Integrating Energy and Economy models based on the Dynamic Input-Output framework

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Abstract

Power sector is recognized as pivotal in meeting the long-term national environmental targets. For this reason, it is fundamental to develop methods and models able to comprehensively assess the economy-wide implications due to the implementation of new energy technologies or energy policies.

The scope of bottom-up energy models is usually limited to the national power sector, by determining its power output on an hourly basis with high technology disaggregation, or by planning optimal future capacity expansions. However, these models are unable to capture the linkages between the power sector and other sectors of the economy. On the other hand, top-down macroeconomic models provide a comprehensive picture of the economy, but they suffer from high space and time aggregation, being unable to represent the behavior of power technologies with high temporal detail. Several attempts to link bottom-up and top-down models can be found in the literature: despite this, a fully dynamic, integrated energy-economy model is still lacking.

In this paper, the Duchin's Rectangular Choice of Technology model (RCOT) is reformulated based on a Dynamic input-output framework: technical coefficients and final demand of electricity (per hour) and of other products (per year) are exogenously provided to the model, which endogenously returns the optimal power production broken down by energy technology and by economic sector on an hourly basis, in order to meet a set of given technical and economic constraints. The model is applied to Italy in 2011 as case study, based on data retrieved from Exiobase v.3, International Energy Agency and by the Italian electricity distribution authority.

Results of the case study reveal that the proposed approach may be suited for investigating several research issues by comprehensively considering the linkages among all the national productive sectors (e.g. technologies integration, economic policies, competition for natural resources, etc.).

Keywords: Dynamic Input-Output models, Rectangular Choice of Technology, Energy modelling, Optimization models, Power sector.

1. Introduction

According to the latest authoritative projections of International Energy Agency (IEA), the national power sector will play an increasingly central role in modern economies (IEA and AIE, 2018), and the paramount relevance of consistent and reliable long-term strategic energy planning is thus widely recognized by policymakers. Nowadays, energy is closely linked to a confluence of significant problems and chances to progress in several areas and sectors (Pfenninger et al., 2014). Indeed, energy modelling has not been confined in power sectors boundaries anymore, but analysts and policymakers are dealing with interrelated issues from multiple fields: resilience to crisis and security, instability of electricity transmission grid, economic growth, smart cities, and environmental concerns like climate change and other sustainability issues.

Strong research efforts are devoted to the development of large-scale energy system models, that are useful to provide a mathematical representation of the national energy system behavior once the demand of energy and the available technologies are exogenously characterized. Such models are useful to assess future energy scenarios and the economic and environmental implications due to prospected policy interventions and constraints (Ringkjøb et al., 2018). Concerning current challenges in energy modelling, the following major themes are identified by the literature: first, to enhance the time and space resolution of the model, with the purpose to reproduce short-lived events and trends, and to address geographical specific problems; secondly, to improve the representation of the energy sector complexity, being able to describe large penetration of renewable energy technologies and to properly take into account linkages and interactions between the power sector and other industries in the economy; third, a greater emphasis on capturing the behavioral dimension is suggested (Pfenninger et al., 2014). Moreover, a transition towards models fully based on open source codes and open data is also advocated by the literature (Pfenninger et al., 2018; Weibezahn and Kendziorski, 2019). Latest developments of the Industrial Ecology discipline provides theoretical and methodological background that may effectively support researchers in addressing these issues, offering a new perspective to address modelling challenges and systems complexity (Pauliuk et al., 2017).

With reference to Figure 1 (left side), the purpose of energy systems models consists in providing a representation of the behavior of the energy system with high temporal detail (i.e. energy dispatch strategy, production technology mix, costs and environmental emissions, etc.) once the overall energy demand and the technical features of the analyzed technologies are exogenously defined. Several types of energy models are currently available, differentiated based on the analyzed scales, coverage scopes, energy carriers, mathematical approach, etc.: recent comprehensive reviews of energy systems models can be found in the literature (Després et al., 2015). In this perspective, the energy system is modelled as isolated from the rest of the economy, and the model is thus unable to tackle the linkages and interdependencies between the energy sector and the other sectors comprehensively.

On the other hand, traditional *top-down* macroeconomic models – and Input-Output models among others – focuses on the mathematical description of production and consumption activities of all the sectors of the economy in a time frame of one year. Several advances have been done so far with the purpose of improving the technological description of different sectors of the economy by means of Input-Output-based techniques: two distinguished examples are the *Rectangular Choice of Technology* (RCOT) model (Duchin and Levine, 2011) and the *Waste Input-Output analysis* (WIO) (Nakamura and Kondo, 2002). However, despite their sectoral comprehensiveness, these models are unable to provide a detailed description of national energy system, reproducing its realistic behavior in response to exogenous shocks, and this is mainly due to the lack of an appropriate time resolution.

