification of end-use sectors combined with power sector decarbonisation, I here focus on the power sector model FTT:Power as the most prominent example (Mercure, 2012; Mercure et al., 2014). However, the conceptual framework is universally applicable to a wide range of diffusion processes in other sectors such as transport (Lam et al., 2018), heating (Knobloch et al., 2018), and industry (Vercoulen et al., 2019).

FTT:Power is a simulation model of technology diffusion in the power sector by Mercure (2012) and an integral part of the macroeconometric E3ME model that is often used for policy analysis (Mercure et al., 2018, 2021). It draws on a parametrisation of pairwise competition of technologies for market shares by coupled differential equations, which gives rise to S-shaped adoption curves. The idea of modelling technological change as a process of gradual substitution dates back to Marchetti and Nakicenovic (1979), who first empirically described and projected these dynamics for the energy system, with further evidence for the arising S-curves in Grübler et al. (1999), Hansen et al. (2017), and Madsen and Hansen (2019).

¹In line with previous studies, MIND includes an exogenous scenario on these energy sources, which assumes a gradual phase-out of traditional biomass and nuclear (WBGU, 1995).

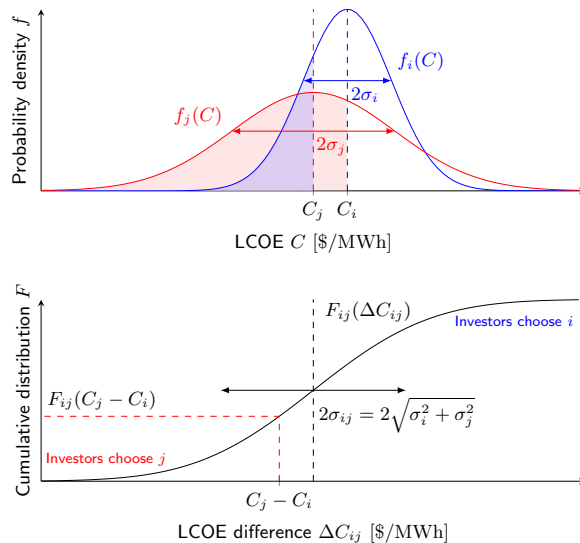


Figure 3: Illustration of investor heterogeneity in FTT:Power with two competing technologies i and j . In the upper part, investors perceive LCOEs as distributed, with mean values $C_i > C_j$ and standard deviations $\sigma_i < \sigma_j$. In the lower part, the cumulative distribution function of the LCOE difference ΔC describes the overall investment decision, in which investors tend to prefer j over i . For illustrative simplicity normal distributions instead of Gumbel distributions are shown. Illustration adapted from Mercure (2012).

The micro-foundations for this evolutionary theory of innovation have been theoretically derived in Mercure (2018). Starting from the premise of utility-maximising agents with heterogeneous preferences, non-equilibrium path-dependent dynamics emerge as agents learn from each other with a certain time delay. Accordingly, innovations are not adopted instantaneously, which stands in stark contrast to the implicit assumption of representative agents in MIND. On the macro level the intricate and convoluted dynamics of interacting agents collapse into a simple set of differential equations, which form the basis of FTT:Power.

Figure 2 shows the general structure of FTT:Power. In contrast to a substantial body of literature that only uses the S-shaped framework *ex-post*, the model determines the inherent scaling parameters of the diffusion process from *ex-ante* knowledge about underlying technology turnover rates, generation costs, and further grid stability constraints (Mercure, 2015). The evolution of technology shares S for a technology i within one time step is then governed by the central shares equation

$$\Delta S_i = \sum_j S_i S_j (A_{ij} F_i(\Delta C_{ij}) - A_{ji} F_j(\Delta C_{ji})) \Delta t, \quad (4)$$

where A_{ij} denotes a non-symmetric substitution frequency matrix that takes life times and lead times into account, ΔC_{ij} denotes cost differences between technologies i and j in terms of the levelised cost of electricity (LCOE), and F_i and F_j denote cumulative distribution functions to model investor heterogeneity as explained in the upcoming paragraph. The empirical motivation therefore is to describe S-shaped technological diffusion as a process that is driven by technological properties (A_{ij}), economic cost advantages (ΔC_{ij}), and an aggregate representation of agent heterogeneity as a proxy for behavioural frictions ($F(\Delta C_{ij})$). FTT:Power includes learning curves and economic resource potentials, which both affect ΔC_{ij} (Mercure and Salas, 2012, 2013). Note that because costs change nonlinearly over time, and grid stability issues introduce additional constraints, FTT:Power does not yield a logistic growth curve estimate in the form of a mathematical function with fixed parameters, but instead simulates the diffusion of technologies step-by-step. The model resolves 24 power technologies in 61 regions.

FTT:Power represents investor heterogeneity in an aggregated way by using statistical cost distributions, which are a direct manifestation of the diversity of agents (Mercure, 2015). For the power sector, this relates to diverse investors, who are subject to specific company requirements, regional particularities or broader

issues of societal acceptance, which are all either unknown or difficult to enumerate. According to discrete choice theory, if the probability densities of costs for each technology $f_i(C)$ and $f_j(C)$ follow Gumbel distributions, the overall investment share of investors, who favour j over i follows a logistic distribution. This is illustrated in Figure 3. The limiting case of very low diversity (i.e. $\sigma_i^2 \rightarrow 0$ and $\sigma_j^2 \rightarrow 0$) coincides with the standard representative agent of neoclassical economics, where a sudden flip of investment choices is already triggered by a very small price difference ΔC_{ij} .

The version of FTT:Power used in this work also improves the representation of integration challenges of variable renewable energies (VREs) by using residual load duration curves from Ueckerdt et al. (2017). The soft-link therefore also includes a state-of-the-art approach for modelling VRE intermittency (Pietzcker et al., 2017). To account for likely flexibility improvements, I gradually ease the respective constraint over time (for details see Appendix A.2).

While FTT:Power therefore covers several aspects that could benefit IAMs (see *linking benefits* in Section 2.3), by design it cannot be used to produce scenarios on its own, but only to assess the impact of given scenarios. This relates to the understanding of E3ME and the FTT models as fully descriptive impact assessment models in contrast to normative policy optimisation IAMs such as MIND. The following soft-link attempts to reconcile these opposing views.

4. MIND-FTT: Soft-linking MIND with FTT:Power

The MIND-FTT soft-link is a methodologically novel approach that dovetails the strengths of techno-economic optimisation and socio-technical simulation, two distinct and often opposed modelling paradigms. Following the scheme, MIND computes economically efficient mitigation pathways that comply with a given climate target from a social-planner top-down perspective, while FTT:Power assesses the plausibility of these pathways with special attention to temporal transformation dynamics from a bottom-up perspective. The non-trivial convergence of the joint model demonstrates the fruitful potential for such model integration.

Figure 4 shows the general structure of MIND-FTT, merging both model diagrams. The two key coupling variables are global carbon prices and renewable energy shares as indicated by the orange ellipses and arrows. The optimal global carbon price of MIND is applied to every region of FTT:Power, which simulates the corresponding diffusion pathways in terms of market shares for all power technologies. Subsequently, these are aggregated and used to constrain the optimisation of MIND in the following iteration, which affects the carbon price. This iterative cycle continues until convergence to a joint equilibrium is reached.

