ENERGY SYSTEM MODELLING FOR REGIONAL POWER SECTOR'S DEEP DECARBONISATION—MODELLING ASPECTS AND CHALLENGES

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Abstract

Power sector deep decarbonisation challenge the current energy system to integrate a wider range of low-, zero-, and negative-carbon electricity supply technologies. Multiple layers, segments, and networks of the time-dependent and geospatially distributed resources, processes, and consumers represents the complex interactions of electricity supply chain processes. Suitable methods and tools are necessary to derive relevant insights and analysis about the energy system to support the strategic plan energy sector expansion and transition in the region. This paper presents the necessary aspects to consider when modelling regional electricity supply chain system and points out the challenges in the context of deep decarbonisation.

The key aspects and challenges of energy system modelling are derived from literature review. Select energy system modelling frameworks are presented, and the extent to which they consider these aspects and how they tackle challenges are discussed.

The results identifies key aspects of energy system modelling for the assessment of regional electricity supply chain capacity in the context of deep decarbonisation (scope and coverage, system boundaries, level of complexity, spatiotemporal resolutions, model formulation, data, and assessment criteria). Each of the studied modelling frameworks are capable to model generic or specific type of energy production, storage, and distribution network capacities with various level of complexities and scales. There are challenges pertaining to energy system modelling: (1) addressing space and time; (2) balancing model complexity and tractability; (3) integrating social, resource, and environment dimensions; and (4) resolving uncertainty, transparency, and reproducibility. Spatiotemporal resolutions are the major specific challenge considering the complex investment and operational constraints related to resource adequacy, access, suitability, and service reliability. Scale of the model increases when including additional system boundaries, i.e., more detailed conditions of how the complex system interacts. Computational capacity needs to be expanded to include large-scale resource transport and storage on top of generation capacity expansion problem, otherwise simplification of system complexities needs to be addressed. Assessment area expands with including externalities related to energy system development (socio-economy, resource, and environment). The accuracy of the results is also dependent on data quality and can be improved with a more transparent and collaborative process. In discussing these challenges, possible areas for future research are presented and recommendations are made to ensure the continued relevance for energy systems modelling in deriving strategic insights to support policy-making process in the region.

There is still a broad range of opportunities for researchers to contribute to the development of future energy system modelling. Focus on the spatiotemporal uncertainties of renewable resources and the spatial implications of infrastructure deployment are paramount in assessing the costs, potentials, and impacts of expanding the energy supply chain. To summarise, the appropriate or relevance of energy system modelling needs to be reviewed critically for their suitability and trade-offs in tackling region-specific challenges. The approach presented here is one contribution to improve current methods of modelling and analysis of energy system by adding the key aspects for an improved strategic decision support in regional energy planning.

Overview

Deep decarbonisation of the power sector plays a key role in reducing total greenhouse gas (GHG) emissions dramatically to meet climate stabilisation goals (Kriegler et al. 2014). A common strategy is to avoid, reduce or remove carbon emissions from electricity generation and use low-carbon, carbon-free, or negative-carbon electricity to help decarbonise residual emissions from other hard-to-reduce sectors (transportation, building, industry) (Bataille et al. 2016).

The power sector, once a predictable and slow-moving industry, is now a complex system undergoing rapid transformation. Access to affordable and reliable electricity is a key driver of economic growth in modern economies (National Research Council 1986). Countries are in various stages of reforming and transforming their power sectors to better incorporate modern technologies, assure reliability and affordability, reduce harmful air emissions, meet a wide range of environmental goals, and achieve critical developmental objectives. Charting a path towards power sector deep decarbonisation is a complex task, considering the wide-ranging portfolio of technological solutions and respective challenges.

Energy system models provide the integrating framework that assists energy policy and industrial decision makers at different levels (global, regional, local) in assessing different strategies and possible outcomes (Strachan, Fais, and Daly 2016). Note that the main goal of modelling was 'not to compute precise but to gain insight into any complex system'. Wide range of uncertainties, assumptions, exclusions, and simplifications limit the model capability in determining the exact outcome (Huntington, Weyant, and Sweeney 1982; Hamming 2012).

Considering the modelled system boundaries and complex interactions are theoretically confirmed, a 'good-fit' model can capture the behaviour of the system in various scenarios acceptably similar to what is expected in real condition. Thus, modelling is suitable for scenario analysis as to help substantiate questions related to systems' capacity deployment and operation (Chermack et al. 2001). This help analysts to understand the increasingly complex sector and develop scenarios of possible development pathways. Formalizing the knowledge about the complex interactions in the energy sector and framework of thinking about the insights and implications related to how the modelled system behaves. Ultimately, supporting decision makers to explicitly state their views on the direction of the energy sector development aimed to achieve given strategic goals.