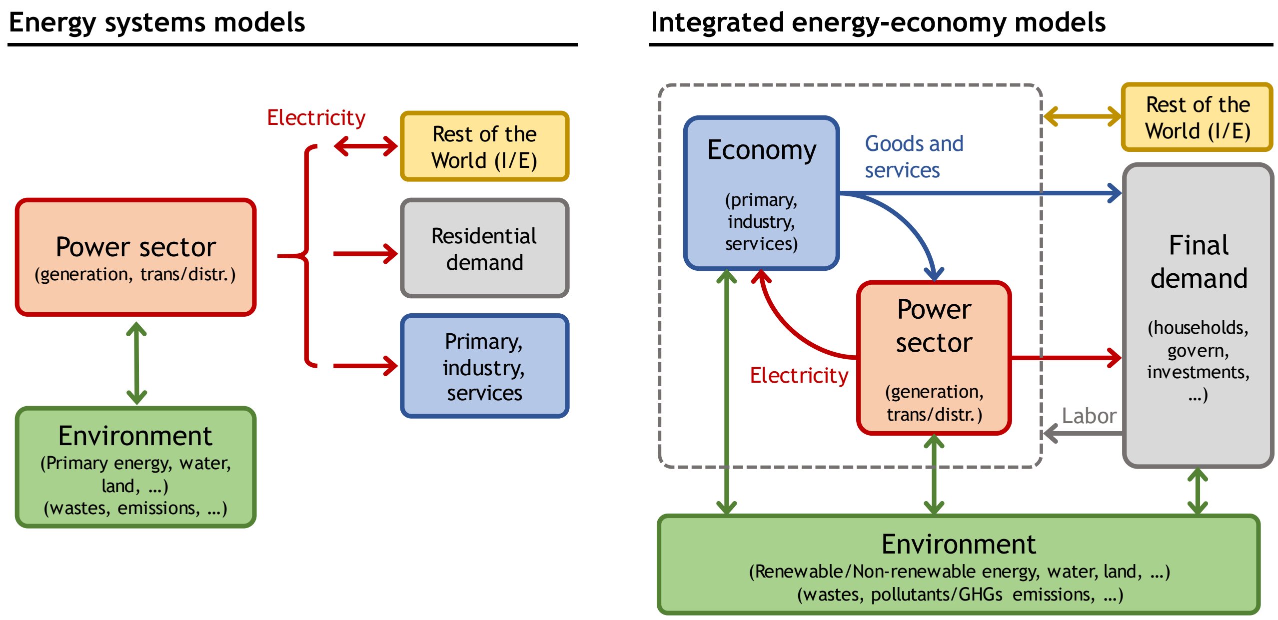

Figure 1. Schematic comparison of traditional *energy systems models* (left side) and *integrated energy-economy models* (right side). (Figure produced by the Author)

For such reasons, much effort has been devoted in recent year towards the integration of bottom-up energy systems models with top-down macroeconomic models (Crespo del Granado et al., 2018): despite the large number of soft- and hard-linked models, recently reviewed and taxonomized (Müller et al., 2018), it seems that a *fully integrated model* able to provide a detailed technological representation of the national energy system with *high temporal resolution* – and without reducing its *economic comprehensiveness* – is still missing.

This paper proposes and tests the *Dynamic Rectangular Choice of Technology model* (D-RCOT), consisting in a reformulation of the basic RCOT model based on a Dynamic Input-Output framework. With reference to Figure 1 (right side), major features of the D-RCOT model are following listed:

- It provides a detailed technological representation of a national power sector operation in one year, providing optimal power production mix among multiple alternative technologies, and increasing time resolution of the analysis to hourly time steps in order to capture power system dynamics usually neglected by top-down models.
- With respect to traditional power system models, it returns the electricity consumption breakdown by economic sectors, enabling to assess the electricity consumption patterns and the industrial electricity demand required to guarantee the operability of the whole economic system.

- It is developed based on the *Python* language and it is based on economic and environmental accountings collected only into open datasets.

2. Methods and models

The *Rectangular Choice of Technology* (RCOT) model (Duchin and Levine, 2011), originally conceived by Duchin and Levine, is a linear programming model that determines the optimal mix of production in a system where multiple technologies are available for producing the same products, under a given set of binding constraints. Considering a system operating in a given time frame (usually a year), and composed by s sectors and p products, with c factors of production, the essential RCOT formulation is provided by system (1). Technical coefficients $\mathbf{A}(s \times p)$, final demand $\mathbf{Y}(s \times 1)$, factors inputs coefficients $\mathbf{F}(c \times p)$ and related prices $\boldsymbol{\pi}_{\mathbf{f}}(1 \times c)$, and factor endowments $\mathbf{f}(s \times 1)$ are provided as exogenous variables, while the model returns the total production $\mathbf{x}(p \times 1)$ that minimize the overall production cost Z, bounded by the availability of factors and the satisfaction of a defined final demand yield.

$$\begin{aligned} &\text{Min} \quad && Z = \boldsymbol{\pi}_{\mathbf{f}} \mathbf{F} \mathbf{x} \\ &\text{s.t.} \quad && (\mathbf{I} - \mathbf{A})\mathbf{x} \geq \mathbf{Y} \\ & && \mathbf{F}\mathbf{x} \leq \mathbf{f} \end{aligned} \tag{1}$$

The RCOT model provides optimal scenarios by potentially considering alternative production technologies in multiple national sectors, hence considering competition for natural resources and sectoral linkages often neglected in other modelling approaches (see section **Errore. L'origine riferimento non è stata trovata.**). Despite its advantages, the RCOT suffers of high spatial and temporal aggregations (input-output data are available for the whole national economy in one given year). While spatial disaggregation can be increased by regionalizing the available data (Andrew et al., 2009), temporal domain is limited to one unique time step (one year). Due to the latter drawback, the RCOT model seems not well-suited for analyzing systems the operation of which is strongly time-dependent: this is the case of electricity, that requires to be simultaneously produced and consumed. In modern national power sectors, not all the technologies can be easily regulated and the operation of non-dispatchable renewables depends on the availability of natural resources: for these reasons, the operation of national power sector should be analyzed by considering a high temporal detail (ideally defining hourly time steps).

Considering the non-concomitance of production and consumption of a specific goods or services that characterizes real processes, Dynamic Input-Output models (DIOM) (Miller and Blair, 2009) systematically address the issues of time dimension in input-output analysis. Given one system composed by s sectors in different subsequent time steps t, even though some products of one sector are properly accounted as inputs of other sectors, part of those could be exploited later in time. The basic and widespread approach to deal with this issue is by defining multiple production balances in the form of equation (2), one for each analyzed time step. Beside technical coefficients $\mathbf{A}(s \times s)$, final demand $\mathbf{y}^t(s \times 1)$ and total production $\mathbf{x}^t(s \times 1)$ are defined for each time steps, and capital coefficients $\mathbf{B}(s \times s)$ characterize the sectoral linkages between time steps.

$$(\mathbf{I} - \mathbf{A})\mathbf{x}^t - \mathbf{B}\left(\mathbf{x}^{t+1} - \mathbf{x}^t\right) = \mathbf{y}^t \tag{2}$$

A variety of national dynamic operational models has been defined so far, investigating economic development strategies, environmental impact of industrial systems and development of the energy sector (Cruz et al., 2009; Pan et al., 2018; Pauliuk et al., 2014); however, based on the knowledge of the Author, every attempt done so far was related to large time steps (usually one year).