MIND and FTT:Power differ substantially in their temporal, spatial, and technological resolution as reported in Table 1. In order to couple both models, I therefore aggregate the 61 regions and 24 technologies of FTT:Power into two single curves that represent fossil and renewable energy shares over time on a global level. However, this aggregation implies no loss of generality as the equilibrium renewable energy share pathway maps directly onto an equilibrium carbon price pathway. When fed into FTT:Power, this carbon price provides the exact decomposition of the aggregated renewable energy share. In the upcoming two sections, I explain the two coupling variables.

Table 1: Resolution of MIND and FTT:Power

	MIND	FTT:Power
World regions	1	61
Energy technologies	4 ^a	24 (18 without CCS) ^b
Time period	1995–2200 ^c	2017–2100 ^d
Time step	5 yr	0.25 yr

^a This includes R&D for energy efficiency, but excludes BECCS (see Figure 1).

^b Six CCS technologies have been deactivated in MIND-FTT.

^c MIND has been tuned to 2015 data.

^d FTT:Power has been extended until 2100.

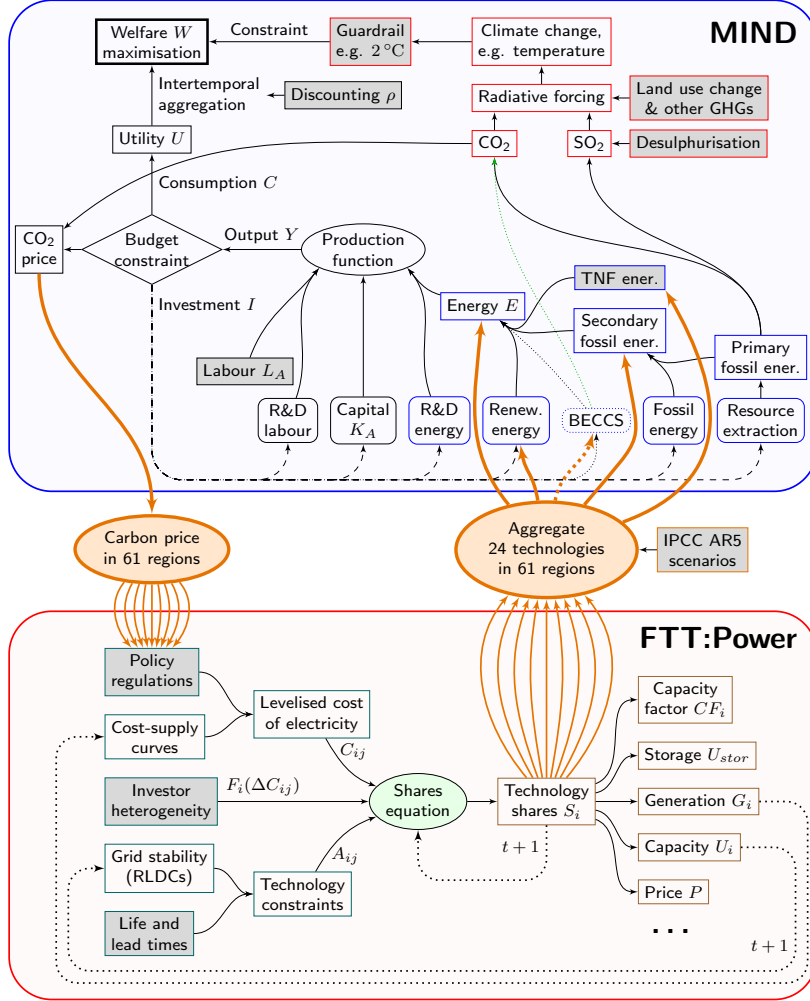


Figure 4: Diagram of the MIND-FTT soft-link, combining Figure 1 (with added CO₂ price) and Figure 2. Orange ellipses and arrows denote the two coupling processes and variables, carbon prices and renewable technology shares. BECCS is an optional technology not explored herein as illustrated by dotted lines.

4.1. MIND to FTT:Power: Uniform global carbon price

The link from MIND to FTT:Power is based on a uniform global carbon price that results from the intertemporal optimisation in MIND. Imposing a global carbon price onto all 61 regions of FTT:Power has an immediate effect on the technology-specific LCOEs and thus on the technology diffusion pathway, depending on the emission intensities of technologies. This conceptualisation implies full international cooperation by assumption. Future research could relax these assumptions by exogenously assuming fragmented action across countries, for example by only imposing the carbon price on a subset of regions. To keep the soft-link as simple as possible, I also refrain from defining other policy parameters offered by FTT:Power such as feed-in-tariffs, subsidies, and exogenous phase-outs, for which MIND would need to be further augmented. This pilot study therefore deliberately leaves aside frictions in the policy process as well as additional policies that could complement carbon pricing.

The optimal carbon price readily follows from the Lagrangian multipliers of the welfare optimisation. After calculating and verifying the optimal, globally uniform carbon price under a given climate target in MIND, it is smoothed by applying a three-period moving average to avoid the craggy shape that otherwise occurs due to the comparably coarse time resolution of MIND. The interpolated carbon price is subsequently

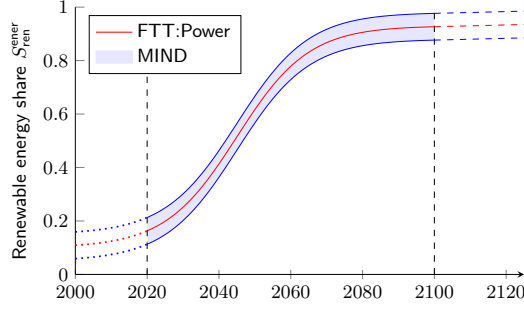


Figure 5: Illustration of the renewable energy share constraint from FTT:Power to MIND. The red line shows $S_{\text{ren}}^{\text{ener}}$ as obtained from FTT:Power. The blue shaded area illustrates the allowed corridor for MIND.

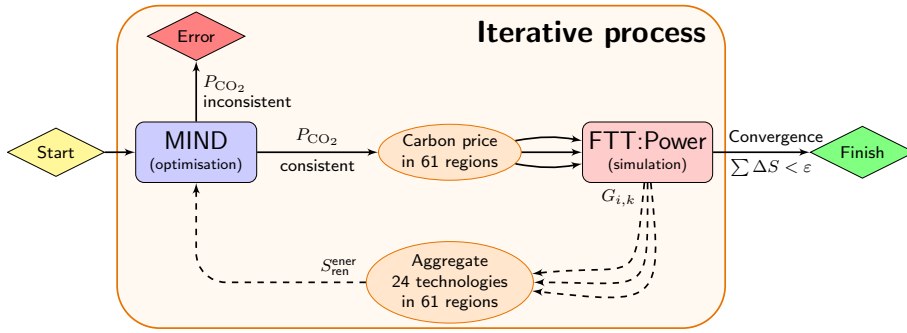


Figure 6: Illustration of the implemented iterative soft-linking scheme.

imposed as a policy parameter for all 61 regions of FTT:Power.

4.2. FTT:Power to MIND: Renewable energy share

The reverse link from FTT:Power to MIND is based on the evolution of technology shares that emerge from the simulation in FTT:Power under the carbon price of MIND. In order to bridge the different resolutions, I calculate a global renewable electricity share $S_{\text{ren}}^{\text{elec}}$ by summing the electricity generation $G_{i,k}$ over technology $i \in R$ over all countries k in relation to total generation G_{tot} . This leads to

$$S_{\text{ren}}^{\text{elec}} = \sum_{i \in R} \sum_{k=1}^{61} \frac{G_{i,k}}{G_{\text{tot}}}, \quad (5)$$

where R denotes all renewable energy sources of FTT:Power, which for simplicity includes all technologies that have a non-positive emission intensity.