In this article, a comprehensive overview of spatial-explicit energy system modelling for the assessment of regional electricity supply chain capacity planning towards power sector deep-decarbonisation and summary of the key modelling aspects and challenges are presented. The "Motivation" section is followed by the "Methodology" section—where necessary descriptions of the review approach are provided. In the "Modelling aspects" section presents the key aspects of energy system modelling to consider in the context of power sector deep decarbonisation, and several current approach to address these aspects. Subsequently, in the "Modelling challenges" section presents the discussion of current and possible future issues related to modelling and assessment. The "Conclusions" section summarises and closes this review.

Motivation

Deep decarbonisation of the power sector comprises of electrification strategies to the masses, shift to higher efficiency plants and shift to lower emitting fuels (i.e., coal and oil to natural gas), large-scale integration of renewable energy sources (RES) electricity, coupling of carbon capture, (transport) and storage (CSS) technologies, as well as carbon dioxide removal (CDR) in the form of bioenergy coupled with CCS (BECCS) and direct-air capture (DACCS). This challenges the current energy planning to integrate a wider set of networks of interconnected energy and CCS processes with a diverse set of low-, zero-, and negative-carbon technologies. This calls for new types of energy system models that incorporate a multiverse of energy carriers, conversion, storage, and distribution technologies and wide-area networks of geospatially distributed processes with finer system complexity and spatial detail. Moreover, the intermittent nature of renewable energy sources (RES) and time-dependent demand profile require strategic analysis of supply-demand matching in detailed short-term operations, with the resulting need for more temporal detail.

These models must also consider a wider range of assessment related to the affordability, security, acceptability, and sustainability that largely influence the feasibility of different deep decarbonisation strategies in the region. And to ensure a high impact of modelling results, improved transparency of modelling assumptions and methodologies are necessary to improve public scrutiny, in line with the principles of open science, free market, and international cooperation.

This review focuses on spatiotemporal-explicit energy system modelling framework for four five reasons:

1. Variability, uncertainty, and location-specificity of RES.
2. Extensive electrification and transmission expansion options.
3. Need to factor in the transportation costs of fuel-feedstock and the geospatial distribution of resources.
4. The need to cost-effectively capture, transport, and store CO2 at scale requires a detailed analysis of CCS infrastructure deployment for wide area CO2 source-sink matching.
5. Region specific protection and conservation values influence the quality and access to energy resources and suitability of infrastructure deployment.

Methods

The aim of this review is to give a comprehensive overview and to discuss the key aspects and challenges of energy system modelling for regional power sector deep-decarbonisation. The key aspects and challenges of energy system modelling are derived from literature review (see **Table 1**). Select frameworks of energy system modelling and analysis are presented, and the extent to which they consider the key aspects and how they tackle challenges are analysed.

Table 1 | Relevant literatures

Publication	Focus
(Kriechbaum, Scheiber, and Kienberger 2018) "Grid-based multi-energy systems—modelling, assessment, open source modelling frameworks and challenges" (Mancarella 2014) "(multi-energy systems): An overview of concepts and evaluation models" (Lopes et al. 2016) "Modelling of integrated multi-energy systems: drivers, requirements, and opportunities"	**Grid-based multi-energy system concepts and modelling**
(Nunes, Causer, and Ciolkosz 2020) "Biomass for energy: A review on supply chain management models"	**Biomass supply chain model**
(Krishnan et al. 2016) "Co-optimization of electricity transmission and generation resources for planning and policy analysis: review of concepts and modeling approaches" (Syranidis, Robinius, and Stolten 2018) "Control techniques and the modeling of electrical power flow across transmission networks" (Samsatli and Samsatli 2015) "A general spatio-temporal model of energy systems with a detailed account of transport and storage"	**Generation and transmission co-optimisation model**
(Kuby, Bielicki, and Middleton 2011) "Optimal Spatial Deployment of CO_2 Capture and Storage Given a Price on Carbon" (Middleton and Bielicki 2009) "A scalable infrastructure model for carbon capture and storage: SimCCS"	**Carbon capture, (transport) and storage (CCS) infrastructure model**
(Kling et al. 2017) "Integrated Assessment Models of the Food, Energy, and Water Nexus: A Review and an Outline of Research Needs" (Grace C. Wu 2020) "Spatial Planning of Low-Carbon Transitions"	**Integrated assessment of energy system externalities**
(Wiese et al. 2018) "A qualitative evaluation approach for energy system modelling frameworks"	**Evaluation of energy system modelling frameworks**

The above list of literature review help determines the key aspects and challenges for modelling the electricity supply chain in the context of deep decarbonisation. For the evaluation of such energy systems and deep decarbonisation pathways, suitable assessment criteria are provided. The review analyses each framework's modelling approach and the extent to which the necessary aspects are considered.