2.1. Model definition, parameters and assumptions

Let us consider one generic national economy with a power sector characterized by multiple and alternative technologies (e.g. coal, natural gas, solar photovoltaic, etc.), a fixed amount of final demand of electricity (by hour) and of other goods and services (by year), and a given amount of factor endowments in terms of labor force (by hour and by sector) and primary natural resources (by hour or year and by sector). Once this economy has been fully characterized, the D-RCOT model enables to determine the total production of each national sector, the optimal power technology production mix and the breakdown of electricity consumption by sector (both with time steps resolution of one hour). Moreover, once the optimal solution is found, the model may also return environmental transactions (pollutants/GHG emissions, water use, etc.), value-added categories, and products imports. Notably, a fixed amount of installed power capacities (GW) is exogenously provided to the model: therefore, this version of the D-RCOT is useful to perform operational assessments of the national power system, and not to plan for power system capacity expansions. Table 1 presents a full list of exogenous and endogenous model parameters.

Table 1. Exogenous and endogenous parameters of the D-RCOT model relative to a single time step (t).

Category	Symbol	Dimensions	Description	Units
Indices	t		Time steps: $1,\dots,nt$ (one hour)	
	s		Sectors: $1,\dots,ns$	
	p		Products (non-energy and energy): $1,\dots,np$	
	r		Exogenous transactions types: $1,\dots,nr$	
	cv		Variable generation costs: $1,\dots,nc$	
Exogenous variables	$\mathbf{A}^t$	$ns \times np$	Technical coefficients	Hybrid
	$\mathbf{Y}$	$ns \times 1$	Final demand per year	Hybrid
	$\mathbf{y}_e^t$	$ns \times 1$	Final demand of electricity per hour	Physical
	$\mathbf{F}_{\mathbf{cv}}^t$	$nc \times np$	Costs coefficients for power technologies	Monetary
	$\mathbf{F}_{\mathbf{v}}^t$	$1 \times np$	Labor use coefficients	Physical
	$\mathbf{F}_{\mathbf{r}}^t$	$nr \times np$	Resources use coefficients	Physical
	$\mathbf{fe}_{\mathbf{v}}$	$ns \times 1$	Factor endowments (labor) per year	Physical
	$\mathbf{fe}_{\mathbf{vh}}^t$	$ns \times 1$	Factor endowments (labor) per hour	Physical
	$\mathbf{fe}_{\mathbf{r}}$	$nr \times 1$	Factor endowments (resources) per year	Physical
	$\mathbf{fe}_{\mathbf{rh}}^t$	$nr \times 1$	Factor endowments (resources) per hour	Physical
	$\mathbf{I}^{*,t}$	$ns \times np$	Special identity matrix	-
	$\mathbf{C}$	$np \times 1$	Vector of power installed capacities	Physical
	R	1×1	Ramping coefficient	-
Endogenous variables	Z	1×1	Overall generation cost (objective function)	Monetary
	$\mathbf{x}^t$	$np \times 1$	Vector of output in time step t	Hybrid

The D-RCOT model is defined in hybrid units, defining power sector transactions in energy units (MWh of electricity) and other goods and services in monetary units (M€): this because hourly data related to production and consumption of energy are available from statistics offices only in physical units. Disaggregation of electricity technologies within an Input-Output table and hybridization process can be carried out based on literature guidance (Hawkins et al., 2014; Lindner et al., 2013).

The full D-RCOT model is formalized by embedding matrices and vectors in Table 1 within a dynamic input-output system. Regarding vectors, time-steps t are stacked one after the other for nt times ($\mathbf{x} = [\mathbf{x}^1; \mathbf{x}^t; \mathbf{x}^{nt}]$), while matrices need to be reshaped into larger diagonal matrices by means of the direct sum operation, as shown in equations (3) to (7). Notably, *special* identity matrix $\mathbf{I}^{*,t}(ns \times np)$ has ones in the diagonal elements and zero elsewhere for non-energy industries, while in the line corresponding to the power sector it presents ones in correspondence with the alternative power technologies and zero elsewhere.

$$\mathbf{A}\left(ns \cdot nt \times np \cdot nt\right) = \bigoplus_{t=1,nt} \mathbf{A}^t = \begin{bmatrix} \mathbf{A}^1 & - & - \\ - & \mathbf{A}^t & - \\ - & - & \mathbf{A}^{nt} \end{bmatrix} \tag{3}$$

$$\mathbf{I}^*\left(ns \cdot nt \times np \cdot nt\right) = \bigoplus_{t=1,nt} \mathbf{I}^{*t} = \begin{bmatrix} \mathbf{I}^{*1} & - & - \\ - & \mathbf{I}^{*t} & - \\ - & - & \mathbf{I}^{*nt} \end{bmatrix} \tag{4}$$

$$\hat{\mathbf{F}}_{\mathbf{v}}\left(np \cdot nt \times np \cdot nt\right) = \bigoplus_{t=1,nt} \hat{\mathbf{F}}_{\mathbf{v}}^t = \begin{bmatrix} \hat{\mathbf{F}}_{\mathbf{v}}^1 & - & - \\ - & \hat{\mathbf{F}}_{\mathbf{v}}^t & - \\ - & - & \hat{\mathbf{F}}_{\mathbf{v}}^{nt} \end{bmatrix} \tag{5}$$

$$\mathbf{F}_{\mathbf{r}}\left(nr \cdot nt \times np \cdot nt\right) = \bigoplus_{t=1,nt} \mathbf{F}_{\mathbf{r}}^t = \begin{bmatrix} \mathbf{F}_{\mathbf{r}}^1 & - & - \\ - & \mathbf{F}_{\mathbf{r}}^t & - \\ - & - & \mathbf{F}_{\mathbf{r}}^{nt} \end{bmatrix} \tag{6}$$

$$\mathbf{F}_{\mathbf{c}}\left(nc \cdot nt \times np \cdot nt\right) = \bigoplus_{t=1,nt} \mathbf{F}_{\mathbf{c}}^t = \begin{bmatrix} \mathbf{F}_{\mathbf{c}}^1 & - & - \\ - & \mathbf{F}_{\mathbf{c}}^t & - \\ - & - & \mathbf{F}_{\mathbf{c}}^{nt} \end{bmatrix} \tag{7}$$