FTT:Power only covers the power power sector, whereas the production function of MIND includes total energy, which also includes energy consumption in other predominantly non-electric sectors. In order to infer a relationship between the renewable *electricity* share $S_{\text{ren}}^{\text{elec}}$ from FTT:Power and the renewable *energy* share $S_{\text{ren}}^{\text{ener}}$ for MIND, I use four stringent 450 ppm and 550 ppm, non-CCS REMIND scenarios from the IPCC AR5 Scenario Database (IIASA, 2015) to determine an approximation of $S_{\text{ren}}^{\text{ener}}$ as a function of $S_{\text{ren}}^{\text{elec}}$ and time. This approach is described in more detail in Appendix A.3. It retains the immediate connection from FTT:Power to MIND for the overwhelming part of the modelled energy transition, while complementing it with plausible rates of mitigation in sectors that are out of the scope of FTT:Power. Limitations of this approach are discussed in Section 6.

In the final step of the MIND-FTT soft-link, MIND is forced onto the renewable energy share pathway from FTT:Power. In order to allow for some numerical leeway in the optimisation, I constrain MIND to a

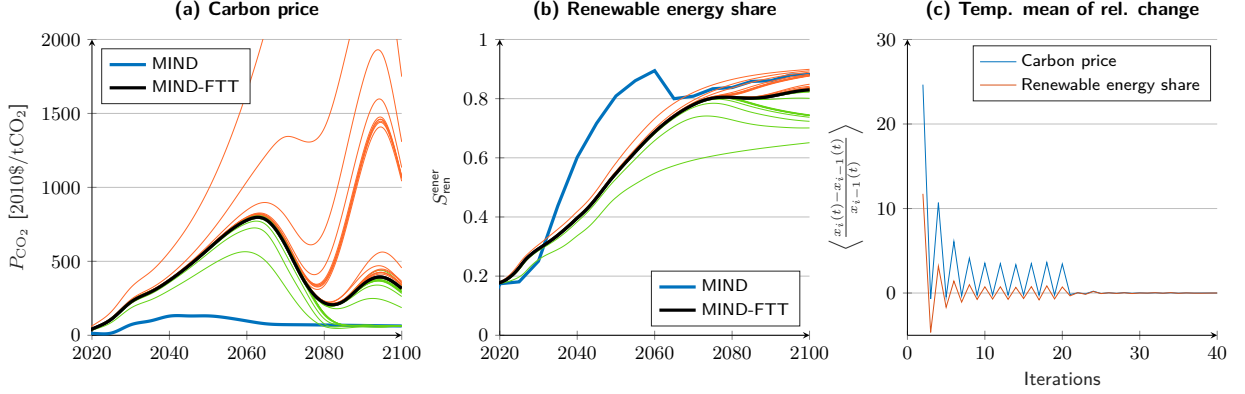


Figure 7: Iterative convergence of MIND-FTT along the two coupling variables, (a) carbon price P_{CO_2} , and (b) renewable energy shares S_{ren}^{ener} for 40 iterations, with (c) the temporal mean of the relative change between two iterations showing oscillatory convergence. The legend only denotes the original values of MIND (in thick blue) and the converged equilibrium of MIND-FTT (in thick black). In (a) and (b), orange lines indicate iterations with an even number and green lines iterations with an odd number, which also shows the oscillations between iterations until equilibrium is reached. In iteration 20, the convergence is accelerated by calculating the carbon price as a weighted mean of the past three iterations, which dampens the oscillations and quickly leads to a stable equilibrium. Since S_{ren}^{ener} is much less sensitive to changes in P_{CO_2} than vice versa, in (c) the values for S_{ren}^{ener} have been multiplied by a factor 100.

symmetric corridor of renewable energy shares as indicated in Figure 5. This corresponds to requiring

$$S_{ren}^{ener}(t) \stackrel{!}{=} \frac{E_{ren}(t) + E_{TNF}(t)}{E(t)} + \varepsilon(t) \quad \text{with} \quad |\varepsilon(t)| \leq \Delta S_{ren}^{ener} \quad \forall t \in [2020, 2100], \quad (6)$$

with ΔS_{ren}^{ener} as a free parameter, set to 2%. These two coupling mechanisms are then run in an iterative scheme until the coupling variables converge towards the equilibrium steady state of MIND-FTT as illustrated in Figure 6.

5. Results: 2 °C scenario

This section presents key results of MIND-FTT for an exemplary 2 °C scenario, which (i) confirm the convergence of the bi-directional iterative soft-link, (ii) exemplify the effects of gradual technological change on optimal mitigation pathways, and (iii) demonstrate the potential of model integration for future research. In the upcoming sections, I firstly describe the convergence process, secondly display the underlying S-shaped technology diffusion trajectories, and thirdly illustrate how the results of MIND-FTT compare with those of MIND.

5.1. Iterative convergence

Figure 7 shows the convergence of both coupling variables, renewable energy shares S_{ren}^{ener} and carbon prices P_{CO_2} for 40 iterations in comparison to the results of MIND. Both show a family of curves that dynamically converge to an equilibrium pathway.

The iterative convergence of MIND-FTT is a non-trivial outcome and the main methodological achievement of this study. The joint model converges because the soft-link constitutes a negative feedback loop, which stabilises the system to equilibrium. Leaving time dependencies aside, a simplified notation reads

$$P_{CO_2} \uparrow \xrightarrow{\text{FTT}} S_{ren}^{ener} \uparrow \xrightarrow{\text{MIND}} P_{CO_2} \downarrow, \quad (7)$$

which may be explained as follows. As a starting point, suppose that P_{CO_2} increases between two iterations, which affects the LCOEs in FTT:Power, leading to a rising renewable electricity share S_{ren}^{elec} and thus also to a rising renewable energy share S_{ren}^{ener} . Imposing this higher share on MIND implies that relative to

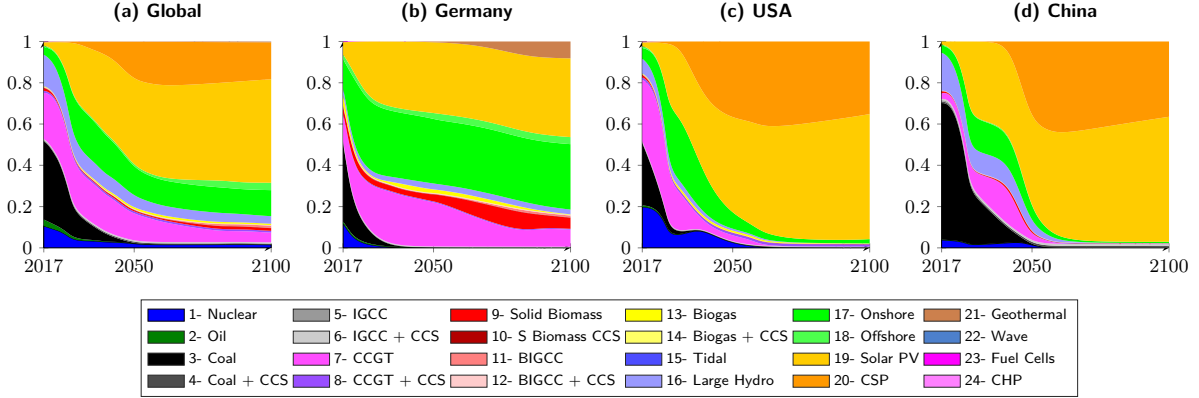


Figure 8: Equilibrium technology shares from FTT:Power, (a) globally aggregated, and (b)-(c) for three exemplary countries (out of the total 61) under the equilibrium MIND-FTT carbon price of Figure 7a. While fossil fuels are phased out quickly across regions, the projected technology portfolios clearly differ. (B)IGCC stands for (biomass) integrated gasification combined cycle (not visible), CCGT for combined cycle gas turbines (in pink), CSP for concentrated solar power (in orange), and CHP for combined heat and power (not visible).

