A OVERVIEW OF ENERGY MODELLING TOOLS RELEVANT FOR ENERGY EFFICIENCY PROJECTIONS

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In order to define an appropriate energy regulatory policy at the state level, encourage energy efficiency, control the level of final energy consumption and select production technologies, it is important to choose an adequate approach to energy modeling. Hence, this paper will focus on the overview of the most important energy modelling tools. Energy models can be developed for efficient forecasting, planning, design, operation and optimization of energy systems. The heterogeneity of applied energy models and the energy scenarios defined in them require specific, technically advanced skills for an adequate assessment of movements in such a multidisciplinary discipline. The paper analyzes crucial differences between tools, giving an useful insight in contemporary research of energy efficiency projections. A overview of these tools is essential for sustainable energy development and efficient business of energy companies. A comparative comparison of energy modelling tools is also shown, with the intention of pointing out the importance of all models and their differences, in order to indicate which area of investigation is especially significant for a particular model.

Keywords:
energy economics, energy modelling, energy efficiency, top-down modelling, bottom-up modelling

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1 Introduction

In order to define an appropriate energy regulatory policy at the state level, encourage energy efficiency, control the level of final energy consumption and select production technologies, it is important to choose an adequate approach to energy modeling (Sanchez-Escobar et al., 2021). Energy models can be developed for effective prediction, planning, design, operation and optimization of energy systems (Kondili, 2010). Energy modeling can also be described as a process that contains three interrelated activities: model formulation, parameter estimation and model validation (Labys, 1982).

Today, due to the advanced possibilities of using computers and computer programming, the total number of energy models and their complexity are constantly growing. The models differ considerably in terms of structure and scope of application, while the complexity of the obtained results often presents a challenging task for analysts in the mentioned field. It is also significant to point out that "the modern energy economy requires more and more advanced models for realistic assessment of future trends in the energy sector" (Backović et al., 2024, p. 200).

The relevance of energy models is also reflected in the implementation of energy decarbonization strategies. Four main challenges facing modern modeling of energy systems are (Fodstad et al., 2022):

1. time and space for which the model is defined,
2. research into multi-energy systems (optimal coordination between different energy categories, in English MES - Multi-Energy Systems),
3. modeling with a focus on uncertainty,
4. examining the behavior of energy consumers and modeling the energy transition.

Energy planning and scenario creation within the model have two key goals: providing guidance and projections on future energy systems, as well as providing support to decision makers for the development of short-term and long-term energy strategies (Cao et al., 2016). Comprehensive and integrated energy planning should take into account the potential of increasing energy efficiency in order to reduce the need for investments in new technologies of electricity production and transmission (Wang & Brown, 2014). The same authors add that improvements in knowledge-based energy modeling are of crucial importance for planning the expansion of energy transmission and distribution, as well as for the optimization of the energy regulatory policy support mechanism.

2 Types of energy models relevant for energy efficiency projection

Energy systems are the subject of research primarily within two areas: (1) energy economics and (2) process system engineering (Subramanian et al., 2018). The process systems engineering approach is also based on economic foundations, such as minimizing the life cycle costs of rational investments, assessing the impact of market failures on the adoption of energy efficient technologies, efficient allocation of resources and other economic theses (Sanstad & Howarth, 1994).

The problem of information asymmetry causes the bounded rationality of consumers, which is another challenge for energy modeling. Contemporary macroeconomics also indicates an increasing division in the distribution of information and knowledge, that is, gradual asymmetry. Thus, while some market participants have all the necessary information for decision-making, another market group has none (Jakšić & Praščević, 2014).

Energy models can guide decision-making on investments in additional capacities for electricity generation by defining different strategies for meeting future energy requirements and environmental protection goals (Heuberger et al., 2017). There is a need to model more efficient final energy consumption at the global level. The development of the model filled the gap between techno-economic and macroeconomic models. "What if" analysis of simulation energy models showed in certain cases a more important contribution than optimal decision modeling.