The model is formalized as a linear optimization problem, the *primal* formulation of which is provided by (8).

$$\begin{array}{lll} \text{Min} & Z = \mathbf{i}_c \mathbf{F}_{\mathbf{c}} \mathbf{x} & \\ & & \\ \text{s.t.} & \mathbf{i}_{t,s}\left[\left(\mathbf{I}^* - \mathbf{A}\right)\mathbf{x}\right] \geq \mathbf{Y} & (a.1) \\ & \left(\mathbf{I}^* - \mathbf{A}\right)\mathbf{x} \geq \mathbf{y}_e & (a.2) \\ & \mathbf{i}_{t,s}\mathbf{I}^*\left(\hat{\mathbf{F}}_{\mathbf{v}}\mathbf{x}\right) \leq \mathbf{fe}_{\mathbf{v}} & (b.1) \\ & \mathbf{I}^*\left(\hat{\mathbf{F}}_{\mathbf{v}}\mathbf{x}\right) \leq \mathbf{fe}_{\mathbf{vh}} & (b.2) \\ & \mathbf{i}_{t,r}\mathbf{I}^*\left(\mathbf{F}_{\mathbf{r}}\mathbf{x}\right) \leq \mathbf{fe}_{\mathbf{r}} & (c.1) \\ & \mathbf{I}^*\left(\mathbf{F}_{\mathbf{r}}\mathbf{x}\right) \leq \mathbf{fe}_{\mathbf{rh}} & (c.2) \\ & \mathbf{x}^t \leq \mathbf{C} \quad \forall t & (d) \\ & \left|\mathbf{x}^t - \mathbf{x}^{t+1}\right| \leq R\,\mathbf{x}^t & (e) \\ & \mathbf{x} \geq 0 & (f) \end{array} \tag{8}$$

Where $\mathbf{i}_c$ is the summation vector (9) and $\mathbf{i}_{t,j}$ is the summation matrix (10) for $j = s, r$ over time.

$$\mathbf{i}_c\left(1 \times nc \cdot nt\right) = \left[1 \quad \dots \quad 1\right] \tag{9}$$

$$\mathbf{i}_{t,j}\left(nj \times nj \cdot nt\right) = \begin{bmatrix} 1 & 0 & \cdots & 0 & & 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 & & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 & & 0 & 0 & \dots & 1 \end{bmatrix} \tag{10}$$

Problem (8) consists in the minimization of the overall yearly variable electricity generation cost (Z), assumed as the sum different components (nc in matrix $\mathbf{F}^t_{\mathbf{cv}}$): *variable operation and maintenance costs* (covering plant activity, labor and capital), *fuel costs* and *cost of imported electricity*. With respect to the basic RCOT model (1), factors $\mathbf{F}^t_{\mathbf{cv}}$ are already expressed in monetary units and do not require to be multiplied by the corresponding prices. The optimization is subjected to the following set of constraints:

a. The overall yearly production of goods and services (including electricity) must be equal to or greater than the exogenously defined final demand yield (a.1). The same holds for the hourly final demand of electricity, including all residential electricity uses and exports (a.2).
b. The overall requirements of labor force (in hours equivalent) must be equal to or lower than the labor endowments per year (b.1) and per hour (b.2) in each sector. The latter endowment is hardly retrievable in the literature, but it is useful to *drive* the industrial production along the day: for such reason, it is subjected to a calibration process (see subsection 2.2).
c. The overall requirements of natural resources (namely primary renewable/non-renewable energy, water, and land, measured in different units) must be equal to or lower than the resources endowments per year (c.1) and per hour (c.2) in each sector. The latter endowment is particularly relevant in case resources availability is a function of time (such as solar radiation or wind potential). Moreover, these two constraints allow to capture the *competition* for natural resources between energy and non-energy industries, an aspect usually discarded in conventional energy models.
d. Total production of electricity per hour (that is, the operating power capacity) cannot exceed the available installed capacity for each technology. This holds also for imports, that must be lower than the available net transfer capacity between the analyzed country and the rest of the world.
e. The change in output yields of industries and power technologies from one hour to the next one is limited by a *ramping* constraint, which avoid the economic system to allocate all the industrial production in few hours along the day.
f. The hourly production of goods and services (including electricity) must be non-negative.

The above defined optimization problem is characterized by the following main assumptions.

Objective function definition. Essentially, the model works by minimizing the overall power generation operative cost (Z, here assumed as the objective function): it is possible to demonstrate that this is coincident with the maximization of the national welfare under centralized management of power sector by an impartial and all-knowing regulator (Pérez-Arriaga, 2014). This objective function is different compared with the basic RCOT model, that instead minimizes the overall economic factor inputs to all the national sectors. This choice is justified by the fact that the D-RCOT model focuses on the power sector only: therefore, the real govern mechanisms adopted for the definition of power dispatch technology priority is selected.

Constant technical coefficients. All the sectors of the economy work with technical coefficients $\mathbf{A}^t$, energy technologies operative costs $\mathbf{F}^t_{\mathbf{cv}}$ and labor use coefficients $\mathbf{F}^t_{\mathbf{v}}$ assumed as constant in every time step t, and thus representing average inputs and outputs per unit of production. The operation of each sector may be characterized in reality by different activity levels in different hours of the day, the accurate estimation of which would be very complex and subjected to great uncertainty.

Absence of storages. Electricity must be simultaneously produced and consumed in each hour: even if this model version does not include any storage mechanism, the latter could be implemented by defining a suited set of technical constraints (including storage capacities, related losses, costs, etc.), and making the model free to determine the optimal storage strategy by endogenously returning non-zero elements in the extra-diagonal blocks of technical coefficients matrix $\mathbf{A}$ (3). The assumption of contemporary production and consumption also applies to non-energy-related industries: this is a strong assumption (it implies a contemporary operation of all national industries, that are unable to stock products for future uses), but the characterization of storage capabilities for them – although possible in principle – sounds much more complex and subject to high uncertainty.

Constant final demand. In line with the traditional RCOT formulation, both energy and non-energy related industries are characterized by a constant an inelastic final demand: demand elasticities could be introduced in the model to assess the influence of price on demand of goods and services (i.e. the elasticity of demand with respect to price), leading to a formulation close to a partial/general equilibrium model.