E_{fos} , E_{ren} increases, leading to reduced emissions. Under an exogenous climate target this attenuates the emissions constraint in the welfare maximisation, which leads to a reduced carbon price P_{CO_2} . This cascade of effects forms a negative feedback loop as it tends to reduce the impact of perturbations and eventually stabilises MIND-FTT to equilibrium. Unlike other soft-link mechanisms in IAMs that iterate until market clearance has been reached via the well-known dynamics of supply and demand (e.g. REMIND-MAGPIE), the key novelty is that the coupling does not bring two markets into equilibrium, but instead equilibrates the carbon price and renewable technology diffusion pathways.

The equilibrium carbon price exhibits a peak-decline shape, firstly following an exponential increase towards a maximum value of 800 $\$/\text{tCO}_2$ in 2070 and subsequently receding to values below 500 $\$/\text{tCO}_2$. This carbon price is substantially higher than in MIND, which peaks below 150 $\$/\text{tCO}_2$. This is due to the imposed equilibrium renewable energy share pathway as obtained from FTT:Power, which increases substantially slower in mid-century than in MIND, pointing to increased policy pressure that is required to increase the adoption of renewable technologies. In a 2 $^\circ\text{C}$ scenario, the global share of renewable energies reaches 80% in 2075 and only increases slowly afterwards. The results highlight the large policy implications of the pace of technological change on optimal climate mitigation pathways.

5.2. S-shaped technology diffusion

To understand the underlying dynamics of the S-shaped technology diffusion in FTT:Power, Figure 8 shows the evolution of power technology shares in global aggregation as well as for three exemplary countries, all of which are obtained under the equilibrium globally uniform carbon price in Figure 7a. The global technology diffusion in (a) shows that renewable power generation, especially solar photovoltaic (PV, yellow), onshore and offshore wind (dark and light green), and concentrated solar power (CSP, orange), quickly diffuse to a total 80% market share in 2050, while coal is gradually phased out. As a non-renewable, dispatchable technology, combined cycle gas turbines (CCGT, pink) steadily take up a relevant share of the market, pointing to gas as a bridging fuel. Due to the endogenous representation of intermittency challenges of VREs that is part of this new FTT:Power version, wind and solar PV only gradually penetrate the market once they have arrived at large market shares. Aggregating (a) across technologies yields the renewable electricity share and subsequently the renewable energy share as depicted in Figure 7b.

Due to different technology potentials, resource endowments, and initial technology shares, the diffusion of technologies varies substantially between regions, even though fossil fuels apart from CCGT are rapidly phased out everywhere. Germany, for example, exhibits a fairly balanced technology portfolio, with solar PV and wind accounting for at least 60% of generation from 2050 onwards, while the remaining load is almost

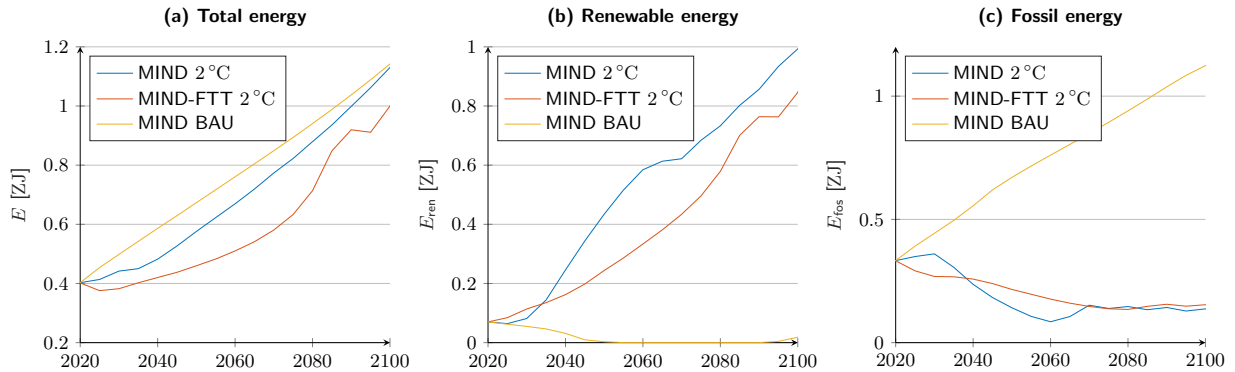


Figure 9: Energy in MIND and MIND-FTT, including a business as usual (BAU) scenario of MIND for reference. Traditional non-fossil energy E_{TNF} is not displayed since its contribution is negligible in the long run.

exclusively covered by CCGT. Under the equilibrium carbon price, both the USA and China transition to power systems that are virtually entirely reliant on solar PV and CSP after 2050, underlining the vast potential of solar power in these countries. In the USA, this implies a rapid transition away from nuclear, coal and gas, where wind power only emerges as a temporary technology that is crowded out again by 2060. In China, coal as the currently dominant electricity source is initially displaced by a mixture of solar PV, wind, hydro and CCGT, while from 2050 onwards the market entry of CSP completely ousts these technologies. Notably, despite subject to the same carbon price, the phase-out of coal takes significantly longer in China than in Germany and the USA as the initial share at about 70% is much larger, which limits the pace of the diffusion. China’s share evolution also vividly illustrates the ‘technology ladder’ concept (Mercure, 2012), where technologies are replaced by each other in a sequential manner with several intermediate technologies.

5.3. Implications in comparison with MIND

This section condenses the most prominent differences between MIND-FTT and MIND. Figure 9 depicts energy variables for a 2°C scenario, with (a) showing that total energy is always lower in MIND-FTT than in MIND, while both are below the values of a business as usual (BAU) scenario.² In (b), the generation of renewable energy is larger in MIND-FTT before 2035, and smaller thereafter, which is an immediate consequence of the imposed renewable energy share in Figure 7b. Panel (c) best shows the effect of technological change inertia as the amount of fossil energy initially drops quicker in MIND-FTT than in MIND, then decreases at a slower pace after 2035 with vanishing differences after 2060. However, in MIND-FTT there is only a minor comeback of fossil energy, which stands in stark contrast to its pronounced renaissance in MIND that results from a sudden increase of cheap fossil fuels in the second half of the century. In MIND-FTT a quick ramp-up of fossil energy turns out to be inconsistent with gradual technology diffusion.

