Energy Economics 56 (2016) 107–116

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

# The database–modeling nexus in integrated assessment modeling of electric power generation☆

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ARTICLE INFO

*Article history:*
Received 25 March 2015
Received in revised form 2 March 2016
Accepted 6 March 2016
Available online 17 March 2016

*JEL classification:*
C61
C68
D57
D58
Q47

*Keywords:*
Integrated assessment
Computable general equilibrium
Model validation
Matrix balancing
Cross-entropy
Database–modeling nexus

ABSTRACT

Integrated assessment models (IAMs) are playing an increasingly important role in long-run sustainability analysis. At their core is a set of global economic and environmental accounts which capture a complete set of inter-industry and inter-regional relationships in the global economy in a consistent manner. While much attention is focused on the raw data and parameterization required to expand or add sectoral detail to IAMs, only rarely is there discussion of how different matrix balancing methods (i.e. translating disparate raw data sources into the consistent database) affect modeling results. This article offers an in-depth look into the database–modeling nexus in IAMs, focusing on the electric power sector which is both a major source of $CO_2$ emissions and a critical vehicle for climate change mitigation. Comparisons of the prevailing matrix balancing algorithms show how the choice of database reconciliation methodology affects modeling results using policy-relevant simulations in the context of the electric power sector. The resulting insights can be applied to the disaggregation of other, technology rich sectors in the economy. We conclude that appropriate selection of database reconciliation methodologies can reduce the deviation between bottom-up and top-down modeling.
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## 1. Introduction

It is increasingly apparent that standalone economic, biophysical, atmospheric, or other data-driven numerical models cannot address long-run sustainability issues which cut across traditional academic boundaries. Such issues include, but are not limited to: anthropogenic climate change; environmental degradation; and energy, food, and water security. Integrated assessment models (IAMs) marry social, economic, and environmental modules within a single framework to offer a clearer picture of how sustainability issues might evolve in the future and how public policies might alter this trajectory. In light of the complex policy issues facing the world today, IAMs with increasing sector-level detail have grown in popularity (Tol, 2006). Correspondingly, it is useful to identify and characterize new sources of uncertainty in IAMs and how they affect uncertainties in policy impacts (Weyant, 2009).

This recent push toward sector-level detail has not always been the norm. Early IAMs such as DICE (Nordhaus, 1992) and RICE (Nordhaus and Yang, 1996) included a single, aggregate economic sector. However, this stimulated interest in IAMs in policy circles which led to a demand for increased sector detail. This has brought the IAM community into intimate contact with the computable general equilibrium (CGE) modeling community. CGE models offer consistent theoretical underpinnings of inter-sectoral and inter-regional interactions across the entire global economy. Furthermore, adding sectoral detail is relatively straightforward and well-studied. As such, CGE models are becoming the preferred economic module in IAMs – especially for energy-related research. For example, 12 of the 18 models used in the EMF 27 study are CGE-based (Kriegler et al., 2014).

Sectoral extensions require disaggregating the largely aggregate sectors in an existing CGE database into detailed sub-sectors to analyze specific technologies and policy shocks (McFarland et al., 2004; Edmonds

☆ Peters acknowledges support from the GTAP Consortium. Hertel acknowledges support from the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research, Integrated Assessment Research Program, Grant No. DE-SC005171.
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http://dx.doi.org/10.1016/j.eneco.2016.03.004
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et al., 2004; Paltsev et al., 2004). For example, in the case of the electric power sector, many prevailing CGE databases (e.g. Narayanan et al., 2012) only include a single aggregate industry[1]; however, increasingly, policies are directed at specific generating technologies (e.g. solar investment tax credits, nuclear phase-out). Further, economic shocks may impact diverse generating technologies in different ways (e.g. a drop in the price of natural gas). Thus, several leading research groups independently disaggregate the electricity sector into electricity sub-sectors which include several generating technologies (Brenkert et al., 2004; Paltsev et al., 2005; Wing, 2008; Burniaux and Château, 2008).

Greater sector-level detail allows IAMs to explore new (and reoccurring) research vistas such as energy policy (Bhattacharyya, 1996), agriculture/biofuel linkages (Kretschmer et al., 2009), and climate policy (Sugandha et al. 2009; Ciscar and Dowling, 2014; Rausch and Mowers, 2014). Introducing the detailed technologies involves two basic tasks: i) disaggregating an aggregate sector in a CGE database into sub-sectors or technologies (e.g. electric power into specific generating technologies) and ii) creating mathematical equations to represent supply and demand in the new sectors. Modelers typically devote the most attention and the greatest amount of documentation to the latter – that is, characterizing the supply and demand behavior in the detailed sub-sectors. Unfortunately, much less attention is placed on the constructing the disaggregated baseline database which defines key economic relationships in the economy and which, as this study demonstrates, can play a key role in determining model outcomes.