Definition of imports and exports. Exports of goods and services (including electricity) are exogenously defined and part of the final demand, in line with conventional single-region Input-Output models. Imports of non-energy products are endogenously defined based on fixed imports coefficients (not listed in Table 1); on the other hand, imports of electricity are fully endogenized into the model: imported electricity competes with endogenous generation and the opportunity for imports of electricity is considered as an additional technological option, becoming part of the optimization problem for meeting final demand.

Spatial aggregation. The model considers the whole national economy as a unique region, without distinguishing the changes in spatial resources endowments, the interregional differences in final demand and the interregional bottlenecks in products distribution (including power transmission constraints). This assumption reflects the intrinsic nature of single-region input-output models, and it could be relaxed by considering multi-regional macroeconomic and environmental data.

2.2. Model development, calibration and application

The D-RCOT model is developed based on the *Python* language; the model and all the input data used throughout the study are shared as open-source material at the GitHub repository "*SESAM Polimi – D-RCOT model*" [link to be provided upon acceptance of the paper]. The steps required for the application of the model are descripted below.

Phase 1. Data collection and preparation. Exogenous and endogenous variable need to be collected and arranged according to the shape reported in Table 1 for one baseline year. The only freely available input-output database able to provide disaggregated power technologies is the *Exiobase* database (http://www.exiobase.eu/) (Merciai and Schmidt, 2018): its latest version (v.3) collects the monetary multi-regional input output tables covering years 1995-2011 for 49 world economies (of which 5 Rest of the World regions), 163 industries per economy (of which 12 disaggregated energy technologies) and several environmental extensions, and it is thus suggested as the preferred data source for macroeconomic and environmental national accountings. In case the country to be analysed is not enclosed within *Exiobase*, other source can be use and power technologies properly disaggregated. The hybridization of the national matrix can be performed relying on electric energy balances provided by *International Energy Agency* (IEA, https://www.iea.org/statistics/) and by local electricity distribution institution, if available. Factor endowments related to labor force can be retrieved from the statistics offices of the country under investigation, while availability of natural resources and other related power system data are collected in two major open datasets, namely https://www.renewables.ninja/ and https://open-power-system-data.org/.

Phase 2. Calibration procedure. The hourly labor endowments per sector $\mathbf{fe}^t_{\mathbf{vh}}$ represents the amount of hours-equivalent available for each sector in each time step: this parameter can hardly be determined based on the available data source, but it strongly affects the final output of the model. Indeed, exceeding the available labor force ultimately results in allocating production activities in an unrealistic manner (for example: all the output of industries may result concentrated in few hours of the day), while a proper definition of the available workforce is necessary to distinguish between night work, day work and relevant breaks in order to shape working practices. For such reason, hourly labor endowments are subjected to a calibration process: the first model run is performed according to (8), but exogenously imposing the total electricity production $\mathbf{x}^t_{\mathbf{e}}$ in each time step (available information for the baseline year) and hence deriving the labor endowments per sector $\mathbf{fe}^t_{\mathbf{vh}}$ as endogenous variable.

Phase 3. Model application. Once the model is calibrated, its application can be performed exactly as reported by system (8), deriving the national production $\mathbf{x}^t$ in each time step for the baseline economy. The model can be adopted to test the economic and environmental effects caused by exogenously induced shocks of different nature: policy interventions (e.g. emissions cap, fiscal policies), economic growth, change of industrial or energy technologies, etc.

3. Case study: operational assessment of the Italian power system

The D-RCOT model is here applied for the analysis of Italy in the baseline year 2011. With reference to sub-section 2.2, the collected macroeconomic and environmental accountings are rearranged according to the modelling needs and the Italian specificities. Because of the demonstrative purpose of this application, and in order to reduce the computational burden of the model, macroeconomic and environmental data have been highly aggregated, in compliance with the sectoral aggregation of energy data provided by IEA. National sectors are grouped into: *Agriculture*, *Industry*, *Transport*, *Services*, *Power*, *Residential* (final demand, including exports). In the same vein, time step for the analysis is 1 hour and the time horizon 1 year: in this application, the year is assumed as composed by *one unique average day type* (24 hours) replicated for all the days of the year.

Table 2. Power technology data assumed for Italy in reference year 2011.

Power technology	Installed capacity [$\mathbf{C}$ - MW]	Operative cost [$\mathbf{F_c}$ - €/MWh]
Coal	9454	21.7
Oil and Derivatives	7281	21.7
Natural Gas	53274	31.6
Biomass and Waste	3886	33.1
Hydro	22109	4.5
Wind	9639	0
Solar PV	12773	0
Geothermal	772	7.2
Imports	6740	90

Coefficients tables and factor endowments are retrieved mostly from the Exiobase v.3 database and from IEA data. Hourly and yearly factor endowments are extrapolated from the same datasets, including labor force and energy available from solar radiation, wind and water sources. The list with features of the available power technology options is provided by Table 2: installed capacity and the operative costs to the Italian power technologies are derived from the electricity distribution institution (*Terna*, http://www.terna.it/) and from grey literature (OECD Nuclear Energy Agency, 2010; Ricerca sul Sistema Energetico – RSE SpA, 2015) (notice that technologies not present in the Italian power mix are excluded, like nuclear power). The electricity final demand is estimate from the Terna database as well.

3.1. Model results and verification

Once the model is calibrated, its application returns the hourly total production $\mathbf{x}^t$ of goods and services (including electricity): even if a multiplicity of economic and environmental results can be derived starting from this parameter (emissions, resource use, value added generation, etc.), only the ones required to verify the model reliability are reported.

Figure 2 shows overall hourly electricity generation for the average day in 2011: results of the model (blue area) are compared with real power generation data, and the latter results underestimated generally by 5% (excluding peak of 15% between 7 and 9 am). The behavior of the model looks thus comparable to real data both in shape and quantitative terms (i.e. the model is verified). Results are slightly different compared to real data, because the model is a simplified view of the complex power sector regulation mechanism (see the hypotheses list in sub-section 2.1), and the model is then uncapable to perfectly reproduce all the complex phenomena occurring in the real power system operation and management.