Turning to the climate system under a 2°C scenario, Figure 10a shows that emissions in MIND-FTT initially drop much quicker, while abatement rates are far below those of MIND after 2035. This outcome results from the high initial carbon prices, which initiate the quick drop in emissions in the beginning, and the more gradual technology diffusion, which makes emission reductions in the mid-term more difficult. In contrast, MIND exhibits a strong emissions increase from 2060 to 2065 of almost 100%. As a consequence, (b) shows that the CO₂ concentration in MIND-FTT peaks later and at a lower value than in MIND, which however only has a mild impact on the temperature anomaly in (c). Again, the focus of FTT:Power on transformation dynamics in time adds an additional layer of friction that prohibits a swift resurgence of emissions due to fossil energy as seen in MIND.

The point of decision in MIND, and thus also in MIND-FTT, is the allocation of output Y to different investment streams and consumption. Figure 11a-b juxtaposes energy-related investments in both models.

²The BAU scenario does not incorporate any climate damages, leaving out the thorny issue of appropriate reference scenarios for simplicity (Grant et al., 2020).

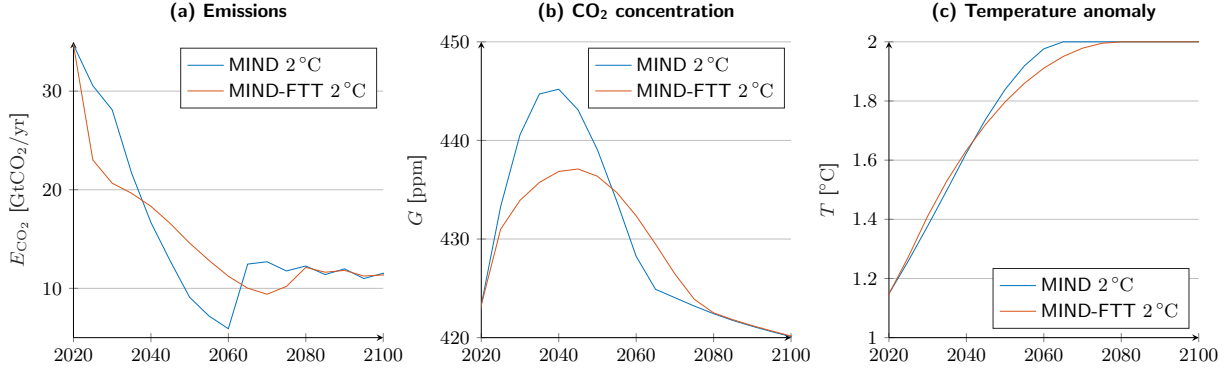


Figure 10: Climate system in MIND and MIND-FTT, excluding the BAU scenario for better visibility.

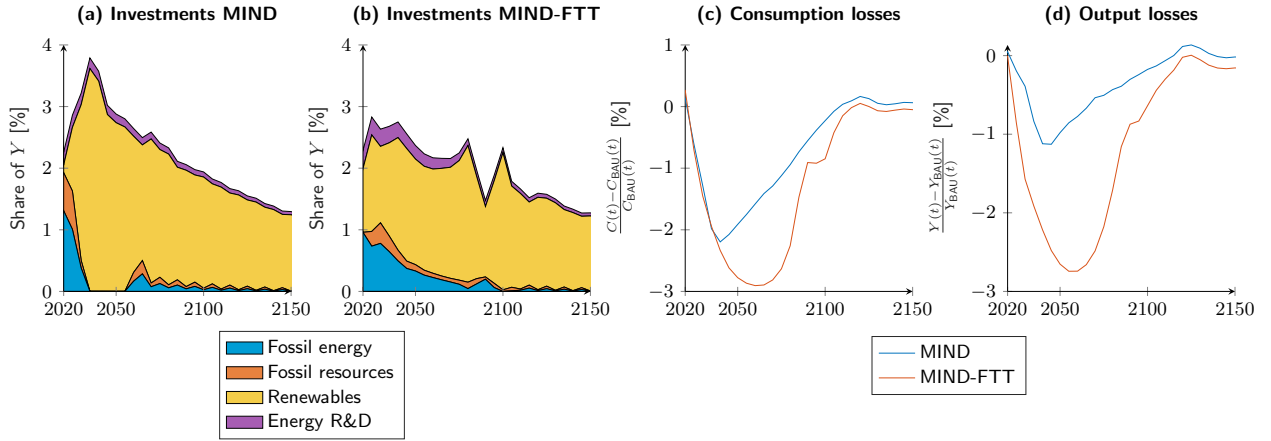


Figure 11: Energy-related investments for a 2°C scenario in (a) MIND, (b) MIND-FTT, and associated (c) consumption losses and (d) output losses. In (b) the craggy shape around 2100 is a minor artefact of the time-limited imposition of the renewable energy share onto MIND.

While MIND exhibits renewable energy investments as high as 4% of total gross world product Y in 2030, MIND-FTT arrives at a more balanced mix with renewable energy investments around 2% of output levels. Investments into fossil energy and fossil resources are completely phased out by 2030 in MIND, returning briefly in 2060, whereas in MIND-FTT they only decrease gradually until 2080. Thus, fossil fuel energy supply and associated investment streams are phased out substantially more slowly than in an idealised, purely techno-economic scenario. To counteract the prolonged provision of fossil energy, energy R&D investments are scaled up significantly in MIND-FTT.

The improved representation of technology diffusion in MIND-FTT incurs further costs, which are reflected in consumption and output losses in Figure 11c-d in comparison to a BAU scenario. This is a direct consequence of the specification of MIND as an optimisation model, which implies that additional constraints as imposed by the soft-link always lead to an economically inferior, yet perhaps socio-politically more realistic, solution. Both consumption and output losses are almost always larger in MIND-FTT than in MIND. The discrepancy with respect to output losses is even more pronounced, where MIND-FTT displays values twice as large for the majority of time.

6. Discussion

The presented approach of merging a top-down, neoclassical, optimisation IAM with a bottom-up, evolutionary, simulation power sector model demonstrates the potential of integrating existing models. This

section discusses the methodological benefits, recapitulates key insights, and describes limitations.

6.1. Linking benefits revisited

On the methodological side, the main achievement is the observation that merging two models from otherwise opposed schools of economic thought with contrasting assumptions is a conclusive, viable and accessible option to harness the complementarities of techno-economic and socio-technical vantage points of modelling energy transitions. As noted in Section 2, merging two existing models contributes to filling the gap between a lack of practical integration studies on the one hand, and the multitude of theoretical roadmaps regarding the integration of societal dynamics into climate policy models on the other hand. Referring again to the benefits of linking techno-economic and socio-technical approaches (Trutnevyte et al., 2019), the present study attempted to contribute to interdisciplinary learning by juxtaposing different assumptions and modelling paradigms, and laid methodological foundations to enhance realism of models with respect to additional frictions that arise from technology diffusion.

6.2. Three key insights

The results of this pilot study at the steady state of carbon prices (from MIND) and renewable energy shares (from FTT:Power) demonstrate that, unsurprisingly, technology diffusion plays a key role for climate change mitigation. Three key insights emerge of MIND-FTT for an exemplary 2 °C scenario.

Firstly, the diffusion of renewable energy technologies is considerably slower, leading to far higher carbon prices with a peak value of 800 \$/tCO₂. This aggregated result emanates from the widely different technology diffusion pathways across countries and is consistent with the upper end of the spectrum of scenarios in the IPCC AR5 (IIASA, 2015). While carbon prices are higher and more enduring than before, they still exhibit a peak-decline shape, which numerically illustrates that policy measures are most urgently required in the short- and mid-term, but may be partially cut back towards the end of the century. This peak-decline shape deviates from the standard exponential price path of the Hotelling (1931) rule, which applies for an exhaustible resource like a finite carbon budget. However, similar peak-decline patterns also emerged endogenously as the optimal pathway when carbon dioxide removal is included (Strefler et al., 2021).