Modelling aspects

To gain useful results from the modelling exercise, it is crucial to model the values that are relevant to the problem (Pfenninger, Hawkes, and Keirstead 2014). In the following sections, several important aspects of energy system modelling that need to be considered within the context of deep decarbonisation will be discussed.

Scope and coverage

Deep decarbonisation of power sector can be achieved through deployment and operation of low-, zero-, and negative-carbon electricity supply technologies, which configuration brings a steep decline to total CO_2 emissions overtime. In the context of regional long-term power sector planning, the development of spatiotemporal-explicit energy system model focuses on the long-term capacity investment planning with considering the short-term dynamics and operational constraints implying to the adequacy, reliability, and security of supply deliveries (Yuan and Ashayeri 2009). The bottom-up planning model comprises of sets of decisions under both capacity investment and operation variables related to how much, where, and what type of technology to deploy (invest) and energy commodity to produce, store or distribute; all to secure adequate, reliable, and cost-effective electricity supplies to demand regions (Prina et al. 2020). This requires consideration of the short and long term dynamics of supply and demand, as well as technological, regulatory, economic and social constraints (Collins et al. 2017). Both capacity and operation decisions influence the potential costs and benefits, ultimately, the value of the system.

The model should cover at least a region that comprises of various sub-regions interconnected with various channels of distribution, which constitutes the network of electricity supply chain from feedstock-transport, production, storage to transmission-distribution. Long-term capacity planning model usually considers a time horizon of 30-50 years, considering the economic lifetime of technology investment and major structural changes (e.g., socio-economic transformation, market restructure). Note that envisioning the deep decarbonisation pathways in line with the Paris Agreement requires a time-horizon up to the end of 21st century. This also include the net-zero targets by early 2nd half of the 21st century. Moreover, short-term operation model accounts for the feasible operation of the planned capacity to deliver adequate and reliable supply.

System boundaries

The system boundary must be carefully defined to comprehensively assess the power sector, focusing on various deep decarbonisation strategies and respective challenges. For power sector, all energy carriers related to input feedstock must be considered in assessing the input-mix of power generation (e.g. biomass, fossil-fuels, RES) as well as co-generations or co-products (e.g. heat or steam) (Mancarella 2014). The power sector has grown complex overtime with the expanding low-, zero-, negative-carbon electricity supply technologies. Various types and layers of energy processes are interconnected along the electricity supply chain. Starting from feedstock and transport, generation, storage, and transmission-distribution; creating value of the region's power sector in fulfilling consumer demand for electricity (Nagurney and Matsypura 2007). Considering the availability of CCS technologies, the boundary of the system expands to include CO_2 capture, transport, and storage technologies (d'Amore and Bezzo 2020). This enables a comprehensive assessment of carbon-negative electricity in an energy supply chain perspective. **Figure 1** represents the power sector coupled with CCS technologies and the physical flow of energies and CO_2 through stages of an interconnected processes (activities) in segments of power sector.