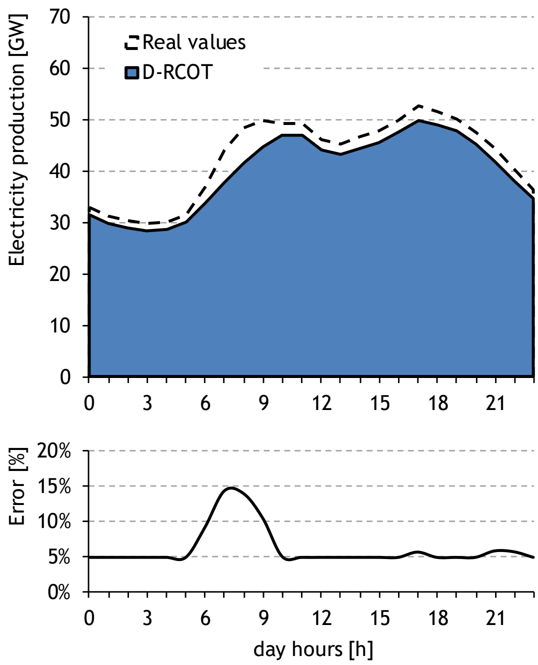

Figure 2. Hourly Electricity production for the average day in Italy in 2011: comparison between the D-RCOT results and statistics data of the Italian electricity distribution institution (Terna). (Graphs elaborated by the Author)

Figure 3 reports the total electricity production classified by power generation technology per hour (for the average day) and per year (subplots A.1 and A.2), where thermal generation technologies are grouped within a dashed line. As expected, the power mix results distributed among base-, mid- and peak-load technologies, returning an overall yearly electricity generation of about 350 TWh/y. Power production mix is dominated by thermal generation technologies (77%), followed by large shares of imports (10%) and hydro (9%), while the rest is covered by other renewables (5%). Differences between model results and power system data are reported per hour and per year (subplots B.1 and B.2): compared to real data, contribution of thermal generation technologies is generally overestimated (about of 7%), while contribution of all the other technologies is generally underestimated. Regarding hydro technology, this underestimation may be due to the assumption of an average endowment of water resource (subjected to great seasonal variability), and to the imperfect representation of the management of water basins. In the same vein, availabilities of wind and solar resources are assumed as an average of time- and space-dependent wind and solar potentials. All these issues may be resolved or at least refined by increasing the analyzed day types (e.g. by considering one day type per month) and regionalizing the input-output economic and environmental data sources. Finally, it should be noted that the electricity imports are not governed by a merely economic mechanism (as assumed by the objective function of the D-RCOT model), but it is also the result of bilateral agreements among countries; moreover, imports may come from different countries and the price of electricity imported is generally subjected to great variability.

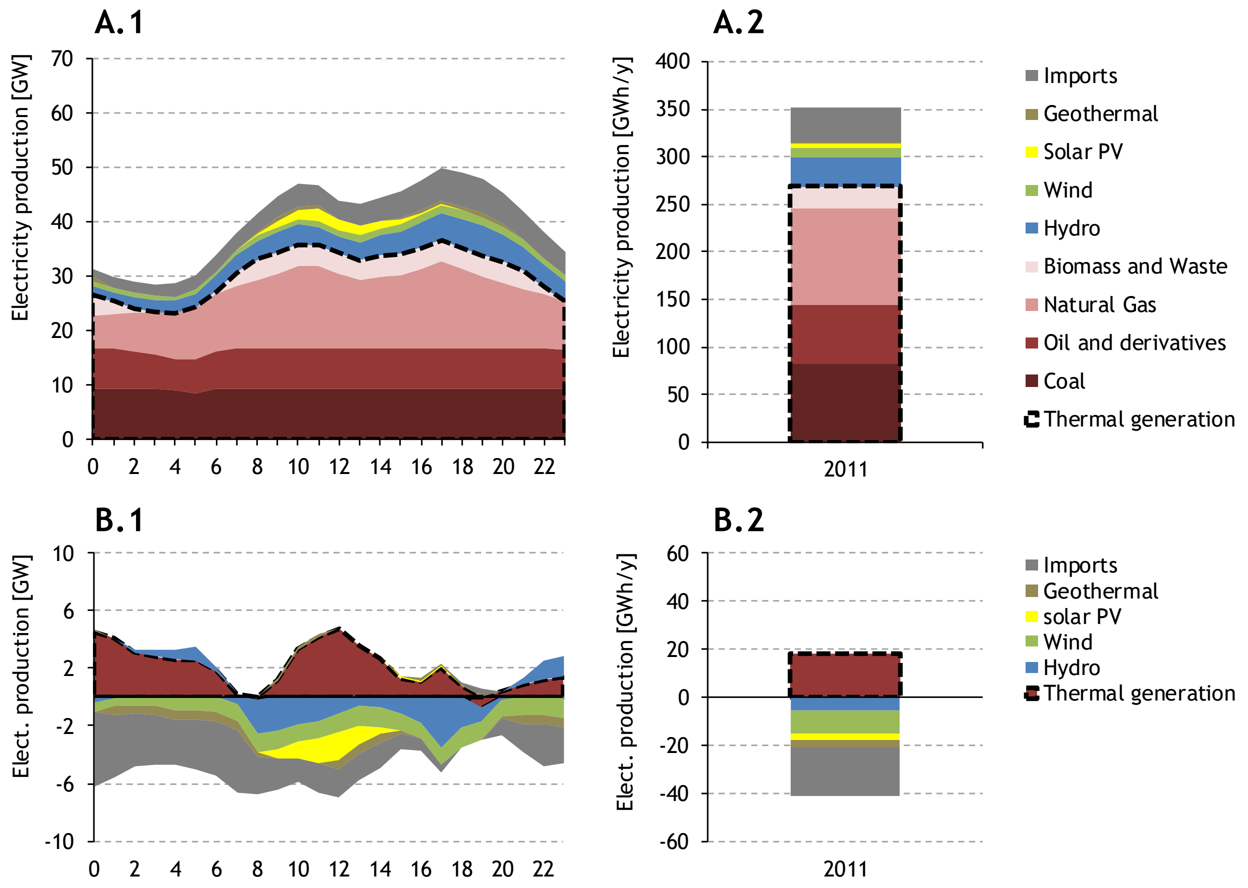

Figure 3. Electricity consumption by source per hour (**A.1**) and per year (**A.2**), and differences with statistics data (from *Terna*) per hour (**B.1**) and per year (**B.2**). All data are related for the average day type of year 2011, assumed as the baseline. Thermal generation technologies are enclosed within the dashed line. (Graphs elaborated by the Author)