Secondly, more gradual technology diffusion leads to less energy consumption at all times, which is accompanied by an increase of renewable energy in the short-term and a more sluggish decrease of fossil energy in the mid- and long-term. This corresponds with the peak-decline shape of the carbon price pathway, which declines again once the major part of the energy system has been transformed. Furthermore, gradual technology diffusion is in line with recent studies concerning the feasibility of scaling-up renewable technologies (e.g. Cherp et al., 2021) and phasing-out fossil technologies (e.g. Vinichenko et al., 2021). Notably, while the declining carbon price points to increasing competitiveness of renewable energies, fossil energy is not phased out completely until 2100. While this is at odds with prominent net-zero emissions scenarios (IEA, 2021), it is merely a consequence of the lack of carbon dioxide removal technologies in combination with optimisation towards a temperature target instead of an emissions budget target in the present study. Future research could investigate this further.

Thirdly, investment streams initiate the energy transition more gradually, leading to larger and delayed economic costs. Investments into fossil energy are only completely phased out by 2080, whereas renewable energy investments remain relatively constant over time. In contrast to Grubb et al. (2021), technological change inertia reduces short-term investment into abatement technologies instead of spurring it. While this seems paradoxical at first, it emerges directly from the combination of idealised policy optimisation in MIND and simulated policy evaluation under gradual technology diffusion in FTT:Power. Both consumption losses and output losses indicate that the additional burden of technological change inertia is primarily borne after 2030, which is in agreement with IPCC (2014). However, in contrast to IPCC (2014), consumption losses start to fade away towards 2100. On a more general note, the outcome of equilibrium models, where climate policy always incurs macroeconomic losses, has recently been criticised in Köberle et al. (2021) for neglecting positive economic effects such as avoided impacts and co-benefits. While such considerations were clearly out of scope for this work, they highlight important avenues for future research.

6.3. Limitations and outlook

There are several clear limitations and shortcomings of this pilot study.

It is critical to bear in mind that a globally uniform carbon price is a theoretical benchmark unlikely to ever be implemented. As the focus of this study was to demonstrate the feasibility of coupling two fundamentally different models and analyse the impact of S-shaped technology diffusion, I regard this as a valid first-order approximation that could however be refined in future research.

On a methodological note, carbon prices were found to be relatively sensitive to changes in the renewable energy share pathway, which in turn depends substantially on the projected integration challenges of VREs. While the implemented methodology of RLDCs is currently the best reduced-form approach to account for the problem of short-term intermittency in long-term models, a more in-depth analysis is encouraged.

Two important limitations arise due to the different model resolutions. Firstly, the different level of technological detail requires the aggregation of all renewable technologies from FTT:Power into a single representative renewable energy share that can be included in MIND. This drawback is a direct result of MIND's simple energy module and could therefore be improved by using a detailed IAM that resolves more energy technologies. This would greatly enhance the realism of the results and also make them more applicable to real-world policy challenges.

Secondly, different sectoral resolutions require assumptions to approximate renewable energy shares from renewable electricity shares in order to estimate plausible decarbonisation rates beyond the power sector (described in Appendix A.3). Even though I use scenario results of the structurally similar REMIND model, this implies that technology diffusion in non-power sectors is not governed by the principles of the FTT models. While this approximation is a reasonable interim solution, future research could extend this study to a more comprehensive coupling, for example linking REMIND with multiple available FTT models, not only for the power sector, but also for transport (Lam et al., 2018), heating (Knobloch et al., 2018), and industry (Vercoulen et al., 2019). This would enable a more immediate mapping of energy technologies and regions and provide a more realistic picture of technological change across sectors.

Furthermore, the depiction of socio-technical phenomena in a quantitative model like FTT:Power is of course limited and does not incorporate the intricacies of societal development, which may follow a different dynamic due to unforeseen or hard-to-quantify phenomena. This is an inherent drawback of any *merging* strategy (see Section 2.3), which naturally cannot capture the full breadth of social science knowledge on energy transitions and interlinked broader societal transitions, but only stylised elements thereof. Future research could address these shortcomings by an improved understanding of technological learning processes and socio-technical feedback loops, also taking into account insights from other branches of economics (Mathias et al., 2020). It is noteworthy that the S-curve theory may also enrich IAMs not only by model integration, but also as a tool to compare growth rates of renewable technologies in IAM scenarios with observed trajectories of growth (Cherp et al., 2021). Notwithstanding this, soft-linking MIND with FTT:Power offers a valuable starting point for future research in an attempt to endogenise additional frictions of energy transitions.

7. Conclusion

This paper attempted to contribute to the endeavour of integrating socio-technical knowledge about energy transitions into techno-economic climate-policy models. I presented a feasibility study of merging insights from two different models by a methodologically novel approach that couples a global optimisation IAM, the MIND model, with a highly resolved simulation model of technology diffusion in the power sector, FTT:Power. The resulting MIND-FTT model demonstrates one possibility to combine the strengths of two models by joining a neoclassical analysis of intertemporal optimality with an evolutionary analysis of technology diffusion. The iterative bi-directional soft-link converges to a joint equilibrium via globally uniform carbon prices and renewable energy shares as the two central coupling variables.

The exemplary results for a 2°C scenario show that, unsurprisingly, the pace of technological change plays a critical role for optimal climate change mitigation pathways since – despite significantly larger carbon prices – fossil energy is phased out more slowly in the mid-term, rendering the energy transition

more costly in total. While first-best analyses provide a valuable benchmark for cost-efficient climate policy, acknowledging additional socio-technical frictions of energy transitions remains a primary concern in order to arrive at scenarios that are not only theoretically optimal, but also practically possible.

As a first attempt to seize the complementarities of techno-economic policy optimisation and socio-technical policy evaluation, MIND-FTT demonstrates the feasibility of merging models to enable improvements in terms of integrating societal transformation in IAMs, especially regarding temporal transformation dynamics (Trutnevte et al., 2019). Further research is necessary in order to test the approach with more comprehensive IAMs and additional sectoral technology diffusion models. Beyond this, more interdisciplinary research on how to model key societal dynamics is urgently required – especially in order to identify key leverage points that may accelerate technology diffusion rather than inhibit it.

Acknowledgements

This work has benefited from a range of people. Firstly, thanks to Hermann Held for suggesting inertia of technological change as the main motivation for the model coupling and for continuous support and mentorship. I am also thankful to Uwe Schneider for technical help with GAMS. Another special thanks to Pablo Salas and Jean-Francois Mercure for hosting me during a research visit at the University of Cambridge and for training with FTT:Power. I furthermore gratefully appreciate helpful comments from Kerstin Hötte and Simon Barth. The soft-link draws on the `gams-matlab` package by Dorfner (2018).

Funding: This work was supported by the Foundation of German Business (sdw), the Cluster of Excellence Climate, Climatic Change, and Society (CLICCS) at the University of Hamburg, and – during the submission and review period – the German Federal Environmental Foundation (DBU).

Declarations of interest: none.