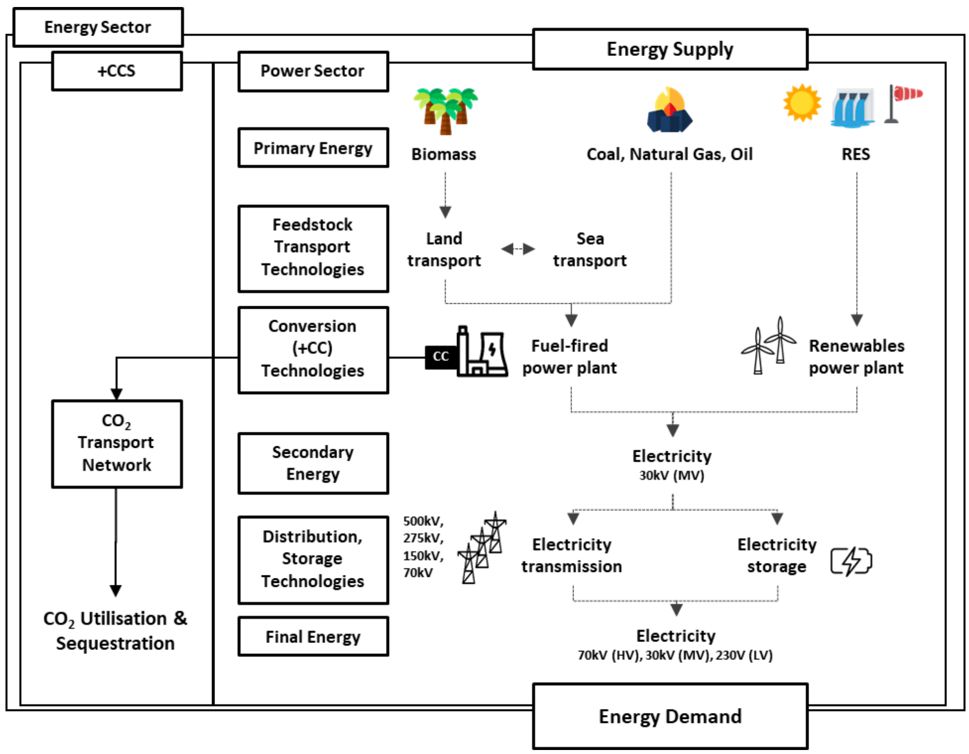

Figure 1 | Schematic of the energy system related to the power sector and coupling with carbon capture and storage (CCS). The power sector includes the stages primary energy feedstock and transport, conversion, storage, and distribution of final energy. CCS coupling at electricity generation facility. The arrows represent the physical flow of energy and CO_2 through stages of an interconnected processes (activities) along the electricity supply chain.

Level of complexity

Conversion and transfers of energy are bound to the law of physics (thermodynamics). Representation of the physical flows of energy along the electricity supply chain can be described in the model with different levels of complexities. For instance, whether or not to consider part-load efficiencies (Kim 2004), simple transport or AC/DC power flows model, electricity storage cycling, CO_2 pressure drop in transport, and other physics properties that significantly influence how the energy system behaves, ultimately the costs and configurations.

The different levels of complexity can be classified into three categories: black-box, grey-box, and white-box model representations. Black-box models are highly aggregated, databased input-output models without a representation of the underlying physical principles. Whitebox models offer higher degrees of detail and are based on physical principles to calculate load flows and conversion efficiencies. Grey-box models use simplified physical representations, and their aggregation level and degree of detail is in between that of a white-box model and a black-box model. Increasing the level of detail leads to increased computational effort and may decrease model tractability.

Figure 2 mapped out various types of models or cases in different spatial coverage and level of detail.

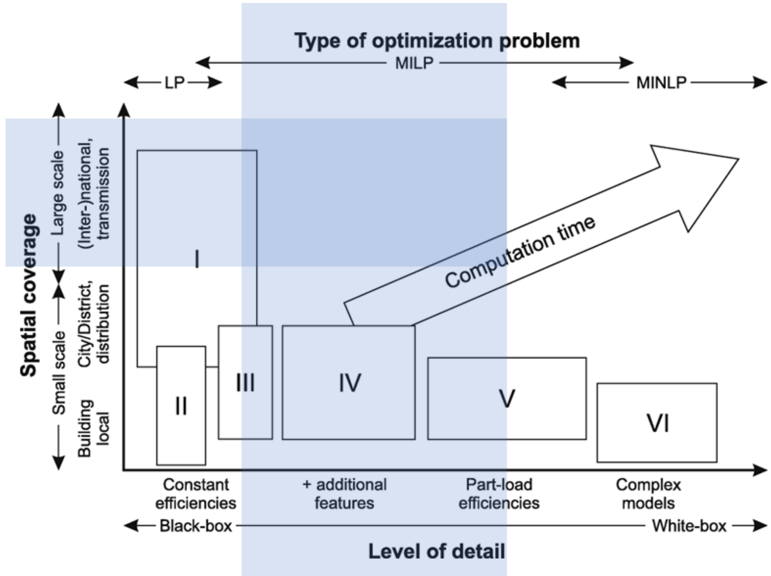

Figure 2 | Classification of existing energy system models according to their level of detail and spatial coverage. I: large-scale grid studies relying on simplified models, II: simple tools for quick assessments of small-scale energy systems, III: building and city district energy system design studies with simplified models, IV: on-site energy system studies with additional features, V: mixed-integer linear programming with part-load efficiencies and VI: mixed-integer non-linear programming with complex models. Electricity supply chain modelling for power sector deep decarbonisation is in the dark-blue box. Adapted from (Kriechbaum, Scheiber, and Kienberger 2018).