Power production classified by technology (Figure 3) is the main result of traditional energy models. The major novelty introduced by the D-RCOT model is the opportunity to breakdown electricity consumptions by distinguishing the end-use sectors (residential and intermediate electricity end-use sectors), as reported in Figure 4. Indeed, while electricity to residential sector and exports form part of the final demand of the power sector (exogenous parameter), the electricity demand of all the other sectors is endogenously determined by the model. With reference to Figure 3, yearly results are cross-checked with IEA data and results in an overall yearly error around 1% for each sector, hence revealing an overall very good fit of model results with real data. Electricity is mostly invoked by industrial sector (36%), followed by services (25%) and by the residential and exports sector (21%). Significant amount of electricity is consumed by the electricity sector (13%), in part due to the allocation on this sector of all the national electricity losses.

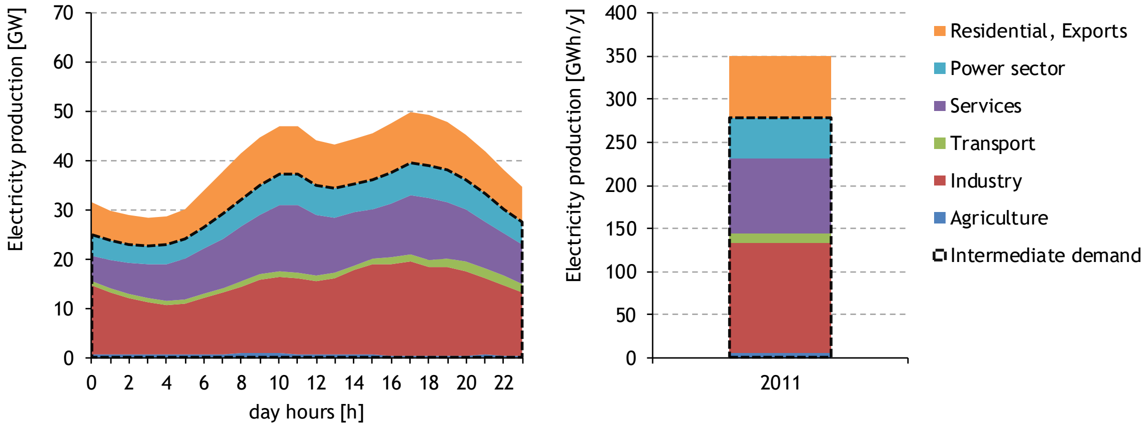

Figure 4. Electricity consumption by sector for the typical day (left side) and for the whole year (right side). Intermediate consumption sectors are enclosed within the dotted line. (Graphs elaborated by the Author)

Finally, Figure 5 reports the labor force used by each sector of the economy in each hour and in the whole year (in Millions of hours equivalent): this parameter is a result of the calibration process (sub-section 2.2), which enables to distinguish shares of workers active in each national sector and in each hour of the average day. As expected, the peaks of hours demand are allocated along the day in a reasonable way, highlighting the periods of the day characterized by highest intensities of working activities. Most of the hourly demand is due to services sector (62%), followed by industry (29%), transport activities (5%) and agriculture (4%). Notice that the labor intensity of day hours and night hours is very different (but never equal to zero).

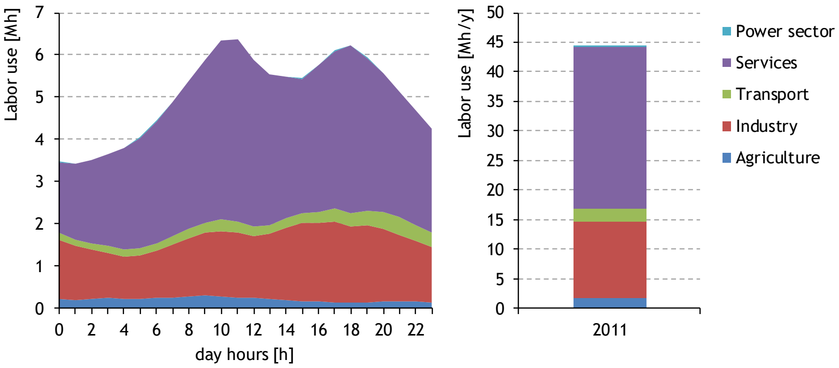

Figure 5. Labor use by sector for the average day (left side) and for the whole year (right side). (Graph elaborated by the Author)

3.2. Sensitivity analysis on key parameters

To assess the influence of uncertain exogenous parameters on the D-RCOT model results, a sensitivity analysis is performed, and major outcomes summarized in Figure 6 in terms of relative change in cost of electricity generation (Z, the objective variable) and overall change in electricity production per year (x_e, GWh/y). Due to their high variability over time, sensitivity is carried out by varying the following parameters one at time:

- Unit variable cost for electricity imports ($F_{C,imp}$, €/MWh).
- Net transfer capacity of imported electricity (C_{imp}, GW).
- Hourly final demand of electricity (y_{ee}, MWh).
- Hourly availability of solar radiation, wind and water potentials ($f_{er,sun}$, $f_{er,wind}$, $f_{er,water}$, TJ/h).
- Hourly labor force availability for power sector and for all the other industries ($f_{ev,e}$, $f_{ev,s-e}$, Mh/h).

Due to the higher variable costs associated to electricity imports compared to other available technologies, any increase in electricity imports cost respectively induces the power sector in displacing the imported electricity with domestic production, and vice-versa. For the same reason, an increase in net transfer capacity of imported electricity do not cause significant changes in the domestic power system operation, while a decrease in the same parameter below -15% forces the domestic energy system in producing electricity through a mix that ultimately results in higher costs (about +5%).