Appendix A. Modelling details

This appendix describes technical details of MIND, FTT:Power and the coupled MIND-FTT model.

Appendix A.1. Production function and budget equation in MIND

The macroeconomic production function of MIND reads

$$Y = \Phi_A \left(\underbrace{\xi_A^L (A \cdot L)^{-\rho_A}}_{\text{Labour}} + \underbrace{\xi_A^E (B \cdot E)^{-\rho_A}}_{\text{Energy}} + \underbrace{\xi_A^K (K_A)^{-\rho_A}}_{\text{Capital}} \right)^{-1/\rho_A}, \quad (\text{A.1})$$

which, from a mathematical viewpoint, is a norm function with Φ_A as a scaling factor. The parameters ξ_A^L , ξ_A^E , and ξ_A^K define the distribution of relative factor shares of labour, energy and capital, respectively. Labour productivity A and energy efficiency B are determined by R&D investments (Edenhofer et al., 2005).

The budget equation simply states that for each time step, produced output Y is either reinvested or consumed,

$$Y = C + I_A + \underbrace{I_{\text{ren}} + I_{\text{res}} + I_{\text{fos}}}_{\text{Energy investments}} + \underbrace{RD^A + RD^B}_{\text{Efficiency investments}} + C_{\text{TNF}}, \quad (\text{A.2})$$

where I denotes investments into capital stock variables and RD investments into efficiency improvements, while C_{TNF} is the exogenously prescribed cost of traditional non-fossil energy sources (Edenhofer et al., 2005). In contrast to FTT:Power, investment decisions in MIND are made by a social planner under full foresight with full information, thereby maximising the intertemporally aggregated social welfare function in Equation 1.

Appendix A.2. Residual load duration curves in FTT:Power

The present work uses a new version of FTT:Power that includes an updated representation of short-term VRE intermittency challenges based on the method and dataset of endogenous residual load duration curves (RLDCs) by Ueckerdt et al. (2017). This approach builds on a *Special Section on Variable Renewable Electricity and Power Sector Dynamics in Integrated Assessment Models* in *Energy Economics* 64, according to which the RLDC methodology is the most suitable reduced-form approach along multiple assessment categories such as investment dynamics, power system operation, temporal matching of VREs and demand, storage, and grid (Pietzcker et al., 2017).

RLDCs demarcate the residual demand that needs to be covered by dispatchable technologies after VRE generation has been deducted. They are obtained by sorting the chronological residual load curves in a descending, histogram-like manner and therefore constitute a ‘purely physical concept only requiring demand and VRE supply data’ (Ueckerdt et al., 2015, p. 1801). The shape of the RLDC changes endogenously, taking the VRE shares of wind and solar PV as input. RLDCs are optimised along the trade-off between storage and curtailment. Herein, I follow the approach of Ueckerdt et al. (2017) who provide a readily usable approximation of the residual load by so-called load bands, which have a fixed capacity factor (CF), while the actual load covered by each load band is determined endogenously depending on the VRE shares.

The implementation of RLDCs in FTT:Power follows the approach of load bands, utilising the dataset of Ueckerdt et al. (2017) that provides the size of all five load bands approximated as a set of third-degree polynomial functions. The load bands range from a base load band with a high CF to a peak load band with a very small CF, which has implications on the diffusion dynamics as technologies can play on their comparative advantages only in certain load bands. Due to the technology-specific cost components in the LCOE, capital intensive technologies with low operational and fuel costs such as coal and nuclear power plants are only profitable under large utilisation rates, i.e. in the base load band. Vice versa, less capital intensive technologies with higher operational and fuel costs such as CCGT power plants are more profitable if not operated year-round, i.e. in upper load bands. Within each time step, the implementation dynamically constrains the maximum share of VRE technologies.

As an illustrative example, consider Figure A.12, which shows the evolution of technology shares in Germany for each of the five implemented load bands in panels (a)-(e) and the relative share of those load bands with respect to total load in panel (f). This constitutes an in-depth look into Figure 8b since multiplying the load band technology shares with the respective relative share of these load bands leads to the total evolution of technology shares. The technology portfolio in the base load band (CF 85%), which is initially dominated by coal and nuclear power, quickly transforms to CCGT, solid biomass and biogas, while from 2050 onwards geothermal power as a capital-intensive technology option starts to take over the market. In the lower-mid load band (CF 50%), CCGT covers the majority of the market, while solid biomass becomes increasingly competitive as carbon prices increase, leading to an accelerated technology diffusion that again recedes simultaneously to the receding carbon price (Figure 7a). In the upper-mid load band (CF 25%) and peak load band (CF 8%), CCGT is clearly the most profitable technology option, while in the backup band (CF 0.1%) oil crowds out hydro power. Panel (f) shows that the VRE share, i.e. wind and solar PV combined, with respect to total load quickly increases to around 60% around 2025, from when on it only gradually increases due to the endogenous intermittency challenges as mediated by the RLDC dataset. Accordingly, the residual load bands of panels (a)-(e) are relegated in volume, implying that the just described technology diffusion dynamics only have a comparably small effect on total shares.

Appendix A.3. Inference of renewable energy shares in MIND-FTT

A critical shortcoming of the MIND-FTT soft-link is the necessary approximation of renewable *energy* shares, required for MIND, from renewable *electricity* shares, obtained from FTT:Power. This issue arises due to the different sectoral coverage of both models, which could be alleviated in future research by incorporating other sectoral models of the FTT family. For this feasibility study, I draw on four non-CCS 450 ppm and 550 ppm scenarios of the REMIND model that have been included in the IPCC AR5 Scenario Database (IIASA, 2015), namely AMPERE2-450-NoCCS-OPT, AMPERE2-550-NoCCS-OPT, EMF27-450-NoCCS, EMF27-550-NoCCS, from the AMPERE (Kriegler et al., 2015) and EMF27 (Blanford et al., 2014) model intercomparison projects.

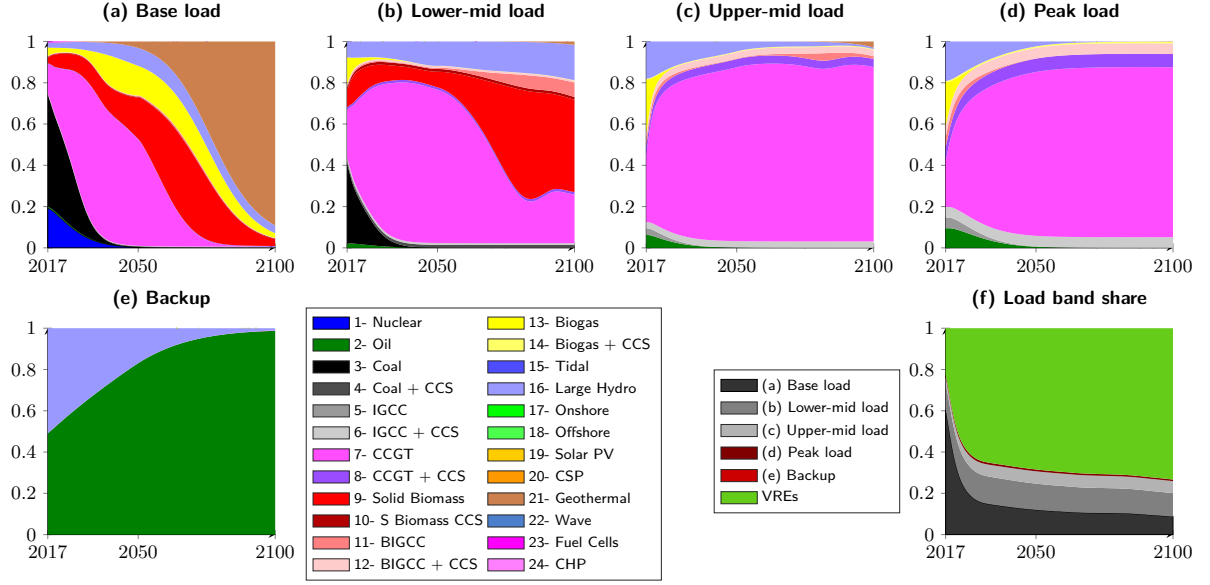


Figure A.12: Technology shares from FTT:Power for Germany in five residual load bands, (a)-(e), and corresponding load band shares in (f). Multiplying the technology shares of each load band with the respective load bands share leads to Figure 8b.