Spatiotemporal resolutions

In the context of electricity supply chain, power sector energy system models should consider spatial and temporal dimensions because energy supply and demand often occur in different locations and in different times. To connect demand with supply, energy transfer infrastructure is necessary. Moreover, to match supply and demand at any time, careful short-term operation of generation, storage, and distribution portfolios are necessary.

Large-scale integration of RES is challenged by the variable, uncertain, and location-specific nature of RES. Timely load-matching of different RES and demand profiles requires flexible storage and auxiliary capacities to back up renewables production when RES availability are low, or when forecasted-generation have been corrected overtime. Integration of large-scale RES further requires long-distance transmissions to transfer large amount of renewables production that are often found in regions afar from demand centres. Fuel-feedstock and CO_2 source-sink matching also require detailed spatial analysis, considering the extensive transport routes and network expansions.

Large-scale global energy system models use aggregated spatial and temporal resolutions to the level of countries (regions of countries) and sub-annual time-slice resolutions. This approach is to account for cross border trade and temporal-fluctuation of energy supply and demand loads at international (inter-regional) levels. Spatial-explicitness of information related to the modelled system can be set at different spatial size or area of modelled locations (e.g., national, district, community levels, or square-grids. Meanwhile, temporal-explicitness can be set at different periods of time representing significant changes in different years, seasons, hours, minutes, seconds, and in shorter periods.

Figure 3 mapped out various types of models or cases in different spatial and temporal resolutions.

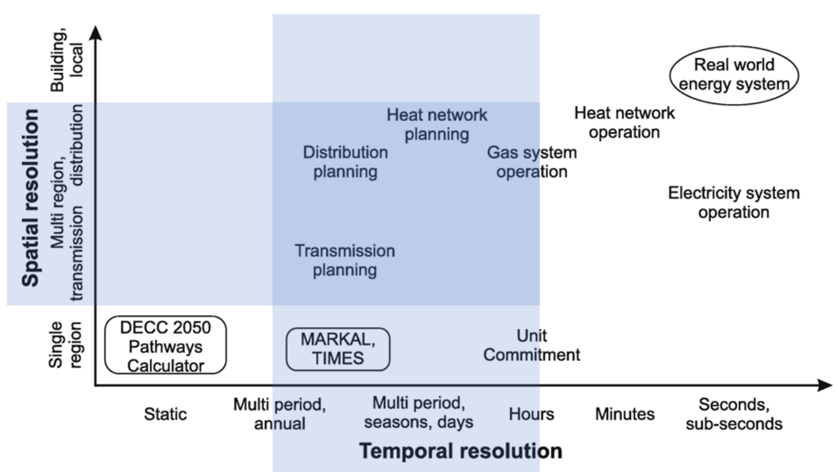

Figure 3 | Spatial and temporal resolutions in energy system models. Electricity supply chain modelling for power sector deep decarbonisation is in the dark-blue box. Adapted from (Lopes et al. 2016; Kriechbaum, Scheiber, and Kienberger 2018).

Model formulation

Based on the approach to describe the problem, there are five groups of energy system models: (1) Simulation model that predicts or forecasts how the energy system might evolve; (2) Optimisation model that provide scenarios of how the energy system could evolve; (3) Back-casting model that provide scenarios of how the energy system should evolve, given the future state; (4) Partial-equilibrium model that assess policy and technology interventions through the analysis of changes in behaviour of supply, demand, and prices in a whole economy with several or many interacting markets, and the interaction of demand and supply will result in an overall general equilibrium; and (5) Agent-based model that consider the full-functioning system as a collection of autonomous decision-making entities called agents, and each agent individually assesses its situation and makes decisions on the basis of a set of rules.