To face an increase in the domestic final demand of electricity, the national power system increases the overall amount of electricity production and the related overall generation costs. Contrarily, decreasing the amount of electricity final demand enables to fully exploit the potential of the available domestic power technologies, resulting in a non-monotonic change in overall electricity production and in a decrease in power generation costs.

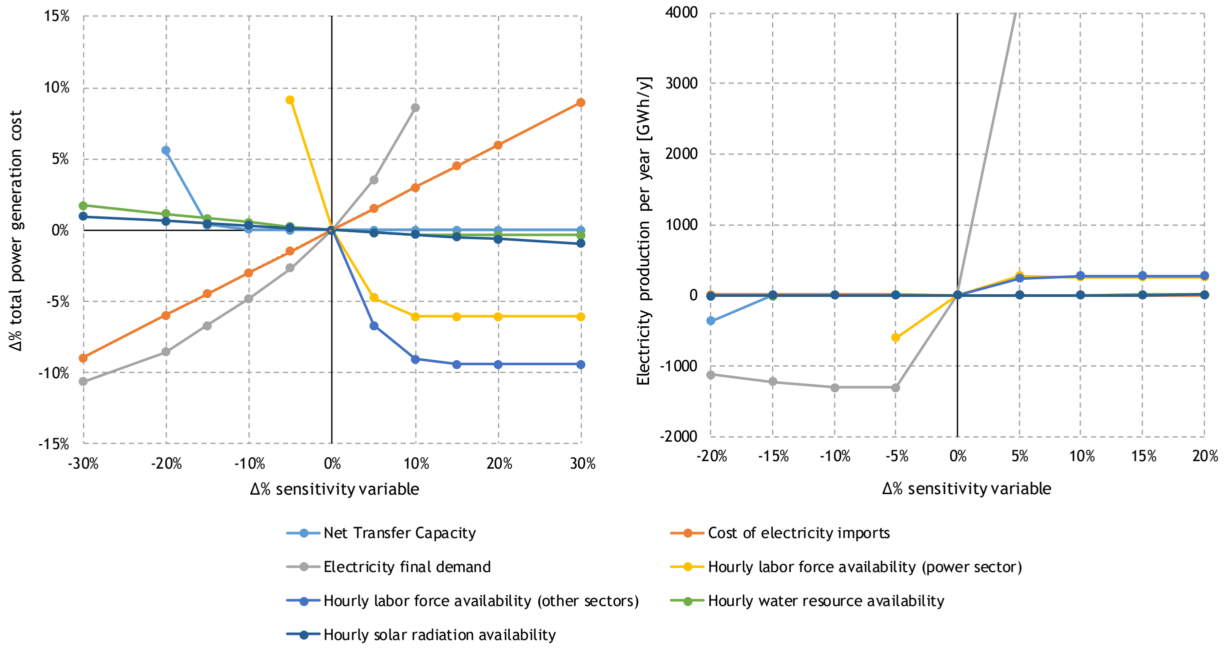

Figure 6. Results of the sensitivity analysis on exogenous parameters. (Graph elaborated by the Author)

Increase and decrease in hourly natural resources availability (solar radiation, water, wind potentials) do not cause relevant implications in terms of generation costs and electricity production. On the other hand, relaxing constraints on labor force availability, the power system seeks to reduce electricity imports and to aim for a larger endogenous production since installed capacity of power technologies is not completely exploited. A larger industrial electricity demand to sustain system operation requires a larger electricity generation in turn, causing a non-linear relationship between labor force availability and overall electricity production. Notably, relaxing labor availability constraint after +15% do not cause any change in overall electricity production and power generation cost.

4. Conclusions and future developments

This research proposes the Dynamic Rectangular Choice of Technology (D-RCOT) model, with the purpose of improve the time resolution of the basic RCOT model based on a Dynamic Input-Output framework, providing a consistent and reliable tool useful to describe the operation of national power systems and in capturing linkages between power sector and other sectors of the economy. The model is formalized as a linear optimization problem and then applied to the Italian economy in 2011 with the intention to present the model capabilities and to verify the rationale that drives the optimization process.

Results of the Italian case study are reasonable and consistent with the principles of power sector regulation, revealing the usefulness, strengths and weaknesses of the proposed modelling approach, and identifying several directions for future improvements. From a theoretical standpoint, the D-RCOT model extends the boundaries of the analysis encompassing the whole national economy and considering the analyzed year as composed by hourly time steps, leading to the following advantages:

- With respect to traditional energy models, the D-RCOT can capture the dynamic behavior of the power sector and its linkages with other sectors; moreover, it allows to breakdown intermediate electricity consumptions by sector. These features enable to investigate the effects that nation-wide economic or environmental policies may cause to the operation of the national power system, properly considering its operative and regulation mechanisms.
- In this perspective, the integrated modelling of power sectors and other sectors of the economy enables to tackle the competition for natural resources among industries and technological alternatives.
- The dynamic formulation of the model enables to endogenously determine the intertemporal linkages among sectors: this may become particularly relevant for modelling future energy technologies, such as electric cars, energy storage options, or distributed energy generation.

On the other hand, the following major drawbacks can be identified, revealing aspects that deserve future improvements:

- Significant amount of data are required to properly define and to calibrate the model: in addition to the national economic and environmental accountings, additional data must be estimated (e.g. coefficients of specific power technologies, factor endowments) and some of them are hard to find at the hourly scale (e.g. hourly final demand of electricity for residential sector, hourly resources endowments).

- Each sector of the economy is characterized by constant technical coefficients, representing its average behavior throughout every hour of the year. This is a strong assumption, since the real hourly production of non-energy-related products may vary every hour.
- The model needs to be calibrated to properly defining sectoral hourly production yields: the proposed approach calibrates the labor endowments per sector and per hour, but the calibration process could be ideally extended to other exogenous variables to better fit the real results.
- The proposed version of the model enables to determine the hourly production yields by each sector in one given year (operational analysis), but it is uncapable to determine the optimal expansion of the power system capacity in future years (planning analysis), which requires to improve the model formulation and its objective function by taking into account investment costs of technologies and growth in final demand of industrial products in future years.

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