Modeling technology specific effects of energy policies in industry: existing approaches and a concept for a new modeling framework

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Abstract

Reducing the climate impact of industrial production is crucial for reaching a long term low-carbon society. The share of about 30% of the total global final energy demand shows the importance of this sector for the global emissions.

The main goal of this paper is to discuss a new modeling framework to be built up for analyzing industrial energy demand and the effects of energy policies on its future development. As technology-specific effects of energy efficiency and renewable energy policies should be investigated the model must provide a detailed representation of technologies. Furthermore policies to overcome barriers to energy efficiency and renewable energies have to be designed according to the characteristics of the respective barriers. These barriers occur in the decision making of energy related investments, therefore the new modeling framework should address this decision making process.

A description of existing models that can address questions in this context and a characterization of the methodologies that should be used in the new modeling framework should open the discussion on strengths and limitations of possible approaches.

The result of this paper is the outlining of a new modeling framework concept and its strengths and limitations. I will conclude with possible next steps in the development and application of this modeling tool.

Keywords:

Industrial energy demand, modeling of investment decisions, energy efficiency and renewable energy policies, effects on technological development

1. Introduction

1.1. Motivation

Industrial energy demand accounts for about a third of total final energy demand worldwide. Therefore it is crucial for reaching a low-carbon society to understand how to broadly introduce energy efficiency and renewable energies in this sector. Due to the immaturity of efficient and renewable energy solutions in many industrial branches and due to the existence of various highly influencing barriers to their installation, understanding the effects of policies to foster efficient and renewable technologies is of high importance.

A new model for investigating effects of respective policies should be built up in order to better understand how to design effective policy packages. Two main reasons account for the choice of methodology for the modeling framework: on the one hand policies should be designed and investigated that specifically address the existing barriers against efficiency and renewable technologies, and on the other hand it should be possible to show detailed impacts of these policies on the use or disuse of certain technologies.

Another motivation is that no model exists for the investigation of the Austrian industry system in detail.

1.2. Research question

The core research questions of this paper are:

- What is the current state of modeling energy efficiency and renewable energy policies and their effects on installed technologies in the industrial sector?
- What are strengths and limitations of a new modeling framework proposed in this paper, both in general and compared to the existing approaches?

This includes a series of sub-questions:

- Which modeling approaches allow conclusions concerning technology specific effects of energy efficiency and renewable energy policies in the industry sector?
- Which models allow technology specific conclusions and which methodological approaches do they use?
- What are strengths and limitations of the existing approaches?
- What can a new approach look like in detail?

1.3. Structure of this paper

In a first step (Chapter 2) the broad variety of existing approaches for modeling industrial energy demand developments are listed and shortly characterized. It is explained why bottom-up models are the only ones to simulate technology-specific effects of energy policies.

A more detailed description of existing bottom-up models is given in chapter 3 focusing on the way the technology choice is modeled. Chapter 4 describes the methods that should be applied for building up a new modeling framework. Strengths and limitations of the proposed methods will be discussed in chapter 5.

2. Approaches for modeling industrial energy demand developments – An overview

The long history of industrial energy demand forecasting and the many different scientific fields that are involved in this research (mainly economics, engineering, operations research and industrial ecology) lead to a wide range of existing energy demand forecasting frameworks with a variety of different methodological concepts. All approaches are appropriate to address specific types of research questions and face advantages as well as drawbacks in their application and significance. (Greening et al., 2007)) distinguish between five different groups of frameworks according to the analytical technique that is applied:

- Energy trend decomposition methods,
- Econometric methods,
- 'Top-down' models,
- 'Bottom-up' or engineering models, and
- Industry-specific micro-economic analyses.

Various different methods exist to decompose the observed aggregated trend of national industrial energy consumption into changes associated with the change of attributed parameters such as the industrial production level, the production structure or the sectoral energy intensity. Although this can lead to useful insights concerning this influence over time and different regions, or be used as a complement for other analysis techniques, the lack of a widely accepted method and the sensitivity of the results to the method applied are major drawbacks of these analysis methods.