Feedstock-transport, energy conversion, storage, and distribution processes can be described in a continuous function of linear and non-linear behaviour (Palensky, Widl, and Elsheikh 2014). To create mathematically tractable models for integrated simulation or optimisation problems, the equations must be brought to a common mathematical problem formulation. The most commonly used are linear programming (LP), mixed-integer linear programming (MILP), mixed integer non-linear programming (MINLP) and dynamic programming (DP) (Beeck 1999). In LP, all relationships are expressed in fully linearised terms with constant coefficients. MILP is an extension of LP as it allows a greater detail in formulating technical properties and relations. It adds decision variables and non-convex relations which allow, for instance, the on/off mode for individual units and lumpy investments. Moreover, MINLP takes into account non-linear objective functions and constraints meaning that it most closely approximates real world systems (Qudrat-Ullah 2016). However, this adds more layer of complexity since the identification of the global optimum among the local optima in non-linear problems requires greater computational effort (Wagner and Wittmann 2014). DP is a method to find the optimum growth path. The problem is divided into several simple sub-problems for which the optimum solution is calculated and then combined to a global solution. This method was applied for example on distributed generation and distribution system expansion planning (Gönen and Foote 1982; Khalesi, Rezaei, and Haghifam 2011) or the optimal operation of a distributed energy system and networks (Tashiro, Tamura, and Yasuda 2011).

Based on the approach to address uncertainties, models can be classified into two: (1) deterministic model uses best-estimates for input parameters and not consider the probability distribution, thus model results are determined by the exact input parameters; and (2) probabilistic model that considers the probability distribution of potential outcomes by allowing random variation in one or more inputs over time.

Data

Finer spatial and temporal resolutions of the model requires appropriate values of both the parameters and independent variables (Lopes et al. 2016). This vast amount of data required for high resolution bottom-up models challenges the modellers. The necessary data is often not available because it is either not measured, commercially confidential, relates to the future, highly uncertain, or bad quality.

Assessment criteria

Choosing the appropriate assessment criterion and indicators are critical to evaluate the feasibility of power sector development and related deep decarbonisation strategies. The most common criteria are technical, economic, social or resource-environment. Qualitative and quantitative criteria do exist, but only quantitative criteria can be used for the mathematical formulation of model. The assessment and performance indicators can derive from an absolute or relative value, and a single- or multi-objective approach.

1. Technical assessment compares the energy efficiencies by comparing energy output to energy input, following the first law of thermodynamics. Assessed for individual components or the whole system over a certain period. To assess the gains of efficiency improvements, a wide range of scenarios and system configurations are compared to one another. This also includes the reliability assessment in evaluating the system technical ability or capacity to secure electricity supply.
2. Economic assessment evaluates the costs of deploying and operating the system. For long-term planning purpose the time value of money is considered using discounted cash flows.
3. Socio-technic assessment evaluates the acceptability of technology deployment around local communities, as well as the socio-economic impacts of energy systems development.
4. Resource assessment evaluates the use of resources throughout the electricity supply chain. For instance, the use of clean water resources for thermal generating units, the use of land for sitting of power supply technologies, and more.
5. Environment assessment evaluates the impacts of energy systems deployment on ecosystem services. This can be measured as in GHG emissions and removals, local pollutants, and more.

Modelling challenges

This section describes the challenges in energy system modelling for regional power electricity supply chain in the context of deep decarbonisation.

Addressing space and time

Models with a high spatiotemporal resolution may require too much computational effort to be solved in an acceptable timeframe. Although a coarse resolution requires less computational effort, it can lead to inaccurate results. This is due its averaging character that may filter out the extreme points when designing the system. For instance, using coarser resolution may not capture the significant of short-term dynamics of resources, flexible operations, and infrastructure sitting conditions that have significant effect in influencing the deployment of energy infrastructure. However, aggregation of data can improve model tractability and to account for unmeasured data (Frew and Jacobson 2016). This can be done by clustering information related to input parameters and independent variables at coarser spatiotemporal resolutions, which is considered a good fit to the scope of analysis. It is important to note that different spatiotemporal resolutions may lead to deviating results. **Figure 4** illustrates the clustered spatiotemporal information, from different processes in a spatial unit, interconnected to neighbouring spatial units and in various time-periods (temporal units).