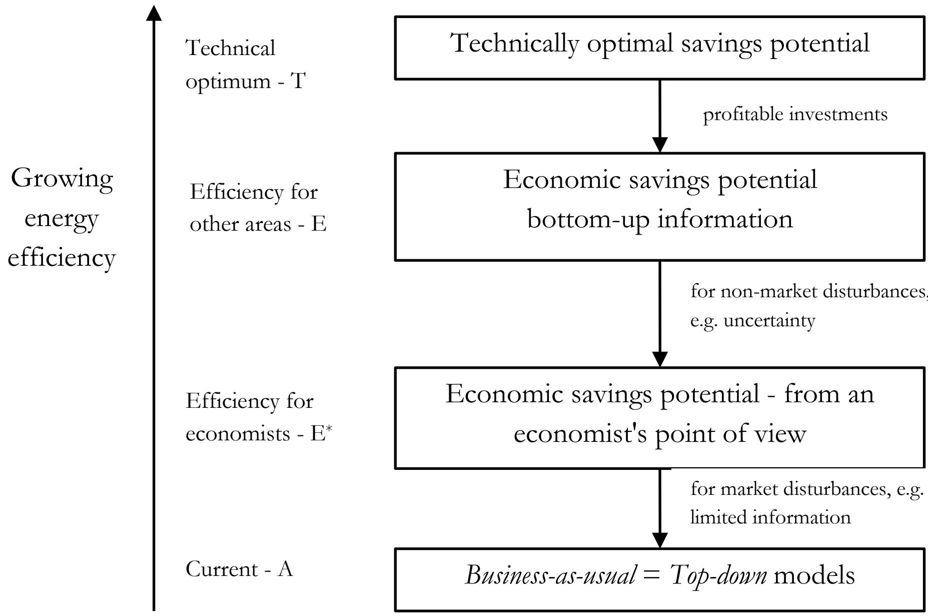

Figure 1: Concepts of energy efficiency
Source: (Koopmans & Te Velde, 2001)

Also important are CGE (Computable General Equilibrium) models, which assume an analysis of a certain market structure and economic dynamics, and then add a certain degree of technological details to the model. One of the first examples of econometric methodologies for forming energy models was the DGEM (Dynamic General Equilibrium Model) model by Berndt and others (Berndt et al., 1981). This model incorporates nine production sectors and an analysis of energy consumption in households according to the defined price formation strategy.

A similar methodology was used for the ZENCAP model of economic development and analysis of capital needs within the energy sector (Codoni et al., 1980). For the regional level, other authors have shown that data envelopment analysis (DEA) can be used to assess with a high degree of certainty whether regions are using their resources efficiently (Martić & Savić, 2001). The DEA method can also be used to investigate the specific impacts of electricity production on the environmental efficiency of the region (Xie et al., 2012).

Regarding the general purpose of creating an energy model, there is first a division into three types of models (Hourcade et al., 2006): (1) models that project future flows of energy with endogenous observation of economic activities using econometric analysis, (2) research into the future of the energy system by forming alternative of scenarios which are then compared with the reference scenario, (3) backcasting – defining the vision of the desired future, and then analyzing the corrections of the current situation for the sake of achieving future goals (also used to evaluate the long-term economic consistency of alternative strategies).

As for the specific purposes, they depend on the research focus of the formed model: (1) energy demand models consider demand as a function that causes changes in the total population, income, energy prices, (2) energy supply models focus on technical aspects and on testing whether the supply can meet the demand for energy, with the inclusion of certain financial indicators, (3) impact models, i.e. impact models caused by the adoption of current energy policy measures, which may lead to changes in economic-financial parameters, social welfare or a change in the protection strategy environment (these models assess the consequences of choosing alternative options) (van Beeck, 1999). Other authors are of the opinion that for integrated energy management it is of particular importance to create a model for managing energy demand (Suganthi & Samuel, 2012).