Econometric methods are used to quantitatively analyze developments of industrial energy consumption and its relation to changes in corresponding statistical data. Existing approaches range from very simple to highly sophisticated. Main advantages of econometric analyses are the identification of causal linkages in the energy demand at varying level of detail. Results of econometric analyses can also be used as complementary inputs to both 'top-down' and 'bottom-up' models. A main disadvantage is that the underlying estimations have to be focused on answering a specific research question, which leads to difficulties in the transferability of the results. As they are based on economic theory not taking into account engineering characteristics, they are not appropriate to carry out technology specific analyses of energy demand developments.

The so called 'top-down' models are also based on economic theory. There are 'top-down' models focusing on the relationship between supply and demand of energy carriers and thus aiming to reflect the dynamics of energy markets. Another type of 'top-down' models uses the input-output statistics as basic input to focus on the interaction between different sectors of the economy. Input-output models therefore provide the possibility to simulate the effects of changes in several technology coefficients on the other parts of the economic system. With 'top-down' models the impacts of energy policies on macro-economic parameters like production of industrial goods, employment, prices, investment etc. can be analyzed. On the other side, the grounding in economic theory hampers the analysis of other than economic policies. Furthermore most 'top-down' modeling frameworks use aggregate production functions, which leads to limited technological detail of the analyses.

'Bottom-up' models of energy demand are characterized by a detailed representation of technologies. Therefore, they offer the possibility to analyze the effects of technology oriented energy policies as well as the technology-specific effects of non technology-oriented energy policies. They allow for a detailed investigation of changes in the technology stock and allow simulating possible future penetrations of emerging technologies. On the other hand the high level of disaggregation of course brings up difficulties in providing the required input parameters. Furthermore future developments of technologies' availability and performance increase have to be assumed.

Industry-specific micro-economic analyses focus on specific industry sectors or even sub-sectors. This allows for a detailed incorporation of all relevant influencing factors that may be difficult to include in more aggregated approaches. Clearly, this type of analysis method neither takes interactions with other industry sectors nor with the broader economy into account.

This shows the broad variety of existing methods for the analysis of industrial energy demand. They range from processing highly aggregated to highly disaggregated data and from focusing on economic theory to concentrating on engineering aspects. Hybrid models have also been developed in the later past to overcome disadvantages of single approaches (see also chapter 3). For the analysis of technology-specific effects of energy efficiency and renewable energy policies it is necessary to have a detailed representation of technologies in the models. The following chapter focuses on existing models offering a detailed technology stock, similar to the modeling framework under development.

3. Review of existing bottom-up models of industrial energy demand

An identification of homogeneous activities or end-uses allows for a detailed representation of technologies that can be used to supply the identified demands. Models that build on a disaggregated description of energy end-uses and activities are widely denominated as bottom-up models (Bhattacharyya and Timilsina, 2009). With the bottom-up approach it is possible to link final energy demand and the demand for energy services via a combination of applied technologies. Depending on the method and the goal of modeling technology choice (Fleiter et al., 2011) distinguish three different types of bottom-up models: Accounting models, optimization models and simulation models. Each of the three types of models can elaborate on different research questions and has its strengths and limitations in doing so.

Accounting models are characterized by an exogenous definition of the development of technology use and normally do not consider energy prices as a parameter influencing the demand for energy. Therefore they represent a powerful tool for the investigation of the economy-wide effects of technological change in disaggregated energy uses due to their simplicity and the offered transparency concerning scenario assumptions. On the other hand, the absence of a technology adoption algorithm does not allow the investigation of effects of policies on energy-related investments because the investment decision process is not modeled. Broadly applied examples for accounting models in the past are the MURE II, MED-PRO, MAED and the LEAP modeling framework. (Fleiter et al., 2011)