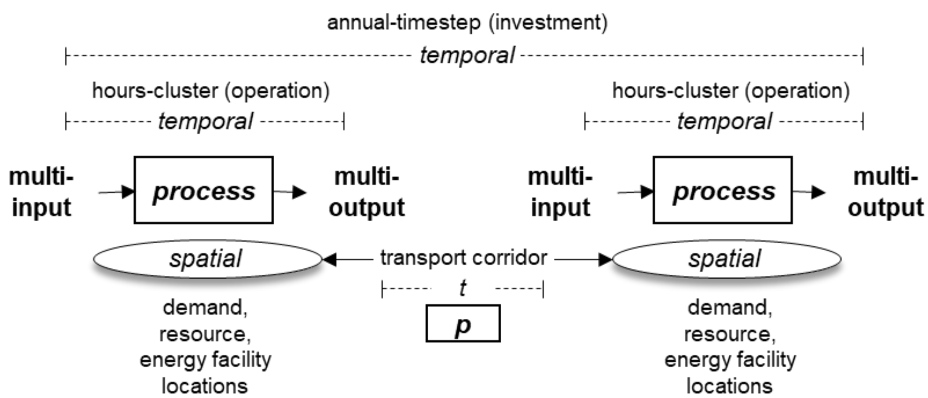

Figure 4 | Illustrative spatial and temporal representations of energy system models.

Selection of spatiotemporal resolutions should consider the extremes where decisions may shift. For instance, to consider differences in distance that may significantly change transport routes, or differences in time that may significantly change the loads of supply-demand.

How a location is represented in the model should well reflect the distinctive features in terms of energy supply and demand to other locations. In addition, spatial resolutions of interconnected energy processes or clusters of processes should consider the significance of distance and suitability for deploying transport infrastructure, thus having significant effect on the energy flows, system costs and feasibility. For instance, 10 to 100 km^2 grid-cells are set to be the spatial units, considering transmission losses and investment costs input data are measured per 10 km and 100 km distances. When network infrastructure is already well developed, a saturated market with close-to-average access quality and costs can be analysed in coarser spatial resolutions or clusters. However, when network infrastructure is not yet developed, higher spatial resolutions are required to analyse the potentials and impacts of expanding the network or routes to feedstock-transport, electricity transmission-distribution, and CO_2 transport.

How time is represented in the model should capture the long-term dynamics of capacity deployment and short-term dynamics of operation. This is a prerequisite to ensure a feasible deployment and operation of the modelled capacities. A multi-period timeline of annual investment analysis can reduce the redundant variables of investment periods, considering that macro conditions may changes and have influence on investment decisions every 5 to 10 years. Moreover, using hours-cluster can improve model tractability through grouping of the values from similar time-periods. To comprehensively assess the feasible operation of securing electricity supply in the region, short-term variations in the power system need to be considered in long-term planning models (Collins et al. 2017).

Balancing scale, complexity, and tractability

The power sector is a large and complex system. The question then arises whether energy systems models are too compact of representation; whether they may over or under-look some important aspects of the systems in analysis by making trade-offs in resolution or by using simplified assumptions. Energy systems become more complex and interconnected as they grow more decentralised, reliant on more diverse energy sources and decarbonisation technologies, and increasingly networked across borders. The issue of complexity is linked to the scale of model.

Usually, a model is either designed to follow the evolution of an energy system in the long term, with coarse resolution, or to analyse the planning or operation of a system over a shorter period with fine resolution. "Scale", in this context, means the relative size of the boundary of an analysed or modelled system, so a large-scale model covers an entire continental region with coarse resolution, while a small-scale model covers a single location with high resolution. Integrating information across these different scales with their appropriate resolution is still a challenge due to associated computational demands.

To improve tractability model formulation can adjusted to simplify problem representation by using constant coefficients and aggregated values in a coarser spatiotemporal resolution. Another way is to decompose the problem into multiple stages. Forward-looking planning use dynamic recursive model to account for future changes that are impacted by successive implementation of decision variables in the previous period (J. Van Den Bosch and Honderd 1985).

Multi-dimensions feasibility assessment

Recognition of co-benefits and adverse side-effects of energy system development and related deep decarbonisation strategies are critical to ensure project feasibility. Different technologies or strategies may have distinctly different benefits-risks profiles (Luderer et al. 2019). Climate Change Mitigation (UNFCCC 2015) and Sustainable Development Goals (SDGs) (IAEG-SDGs 2017) provide the integrating framework for assessing the feasibility of energy technology options with considering multi-dimension of interactions between technology, resources, society, and environment. These complex interactions influence the extent of energy technology options to be considered as affordable, secure, accessible, acceptable, and sustainable.