Figure A.13 shows the renewable energy and renewable electricity shares computed from these four scenarios. Panel (a) shows a scatter plot of $S_{\text{ren}}^{\text{ener}}$ and $S_{\text{ren}}^{\text{elec}}$, which immediately suggests an exponential function as a fit. However, this would fail to properly reproduce the temporal dependence of renewable energy shares, shown in panel (b), which reveals that under stringent mitigation targets, renewable electricity shares saturate relatively quickly at values close to 100%, whereas renewable energy shares take more time to follow suit with a distinctively sigmoid shape. In order to cover not only the dominant effect of $S_{\text{ren}}^{\text{elec}}$ on $S_{\text{ren}}^{\text{ener}}$, but also the crucial time dependency of $S_{\text{ren}}^{\text{ener}}$, especially at large renewable electricity shares, I perform a three-dimensional fit of the two-term function

$$S_{\text{ren}}^{\text{ener}}(S_{\text{ren}}^{\text{elec}}, t) = \underbrace{a \cdot e^{b \cdot S_{\text{ren}}^{\text{elec}}}}_{\text{Exponential function}} + \underbrace{\frac{m}{1 + e^{-k(t-t_0)}}}_{\text{Logistic function}} \cdot (S_{\text{ren}}^{\text{elec}})^p, \quad (\text{A.3})$$

with six free parameters, a , b , m , k , t_0 and p . Table A.2 prints the values of these coefficients. The first term constitutes the time-independent exponential fit, while the second term incorporates a logistic function with maximum value m , the logistic growth rate k and the sigmoid midpoint at t_0 . In order to account for the observation that the second term is most important at large values of $S_{\text{ren}}^{\text{elec}}$, i.e. when renewable electricity is close to saturation levels, I multiply the logistic function by a p -order polynomial of the renewable electricity share, $(S_{\text{ren}}^{\text{elec}})^p$. Panel (c) shows the resulting surface fit with an adjusted R^2 of 0.984, which is larger than the purely time-independent exponential fit. MIND-FTT uses this surface fit to determine $S_{\text{ren}}^{\text{ener}}$ from $S_{\text{ren}}^{\text{elec}}$ and time. Since the second term only turns out to be important for very large $S_{\text{ren}}^{\text{elec}}$ values, this approximation retains the immediate connection between FTT:Power and MIND for the overwhelming part of the transition period, complementing it with plausible mitigation progress in a regime of nearly full power sector decarbonisation.

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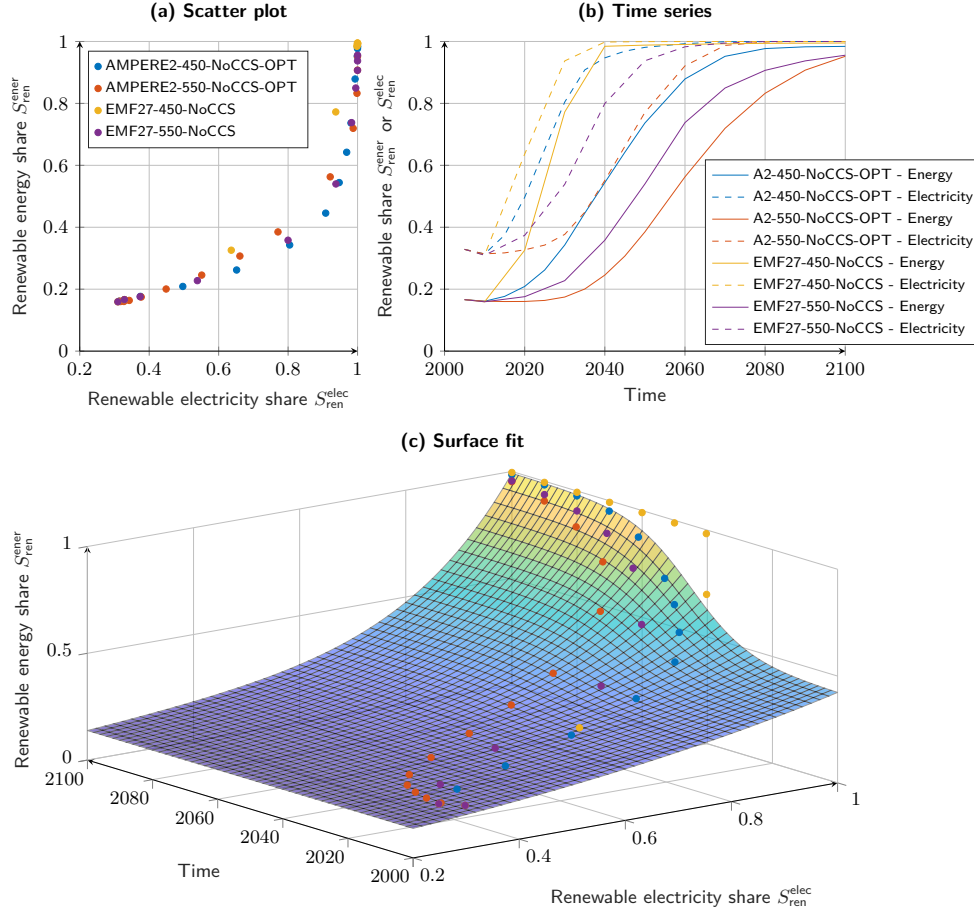


Figure A.13: Relationship between renewable energy shares S_{ren}^{ener} as a function of renewable electricity shares S_{ren}^{elec} (from FTT:Power) and time based on four 450 ppm and 550 ppm REMIND scenarios from the IPCC AR5 Scenario Database hosted by IIASA (2015). Panel (a) shows a time-independent scatter plot of S_{ren}^{elec} and S_{ren}^{ener} , which could be approximated with an exponential function. Panel (b) displays the corresponding temporal evolution of both, which shows that S_{ren}^{elec} saturates more quickly than S_{ren}^{ener} . To account for this, panel (c) shows a surface fit of S_{ren}^{ener} as a function of S_{ren}^{elec} and time (Equation A.3), which is used in the MIND-FTT soft-link.

Table A.2: Coefficient values of 3D surface fit in Figure A.13

Coefficient	Value (95% confidence)
a	0.1047 (0.07262, 0.1369)
b	1.389 (0.7565, 2.022)
m	0.572 (0.4092, 0.7348)
k	0.1149 (0.05858, 0.1711)
t_0	2045 (2039, 2051)
p	5.799 (2.704, 8.893)

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