Energy Strategy Reviews 18 (2017) 73–84

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.ees.elsevier.com/esr

Using resource based slicing to capture the intermittency of variable renewables in energy system models

Mariliis Lehtveer*, Niclas Mattsson, Fredrik Hedenus

Physical Resource Theory, Chalmers University of Technology, SE-412 96, Gothenburg, Sweden

ARTICLE INFO

Article history:
Received 12 April 2017
Received in revised form
16 June 2017
Accepted 12 September 2017

Keywords:
Variability
Renewable energy sources
Energy system model
Time slices
Resource based slicing

ABSTRACT

As the share of wind and solar power is expected to grow significantly in coming decades, it has become increasingly important to account for their intermittency in large-scale energy system models and global integrated assessment models that are used to explore long term developments. However, the scope of these models often prohibits the use of a high intra-annual time resolution that can adequately capture the main characteristics of variable renewables. A more efficient representation is required. In this paper we evaluate resource-based slicing, i.e. selecting time slices based on wind and solar generation rather than e.g. season and time-of-day. We show that resource slicing can capture many aspects introduced by variable renewables such as the need for flexible generation capacity, curtailment at high penetration levels and interactions with baseload and storage technologies, while using only sixteen intra-annual time slices.

1. Introduction

If global warming is to be kept under 2 °C with reasonable certainty, greenhouse gas (GHG) emissions must drop by roughly half by mid-century compared to current levels and continue to decline afterwards [1]. The power system is one of the main sources of emitted anthropogenic GHGs, accounting for about 30% of the total emissions [2], and therefore one of the main targets for emission reductions. Many possibilities exist for supplying energy with low lifecycle emissions such as the use of biomass, wind, solar, hydro or nuclear power. Solar and wind power have a vast physical resource potential but only supply a small share of current global energy production due to historically high costs [3]. However, recent years have seen large cost reductions for both wind and solar photovoltaic (PV) technologies, which has resulted in (and been caused by) an explosive growth of installed capacity [4]. It appears very likely that these technologies will play a major role in the future electricity system if the 2-degree target is to be met.

Yet large scale expansion of wind and solar power brings along another set of challenges. The supply from wind and solar PV technologies is variable in both short and long term and not reliably predictable. Large amounts of wind and solar power complicate systems operation by changing the residual load shape, increasing the uncertainty of supply and the need for reserve capacity. If significant amounts of intermittent capacity are installed in the system, there may be an oversupply of electricity on windy and sunny days, which is likely to result in low or even negative electricity prices. This in turn will diminish revenues for variable renewables as electricity prices tend to be low when they are able to produce electricity, and also for baseload due to decreased utilization and increased ramping. Thus solar and wind generation will have a large influence on all investment decisions and on the total cost of the system. This effect will become more acute with increasing penetration of wind and solar power.

Long-term energy models representing multiple sectors and regions are often used to investigate the questions related to long term developments such as decarbonisation of the energy system. These models typically make a cost-effective choice among large number of technologies and optimise investment decisions over many time periods and over vast geographic areas. This makes these models computationally demanding and simplifications in temporal, geographic and technological detail may be necessary to maintain reasonable running times. Typically time steps of 5–10 years are used in these models [5]. However, supply from wind and solar power varies on much shorter time scales and can be difficult to capture in large-scale models.

Traditionally, models such as POLES, IMACLIM, GET [6–8] etc. have circumvented this problem by simply limiting the amount of

* Corresponding author.
E-mail address: mariliis.lehtveer@chalmers.se (M. Lehtveer).

http://dx.doi.org/10.1016/j.esr.2017.09.008
2211-467X/

variable renewables to 25–30% of electricity production; a level that is widely viewed as possible to integrate into current systems without significant additional costs. This approach limits the role that variable renewables can play in scenarios designed to investigate possible pathways to global climate mitigation, and therefore model results can be misleading. Recently different approaches have been evaluated by various modelling groups to avoid this type of artificial restriction and incorporate intermittency related effects into long-term energy models. For example, Sullivan et al. use additional constraints to capture the capacity credit provided by different penetration levels of intermittent renewables as well as technology dependent flexibility coefficients to account for the increased need for back-up capacity and flexible generation as the penetration of variable renewables increases [9]. These coefficients have been derived by using a unit commitment model with limited grid [9]. Another approach has been to interlink long-term capacity expansion models with short-term dispatch models e.g. Deane et al. [10]. However, this method requires considerable effort to set up both models and ensure the convergence of their results, as well as extensive additional computational resources.