3 Specification of energy models according to the analytical approach

According to the highlighted, analytical approach, energy models are classified into top-down and bottom-up, that is, process-oriented models (Hourcade et al., 2006; Subramanian et al., 2018; van Beeck, 1999). This basic division gained particular importance during the 1980s and 1990s, due to the emergence of the debate on the energy efficiency gap. Comparisons during the 1990s between the analysis of the long-term general equilibrium in the energy sector through top-down models (with optimal allocation of resources within a perfectly competitive market), on the one hand, and conventional macroeconomic models of short-term dynamic analysis, on the other hand (Grubb et al., 1993). In order to clearly see the difference between the currently available, advanced energy models, the following table shows the basic characteristics of the models according to their type and the methodology they use.

3.1 *Top-down* energy modelling tools

Top-down models use aggregated data to conduct synergy analysis between sectors (Sanchez-Escobar et al., 2021). The mentioned models include the analysis of the entire economy considering ongoing market distortions, money spillovers and income effects for different economic subjects, with pronounced endogeneity of economic activities in the period of the energy crisis (Böhringer & Rutherford, 2008).

Although engineering bottom-up models may underestimate costs by neglecting the technology implementation process, economic top-down models tend to overestimate costs while omitting the potential for structural change and energy efficiency growth resulting from regulatory policy incentives (Grubb et al., 1993). Top-down models are formed with the assumption of efficient allocation of all energy inputs and final goods by a competitive market, and this also applies to CGE models. On the other hand, bottom-up models point to additional opportunities to improve energy efficiency through state support mechanisms (Hourcade et al., 2006). Also, top-down models seek to form a holistic perspective of the economy, but looking at the energy sector in an apparently simplified and aggregated way.

Conventional top-down models have trouble assessing the combined effect of price-based regulatory policies (such as carbon taxes, tradable energy permits) and regulation of specific energy production technologies, given that they register technological change as an abstract, aggregate phenomenon—implicit with aspect of substitution elasticity (Hourcade et al., 2006). Essentially, these models primarily examine the consequences of regulatory policy on public finances, economic competitiveness and employment levels (Hourcade et al., 2006). Some of the advantages of the top-down model are (Vogt, 2020):

1. low costs and quick implementation based on routine collection of available data,
2. easy identification and quantification of the effects of equipment replacement for the energy system,
3. historical data for a time period of only one year is sufficient for modeling,

4. the model quickly recognizes changes in final energy consumption caused by the appearance of unknown factors such as unplanned changes in operating procedures.

There are also certain disadvantages of the mentioned models (Vogt, 2020):

1. if the data collection is not carried out in an appropriate way, a low degree of accuracy of the model can be obtained,
2. if the model shows results that deviate significantly from the expected, it means that the process, technology or piece of equipment that led to the deviation cannot be recognized, but the entire system must be modeled again,
3. specific knowledge in the field of statistics is required, more precisely the description of the statistical validation of the model is difficult to present without prior knowledge of the model.

3.2 *Bottom-up* energy modelling tools

Contrary to top-down energy models, bottom-up models contain more technological details and use an economically driven approach to evaluate the technologies used. The assumptions of the model are defined with reference to technological diffusion, investments and operating costs of power plants (Herbst et al., 2012). Considering that they provide numerous possibilities for clarifying the reasons for the occurrence of certain outcomes within the energy sector and considering that they are based on high program complexity, these models can reliably project the adoption of new energy production technologies, with the aim of informing about new support mechanisms for regulatory energy policy (Adams, 2019).

The failure of certain consumers and companies to minimize the costs of required energy services is often related to the dynamic nature of energy efficiency development and the complexity of the diffusion of efficient technologies (Sanstad & Howarth, 1994). Therefore, the general theory of economic balance can be used to show the outcome of the adaptation of new production technologies to the energy system, but within the same theory, the analysis of the dynamic process that led to their application is neglected.