Even though initially created for modeling the supply side of energy systems some optimization models have been expanded to cover parts or even the whole demand side as well. This interconnection of supply and demand side of energy systems allows the competition of investments on both sides of the system. Therefore these models allow examining the effects of financial policies affecting both the supply and the demand side. Optimization models perform technology adoption with the goal of minimizing the total system costs. As existing models show the optimization algorithm basing these models leads to difficulties in explicitly addressing non-optimal investment behavior of firms. Important representatives of optimization models with a detailed representation of technologies on the demand side are the IEA's MARKAL model, the DNE21+, AIM and the PRIMES model. (Fleiter et al., 2011)

Simulation models of industrial energy demand aim at reproducing the decision making process of energy related investments in industry. They therefore offer an appropriate tool for investigating the effects of energy efficiency and renewable energy policies on the outcomes of these decisions. While all bottom-up simulation models have an explicit technology adoption algorithm, these algorithms differ strongly between the various existing models.

A bottom-up simulation model developed in the 1990's is the ENUSIM end-use model. It covers explicitly the United Kingdom and was used for various forecasting and policy implication analyses. (Bhattacharyya and Timilsina, 2009) In the simulation of energy-related investments both economic and behavioral factors are considered. While the industrial output growth, relative prices of fuels and the investment discount rate determine the potential for technological change behavioral aspects influence the pace and extent of the technological change. The diffusion curves relying on the 'S'-shaped product-cycle pattern are exogenous input to the model. (Fletcher and Marshall, 1995)

An important representative of the industrial bottom-up models is the Industrial Demand Module (IDM) of the National Energy Demand Modeling System (NEMS). It is used to generate the Annual Energy Outlook of the US Energy Information Administration. In determining technological change it distinguishes two different types of technologies: process and cross-cutting technologies. In case of process technologies fixed annual replacement rates are used for new installations, while for determining the annual rate of retrofitting energy prices are taken into account. For simulating the replacement of cross-cutting technologies also costs are taken into account using a payback time threshold. (EIA, 2011)

A bottom-up industrial simulation model highly advanced in simulating energy-related investment decisions and in considering barriers to energy efficiency is the Dutch SAVE Production model. It was developed at the Energy Research Centre of the Netherlands (ECN) since the early 1990's. In the energy-related investment decisions economic as well as non-economic factors are taken into account. Costs and profits determine the internal rate of return of technologies. Risk is taken into account affecting the internal rate of return. Non-financial barriers influencing the decision making process such as bounded rationality or imperfect information are cumulatively taken into account limiting the speed of market diffusion. Psychological effects of energy price changes and energy efficiency policies are also included in the decision algorithm. For calculating the replacement rate of technologies a normal distribution around the average lifetime is used. (Daniëls and Van Dril, 2007)

The CIMS model is an example of a hybrid modeling framework combining a detailed bottom-up representation of end-uses and technologies with a top-down macro-economic modeling of energy markets. The model is designed to simulate policies for the Canadian industry sector. For the calculation of the market shares of newly installed technologies the capital costs, operation and maintenance costs and energy costs as well as three further parameters are considered: the weighted average time preference (reflects the applied discount rate), heterogeneity in the markets (increasing heterogeneity leads to decreasing dominance of single technologies), and a factor for all other intangible costs and benefits influencing the investment decision. (Murphy et al., 2007)

4. Concept for a new modeling framework

As already argued the intended model should reproduce the decision-making process of investments in energy related technologies. From the results we expect to gain insights and a better understanding of the effects of different ways of policy intervention on these energy-related investments. Therefore the model is planned to consist of three different steps applying both optimization and simulation methods: Firstly the year in which a company is going to replace or retrofit an existing technology is calculated, then the decision what is going to be installed or to what level it is going to be retrofitted is drawn. These two steps are going to be performed a large number of times with varying input parameters according to the Monte-Carlo methodology. In a third additional step an optimization of the distribution of financial policies is intended to be integrated.