The disaggregation process consists of two basic steps: i) collecting technologically-rich, sector-detailed (often termed "bottom-up") data which, when price and quantity data are combined, imply some value flows in the new sub-sectors and ii) a method to allocate these estimated value flows across sub-sectors while meeting CGE accounting ("top-down") constraints. Unfortunately, the disaggregation process used in constructing the newly disaggregated database is often weakly or even wholly undocumented. When the disaggregation process is published, the focus is on the bottom-up data and less so on the construction method. Lenzen (2011) argues that models based on the disaggregation of sectors into individual activities generally perform better than modeling the aggregate sector, even when the information used to disaggregate is fragmentary. But how should this fragmentary information be combined and reconciled with the key economic relationships implied by the original top-down data?

This article shows that the choice of database reconciliation methodology has a significant impact on modeling results. Four commonly used disaggregation methods are compared: i) the pro rata method used by Marriott (2007), Lindner et al. (2014), and Arora and Cai (2014), ii) minimum sum of column cross-entropy (MSCCE) (Golan et al., 1994; Robinson et al., 2001), iii) RAS (e.g. Lahr and de Mesnard, 2004), and iv) share preserving cross-entropy method which does not impose a column constraint (SPCE) (Peters and Hertel, 2016). The experiments use identical bottom-up data to create the balanced matrices and are then taken as input to a simple partial equilibrium (PE) model which allows us to analytically trace how economic relationships, which arise from the different disaggregation methods, impact modeling results.

The modeling analysis focuses on three contemporary economic shocks. Simulation results using the four different balanced databases are compared to simulation results using the unbalanced data to determine how well they replicate the bottom-up results. The first is a technology-specific capital subsidy (e.g. an investment tax credit). This is useful since it highlights the value of preserving the cost structure in the sub-sectors. In this specific experiment, deviations from the bottom-up data in terms of electricity production range from −2% to 36% in magnitude depending on matrix balancing method, indicating significant economic deviation between methods. The second example involves a shock to the price of natural gas (e.g. a result of the shale gas boom in the United States). Finally, a sector-wide capital tax (e.g. removal of a sector-wide tax credit) is considered. This experiment illustrates the importance of preserving "row shares" in the reconciled database (i.e. the relative capital intensity of different technologies in the power sector). This experiment shows that not only magnitude, but also direction of simulation results can differ based on matrix balancing method. While the deviation in balancing method is also dependent on the original deviation between the bottom-up and top-down data, the conclusions drawn here, using real data, indicate that economic results can be highly dependent on the balancing methods used to construct a CGE database and flow directly from the mathematical features of the algorithms.

In current practice the database construction methods used in IAMs are, at best, not adequately documented. This point will only increase in importance with the increasing demand for more highly resolved analysis of critical sectors in IAMs. The results shown in this article advocate for greater introspection at the database–modeling nexus. More broadly, the authors hope it will redirect attention back to the validation of new and innovative CGE and IAM extensions. Finally, the results provide evidence that the appropriate selection of matrix balancing methods can reduce the overall deviation between bottom-up and top-down modeling.

## 2. Database construction

This article focuses on the matrix balancing methods used to reconcile bottom-up data with the aggregate databases required by top-down IAM and CGE models. Schneider and Zenios (1990) provide the following description of the matrix balancing problem: "Given a rectangular matrix **A**, determine a matrix **X** that is close to **A** and satisfies a given set of linear restrictions on its entries." Matrix balancing for disaggregation of a sector in I-O, SAM, and CGE databases consists of the matrix **A**, with elements $a_{it}$, where $i$ is the input and $t$ is the new sub-sector, constructed from the values implied by the bottom-up data for the disaggregate sectors. The linear restrictions, here, are the top-down economic accounting conditions (e.g. supply equals demand) and any other restrictions (e.g. non-negativity) required for modeling. Matrix balancing methods generally differ in how they define the "closeness" of **X** to **A** (e.g. an objective function) and the set of required constraints.

### 2.1. Bottom-up data and the A matrix

The example presented in this paper is a disaggregation of the electricity sector for the 129 regions in the Global Trade Analysis Project (GTAP) version 8 database (Narayanan et al., 2012). Here, the original power sector is disaggregated into seven new electricity sectors: nuclear, coal, gas, oil, hydroelectric, wind, and solar power. The data used for the disaggregation for this paper are:

i) $q_t$ — electricity production (in GWh) by technology, $t$ (IEA, 2010a, 2010b),
ii) $u_i^*$ — total value of inputs, $i$, (in US dollars) to the aggregate GTAP electricity sector, and
iii) $l_{it}$ — levelized (i.e. annualized cost in US dollars per GWh) capital, operating and maintenance (O&M), fuel, and effective tax costs of electricity for generating technologies (IEA/NEA, 2010).

The data and formulations presented here are reduced to a single region; each regional database can be estimated independently. The elements of matrix **A**, $a_{it}$, are thus the product of the levelized input

[1] The motivating example in this article is a disaggregation from an aggregate electricity sector into several generating technologies. However, the discussion of the database-modeling nexus is general to disaggregations of other sectors and extendable to estimating entire matrices.

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