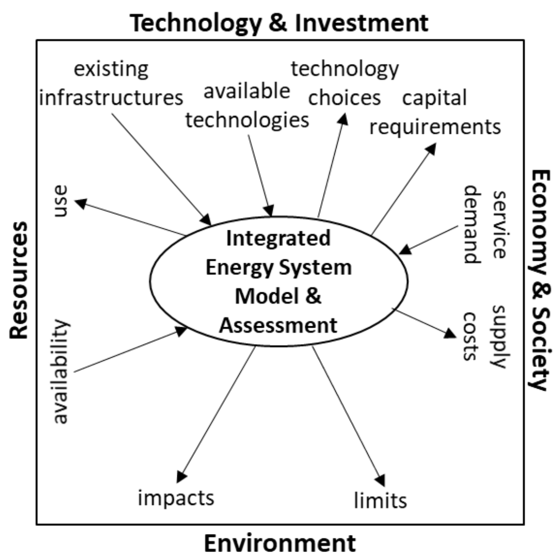

Figure 5 | Integrated energy system model and multi-dimensional feasibility assessment criteria. Adapted from (Lopes et al. 2016; Kriechbaum, Scheiber, and Kienberger 2018).

Models using top-down approach try to provide a holistic perspective of the wider socio-economy (this includes economic growth, employment, trade), resource, and environment, but only consider the energy sector in a simplified and aggregated manner (Kling et al. 2017). In comparison, bottom-up models incorporate rich technological detail and use an economically driven approach for evaluating technology investment (Prina et al. 2020). This allows them to provide more detailed outlooks on future supply and demand and possible technology utilisation. Coupling or linking technology-rich bottom-up models and economy-wide top-down models can integrate large set of externalities to be considered without significantly increase computational effort.

Resolving uncertainty, transparency, and reproducibility

Uncertainty in models is being tackled in various ways. One way is to extend existing large-scale models by including uncertainty or probability distribution via stochastic modelling. For instance, probabilistic approaches, possibilistic approaches, interval programming, and robust optimisation (Aien, Hajebrahimi, and Fotuhi-Firuzabad 2016)). Another way is to use new models designed from the ground up to address the challenge.

It is common to construct scenarios that contain sets of assumption for the inputs to the model. These values are chosen to represent range of estimates deemed to be acceptable, or to test the limits of future decision space. However, hindsight can reveal major errors with the choices made inevitably influenced by opinions around the time of analysis (Trutnevyte et al. 2016).

Data aggregation and downscaling are necessary when data at given resolutions are not available, instead is available in coarser or in finer spatiotemporal resolutions. For instance, downscaling energy drivers from global scenarios to regional levels using tailored methodologies (van Vuuren, Lucas, and Hilderink 2007). Or aggregating wind potential from finer to coarser resolution, to improve model tractability when considering wider spatial coverage.

Finally, by making model and analyses more transparent and reproducible, modelers are supporting a more collaborative process towards informed discussion on the uncertainties and assumptions inherent in complex energy systems models through. Open data, open source, and open access can improve transparency and access of energy system modelling (Pfenninger et al. 2018; Kriechbaum, Scheiber, and Kienberger 2018). Open-source modelling framework covers the input data processing, model formulation, software selection, results, and post-processing. An open and transparent modelling framework can help scientific community to collaborate, thus increasing the reproducibility, and ultimately, brings higher impacts of modelling activity.

Conclusions

This paper provides an overview of the current research and challenges of modelling the energy system for power sector deep decarbonization. Key modelling aspects and challenges that need careful attention in model development of modelling grid-based energy carrier systems have been discussed.

Suitable methods and tools are necessary to derive relevant insights and analysis about the energy system to support the strategic plan of expanding and transitioning the power sector. To provide a robust and efficient future electricity supply in the region, strategic assessment using energy system model should incorporate the complex interaction between various energy carriers and processes, as well as represent load flows in the extensive energy networks. Moreover, to account for supply adequacy, reliability, and security of the system, the model should consider higher level of detail related to energy physics and spatiotemporal resolution. Model formulation and data need to be adjusted to best substantiate the problem in question.

The challenges discussed show that there are opportunities for future research in improving the modelling and assessment techniques. Coupling of short-term operation model with long-term capacity planning model are important to assess the operating feasibility of the planned capacities. This also becomes challenging, with demanding level of detail and spatiotemporal resolution. Moreover, accounting for externalities will increase model complexity. Techniques of downscaling and aggregation are necessary to fill in the information gaps in different spatiotemporal resolutions, and 'credible' assumptions are helpful to maintain model tractability when data is not available nor when the problem is too complex. Soft-link bottom-up with top-down energy economics models can provide a more tractable integrated energy system model in assessing multi-dimension feasibility. Open data, open source, open access supports mass collaboration and can help improve modelling and analysis with diffusion of best-practices and know-hows and access to input data and model results for analysis.

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