In reality decision making processes concerning energy-related investments in industry are executed on the level of individual companies. Each investment thereby should maximize the companies' benefit[1] according to economic criteria such as payback period or Net Present Value, but also depends on non-economic criteria. Such criteria are e.g. (environmental) reputation or the availability of information concerning the existence and performance of technological opportunities. In each single investment decision these parameters are influencing the resulting technology to be chosen for a defined application with each company having its own validation (importance) of these parameters. To model the influence of economic and non-economic parameters on the investment decisions in the companies a **Logit-model** will be used, calculating the different probabilities of the possible outcomes of single investment decisions. The determination of the probabilities of several possible technology options for the same application is based on a utility function for each

[1] and is therefore optimized from the company's perspective

option, which will be calculated according to weighted economic and non-economic parameters.

In order to address the variety of possible combinations of individual importance and values of the parameters influencing the investment decision a **Monte-Carlo** simulation will be performed. This means that a large number of single investment decisions will be drawn where the combination of the individual importance factors are randomly chosen. The main advantage of a Monte-Carlo Simulation is that if a relevant amount of input parameters is defined via distributions (and not in terms of discrete values), randomly choosing the combination of inputs allows to get significant results even with a relatively low number of simulations. It also allows to vary the input parameter within a broader range, considering, if available, the covariance matrices as well, even though this requires a large number of simulations[2]. Preparing the input parameters in form of distributions makes sense as they normally results of empirical studies or statistical surveys. For example, the size of a company is influencing the way of making investment decisions: the larger the company is, the higher is the availability of capital. Another example is the type of enterprise, which influences the investment characteristics: smaller enterprises handled by families rather invest in technologies with high payback periods than big joint-stock companies. Both the size of companies and the form of enterprise is statistically available in form of distributions over the various industrial branches.

To increase the utility of the Monte-Carlo methodology and in order to address the uncertainties concerning the future development of highly influencing parameters such as energy prices, CO_2-prices or **technological learning,** these parameters will be prepared in form of distributions.

[2] Since simulations are independent from each other, the Monte-Carlo-Technique allows to gain from multi-core computers much more easily compared with a more complex models, that deals with distributions and their convolution (even in a numerical convolution approach)

For calculating the period a company is going to replace or retrofit an existing technology, both the efficiencies of the technologies in place and the age of these technologies will be fed in form of distributions. According to the Monte-Carlo methodology the replacement period will be randomly chosen for each simulation of an individual decision. This defines the year in which a technology is changed due to predefined lifetime distributions of the technologies and the competitiveness of the existing technology compared to new ones. Retrofitting of technologies in place should also be taken into account accordingly and should be influenced by energy price developments.

The result of the Monte-Carlo simulation will be probability distributions of technological developments in the different industrial sub-sectors for the pre-defined simulation period. The comparison of different input parameter settings concerning political intervention then leads to conclusions concerning their effects on the technological developments in the different branches. This, of course, requires the definition of reasonable policy settings.

In order to distribute public money for subsidies or penalties in an optimized way, we intend to implement a third step in the decision model. This step is set on top of the previous steps and consists of an optimization algorithm that allows for an automatic variation of financial aid and penalties in order to determine the distributions leading to the highest increases in efficiency or renewable penetration in certain sectors or over the whole industry.

A calibration of the model will be performed via simulating past time periods and comparing the results with statistical data.

5. Discussion

Various approaches have been used to investigate the influence of energy efficiency and renewable energy policies and how they affect the industry sector. As described in chapter two and three a bottom-up techno-economic simulation is needed to analyze technology-specific effects of such policies. If empirically observed, non-optimal investment behavior is indented to be considered in detail. The bottom-up simulation of investments in industrial energy-related technologies also allows for an in depth incorporation and investigation of barriers to energy efficiency and renewable energies since these barriers occur in the investment decision process. Moreover, political intervention efficiently fostering energy efficiency and renewable energies has to address the corresponding barriers. This increases the importance of enhancing the bottom-up simulation approach for policy development.