Wind and solar power, however, are not the only sources of variability in the power system – the demand for electricity is also fluctuating over time. To describe the variability of demand in large energy system models, a time slice approach is often used. This involves implementing a coarse load duration curve for electricity demand, in which hours with similar levels of demand are grouped together (typically day/night, week-day/week-end, and seasons). Attempts have been made to extend this demand-based approach to improve the treatment of variable renewable supply. For example, Ludig et al. investigate the effect of increased time resolution of traditional demand-based slicing on capturing the variability of renewables and find that higher temporal resolution helps to capture the variability of demand and solar infeed, but does not adequately represent the variability of wind generation [11]. Nahmmacher et al. propose an approach for selecting representative days i.e. consecutive time slices that represent both varying demand levels but also variable renewable supply for long term energy system models as well as summarise other attempts in that direction [5]. They find that selecting six representative days with a temporal resolution of 3 hrs sufficiently describes the characteristic fluctuations of variable generation and demand. This results in 48 time slices per model year, which may make the approach inapplicable for very large scale energy models due to high computational requirements. Poncelet et al. explore the trade-off between techno-economic and temporal detail in models and suggest based on their results that the temporal representation should be prioritised in model development [12]. In addition, they compare time slicing to the representative days approach and find that representative days can highly improve the temporal representation of the system if chosen correctly. Ueckerdt et al. explore a method using residual load duration curves that adapt to the penetration level of variable renewables [13]. This approach captures the relationship between demand and variable infeed, but requires a more complicated set up including a more detailed electricity model to estimate the parameter values that describe how the load duration curves shift with different variable renewable shares, as well as significant amount of data for accurate approximations. Additionally, this approach leads to nonlinearities that increase the computational demands even further for models that are otherwise linear.

The aim of this paper is to demonstrate an implementation based on grouping hours by solar and wind infeed that we call resource based slicing and evaluate the number of slices needed to sufficiently well capture the variability of wind and solar generation. We show that around 16 slices can be sufficient to capture aspects of variable renewables, such as need for flexible generation capacity, curtailment at high penetration levels and interactions with baseload and storage technologies.

2. Method

2.1. The GET model

We introduce resource-based slicing into the Global Energy Transition (GET) model first developed by Azar and Lindgren [14] and further developed in Hedenus et al. and Lehtveer and Hedenus [6,8]. GET is a cost minimizing "bottom-up" systems engineering model of the global energy system set up as a linear programming problem. The model was developed to study carbon mitigation strategies with an objective of minimizing the discounted total energy system cost for the period under study (in general 2000–2100) while meeting both a specified energy demand and a carbon constraint.

The model focuses on the supply side and has five end use sectors: electricity, transport, feedstock, residential–commercial heat and industrial process heat. In each sector various technologies are available to meet the demand. Technologies are described by the energy carriers they can potentially convert, and are parameterised using e.g. investment and fuel costs, efficiencies, capacity factors and carbon emissions. Demand projections are based on the MESSAGE B2 scenarios with increasing global population, intermediate levels of economic development and a stabilisation level of 450 ppm CO_2 by 2100 [15]. GET has a single demand node for each region and thus the electricity grid is not explicitly modelled. Transportation demand scenarios are based on Azar et al. [14] and assume faster efficiency improvements in the transport sector than in the B2 scenario. The model has perfect foresight and thus finds the least cost solution for the entire study period with a discount rate of 5%/year. Consequently, scarce resources such as oil and biomass are allocated endogenously to the sectors in which they are used most cost-effectively. The resource base for conventional energy sources was updated for this model version based on [3] and [16].

In the model version developed in this paper, GET 9.0, the world is divided into 10 regions following IIASA region definitions (except that Eastern and Western Europe have been merged into one region): North America (NAM), Europe (EUR), Pacific OECD (PAO), centrally planned Asia (CPA), the former Soviet Union (FSU), Latin America (LAM), Africa (AFR), the Middle East (MEA), South Asia (SAS) and non-OECD Pacific Asia (PAS). The countries and territories belonging to each region are listed in Appendix B.

The current version of GET has several categories of solar and wind power: PV rooftop, PV plant A, PV plant B, concentrated solar power (CSP) with storage A, CSP with storage B, onshore wind A, onshore wind B and offshore wind. The A-versions of each technology have direct access to the electricity grid, whereas the B-versions are available at larger distances from demand and therefore require additional transmission investments; the additional cost is based on [17]. All of these eight types of solar and wind power have five resource classes each. This means that our model requires data on potentials (in GW) for each technology, region and resource class. Additionally, with the introduction of our new resource slices, the model requires data on capacity factors for each technology, region, resource class and time slice. This data is automatically provided by a new global geographical information system (GIS) framework developed for this version of the model.

2.2. Resource based slicing

Our proposed method involves selecting model time slices