Given the nature of incremental technology change, the bottom-up approach is likely to overestimate the economic potential of full penetration of energy-saving technologies. According to Grubb and other authors (Grubb et al., 1993), bottom-up studies of practical application suggest the existence of an even greater potential for reducing emissions of harmful gases and total costs compared to the extrapolation of energy demand of the top-down model. In this way, the authors conclude that the application of the model indicates that top-down is not optimal in terms of the available technologies under consideration, but that significant savings in energy consumption can be achieved by creating a different scenario that would represent the engineering optimum. It should be noted that even CGE top-down models often contain only aggregated data without details on technologies, so disintegration is necessary to disaggregate electricity generation into the results of different generation technologies (Truong & Hamasaki, 2021).

Some bottom-up models include macroeconomic feedback, while others estimate microeconomic behavioral parameters for energy production technology selection (Hourcade et al., 2006). The same authors state that certain top-down models have incorporated technological complexity for energy supply sectors. By comparing the deterministic and stochastic models using the TIMES energy model, it is noticeable that the stochastic interpretation is more realistic for approximating the general costs of the energy system, because it requires the presentation of uncertain parameters specific to the model itself (Seljom & Tomasgard, 2015).

Bottom-up models look at energy efficiency through the reduction of energy use of a certain technology or device compared to a reference scenario. In contrast to top-down modeling of energy demand, ex post research on household income elasticity with a combination of economic and structural variables clearly contributes to the identification of energy use per unit of activity.

Three main areas for bottom-up database management research are presented (Koopmans & Te Velde, 2001): (1) projection of demand for energy and energy services, with reference to the trend of replacing technology based on the use of conventional fuels with technology that uses electricity , (2) energy efficiency depends on the realized strategy of energy development: investments in existing technologies or complete replacement with modern technologies, (3) the model may lack an assessment of the speed of adaptation of the current to perfect ex post efficiency of the energy system, which should be improved in new versions of the model .

4 Conclusion

The existence of two alternative approaches to energy modeling often leads to inconsistency within research and to confusion among analysts when choosing an adequate method. Insufficient availability of information by energy companies is seen as a limiting factor when analyzing energy in a state of market failure. Irreversible investments in energy efficiency that depend on uncertain, future energy prices require the use of high discount rates by investors, especially in case of their aversion to risk (Koopmans & Te Velde, 2001). Dynamic optimization models are used as energy models, which should form the entire structure of the energy sector, taking into account the relevant technological, economic and environmental characteristics of the energy system (Strubegger & Messner, 1987). Hence, the heterogeneity of applied energy models and the energy scenarios defined in them require specific, technically advanced skills for an adequate assessment of movements in such a multidisciplinary discipline (Cao et al., 2016).

The extreme complexity of the choice of technology for the production of electricity and the planning of investments in the energy sector make it a challenge for a detailed analysis. The main reasons for this complexity are the high integration of the energy system, which is shown by the power grid, as well as the variety of technologies for converting resources into final products, i.e. fuel (Kavrakoğlu, 1987).

Directing economic processes towards the stimulation of the development of production technologies that reduce the emission of harmful gases with the greenhouse effect created an additional difference between the aforementioned analytical approaches. Energy policy makers should make decisions about the goals of the energy sector with a view to economic efficiency, environmental effectiveness and political-administrative feasibility of support mechanisms for selected technologies (Hourcade et al., 2006).

For the purpose of forecasting the total demand for energy, the methodological framework of energy models has advanced a lot, especially from the aspect of applicability of the concept of artificial intelligence. Empirical findings point to the fact that there is no one-size-fits-all methodology that would solve all the various challenges faced by business entities in the energy system. Some of the most important model methodologies, the time frame they cover, as well as their advantages and disadvantages indicate their essential importance for the long-term projection of energy efficiency.

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