The proposed modeling framework is based on three different steps:

- A decision whether or not to replace or retrofit an existing technology,
- a techno-economic anticipation of individual investment decisions for different investment situations based on a Logit model,
- and an additional optimization of the distribution of financial incentives over technologies and industrial branches.

Both the first and the second step are performed a large number of times according to the Monte-Carlo simulation technique.

An advantage compared to existing bottom-up models of industrial energy demand is the use of distributed input parameters. This allows for a consideration of the variety of different investment situations and for considering the differences in the individual importance of influencing parameters. It also considers the uncertainty with respect to input data, e.g. regarding the current use of technologies in different industry sectors. Using mean values as input factors instead of their distributions ignores relevant details of the system, especially in non-linear processes. Furthermore, using the mean values as input factors instead of their distributions, additional information on the distribution of outcomes is lost. The Monte-Carlo simulation yields probability distributions of certain technology development trajectories. Therefore, the outcome of the modeling is not only a certain disaggregated technology and energy demand trajectory, but also contains information of its probability and the width of its distribution over time.

Although this method seems promising to provide new insights how to design effective industrial energy efficiency and renewable energy policies there are difficulties and open questions concerning the realization of the modeling. A pre-condition for the modeling is the definition of distributions of the important input parameters such as availability of capital or information, risk tolerance, the reputational preferences, etc. The estimation of these distributions and to correctly account for correlations between various input parameters will be a critical issue and have an impact on the outcomes of the simulations. In order to address this fact an estimation of potential errors will be carried out. Another challenge arising from the Monte-Carlo methodology used in the modeling framework will be the development of a programming framework to effectively compute a large number of simulations and scenarios.

Concerning the structure of the model it is not yet clear what level of disaggregation will be feasible concerning technologies, products, processes and actors. On one hand, this is determined by the availability of data which has to be partly country specific. On the other hand, an increasing level of disaggregation is raising the number of simulation runs to be performed in order to get significant results.

In the determination of the probability that a certain technology is being retrofitted a dependency on the energy price development is planned to be implemented. Rising energy prices increase the probability of retrofitting due to rising annual running costs. Apart from this correlation it is obvious that if a restructuring process takes place in a certain plant it increases the probability for each technology in the plant to be retrofitted. In the model the development of single technologies that are currently in place will be simulated. This means that the stated correlation has to be implemented via distributions of the probabilities of restructuring processes over industrial branches.

The next step in the development of the modeling framework is to perform a sector-specific analysis of the Austrian food industry applying some of the described principles. In upcoming projects the modeling tool should be extended to cover the entire Austrian industry sector.

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7. References

Bhattacharyya, C., Timilsina, G.R., 2009. Energy Demand Models for Policy Formulation - A Comparative Study of Energy Demand Models (Policy Research Working Paper No. 4866). The World Bank - Development Research Group.

Daniëls, B.W., Van Dril, A.W.N., 2007. Save production: A bottom-up energy model for Dutch industry and agriculture. Energy Economics 29, 847-867.

EIA, 2011. Model Documentation Report: Industrial Demand Module of the National Energy Modeling System (No. DOE/EIA-M064(2011)). Office of Energy Analysis, US Energy Information Administration, US Department of Energy.

Fleiter, T., Worrell, E., Eichhammer, W., 2011. Barriers to energy efficiency in industrial bottom-up energy demand models--A review. Renewable and Sustainable Energy Reviews 15, 3099-3111.

Fletcher, K., Marshall, M., 1995. Forecasting Regional Industrial Energy Demand: The ENUSIM End-use Model (Regional Studies No. 29:8).

Greening, L.A., Boyd, G., Roop, J.M., 2007. Modeling of industrial energy consumption: An introduction and context. Energy Economics 29, 599-608.

Murphy, R., Rivers, N., Jaccard, M., 2007. Hybrid modeling of industrial energy consumption and greenhouse gas emissions with an application to Canada. Energy Economics 29, 826-846.