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2009

[Link to publication](#)

Citation for published version (APA):

Mundaca, L., & Neij, L. (2009). *Energy-economy models and energy efficiency policy evaluation for the household sector*. (IIIEE Reports; Vol. 2). The International Institute for Industrial Environmental Economics.

Total number of authors:

2

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Energy-economy models and energy efficiency policy evaluation for the household sector

An analysis of modelling tools and analytical approaches

Luis Mundaca | Lena Neij

09/2009



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Published in 2004 by IIIIEE, Lund University, P.O. Box 196, S-221 00 LUND, Sweden,
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<http://www.iiice.lu.se>

ISSN 1650-1675

Acknowledgements

The authors of this report would like to acknowledge the contribution of Ali Hainoun, Charlie Heaps, Ernst Worrell, Helena Božić, James McMahon, Jonathan Koomey, Leo Schrattenholzer and Michael McNeil. We are indebted to all of them for providing critical input, numerous helpful comments, suggestions and/or clarifications provided at various stages of the writing of this report. All mistakes, omissions and opinions expressed herein remain solely the responsibility of the authors.

Lund, October 2009.

Luis Mundaca and Lena Neij.

Executive Summary

The increased awareness of energy security, continuous escalation of energy prices and growing concerns of global climate change are all contributing to the re-assessment and importance of increased energy efficiency and conservation. Large cost-effective potentials have been estimated (e.g. 25-35 per cent in industrialised countries and >40 per cent in developing nations), however a number of market and behavioural failures have traditionally prevented efficiency improvements. Thus, ever-increasing attention has been given to public policy in providing more aggressive and effective responses to reduce energy demand sustainably. Within this context, the use of bottom-up energy-economy models for evaluating *ex-ante* energy efficiency policy has gained widespread recognition for supporting policy-making. Models provide critical insights, nevertheless the growing complexities of energy systems, environmental problems and technology markets are driving and testing most energy-economy models to their limits.

Energy-economy models are of prime importance to support the most suitable design of policies by assessing whether they are capable of achieving the impacts that would justify their implementation. However, there is limited detailed literature on the development and use of models and corresponding assessments addressing energy efficiency policy – in particular for the buildings sector, which is responsible for at least 40 per cent of energy use in most countries and offers the largest economic potential for the mitigation of greenhouse gases (GHG) globally. To further advance the appropriateness of models from a multidisciplinary energy efficiency policy evaluation perspective, we review and analyse numerous energy-economy models and corresponding modelling evaluation studies on energy efficiency policies to induce technological change. Using the residential sector as a case study, the research presented in this report is separated into five main parts: (1) review of bottom-up methodologies and corresponding energy-economy models; (2) key drivers of energy demand and end-use coverage, (3) choice-determinants for efficient-technologies embedded in modelling methodologies; and (4) the analysis of modelling studies that focus on *ex-ante* energy efficiency policy evaluation. Based on the findings, (5) several research areas to further advance models are identified and discussed.

We first identify four types of methodological categories: simulation, optimisation, accounting and hybrid models. A representative sample of these various methodological categories is reviewed. The report covers the most widely used models around the globe to model energy use in the household sector (e.g. MARKAL, NEMS, MURE, LEAP). The review shows that despite the variety of methodologies and models reviewed, the growth of the household stock is often used as a key and common driver for determining energy (service) demands. Technology representation is mostly explicit and technologically-rich across all the reviewed models. This is a critical requisite for simulating energy efficiency policy instruments or portfolios that aim to induce ample technological change. Regardless the methodological approach, the explicit and rich technological component allows coverage of numerous energy services. All the reviewed models originate from the OECD region and more than 60 per cent of the identified applications focus mostly on developed countries. To some extent, this finding correlates with the claims about the need for more policy evaluation efforts to assist energy efficiency policy and other GHG mitigation options for the building sector in developing countries.

We reveal the gap between decision frameworks and determinants for technology choice used in different modelling methodologies and the ones used by households in reality (as elaborated in the report of Phase I of this research project). For the latter, the number of factors influencing the choices of households is extensive. We find that whereas capital and operating costs are relevant for efficient-technology (non-)adoption, they represent only a part of a great variety of determinants that drives consumer's energy-related decisions regarding technology choices. Factors including design, comfort, brand, functionality, reliability, environmental awareness, among others, are likely to influence the decisions of consumers in reality. Whereas economic variables are used as key determinants for technology choice in energy-economy models, empirical literature shows that a larger variety of determinants need to be taken into account when analysing the process of adoption of efficient technologies.

We then focus on the analysis of more than twenty case studies addressing the application of the reviewed modelling methodologies to the field of residential energy efficiency policy. The analysis shows that

market and behavioural failures are often not explicitly captured. Sometimes the use of implicit discount rates is identified to confront this modelling issue. Regarding policy instruments being evaluated, the majority of the cases focus on regulatory aspects, such as minimum performance standards and building codes. For the rest, evaluations focus on economically-driven policy instruments. Informative policy instruments were identified as being much less modelled. The dominance of economic and engineering determinants for technology choice gives little room for the representation of informative policy instruments. In all cases, policy instruments are represented through technical factors and costs of measures for energy efficiency improvements. In addition, policy instruments tend to be modelled in an idealistic or oversimplified manner. The traditional but narrow single-criterion evaluation approach based on cost-effectiveness seems to dominate the limited number of evaluation studies. However, this criterion is inappropriate to comprehensively address the attributes of policy instruments and the institutional and market conditions in which they work. Modelling results are very context-specific so no generalisations can be made.

Based on the results, we then turn to identifying research areas that have the potential to further advance modelling tools. We first discuss modelling issues as such, including the importance of transparent modelling efforts; the explicit elaboration of methodologies to represent policies; the need to better translate modelling results into a set of concrete policy recommendations; and the use of complementary research methods to better comprehend the broad effects and attributes of policy instruments. Secondly, we approach techno-economic and environmental components of models. We discuss the integration of co-benefits as a key research element of modelling studies; the introduction of transaction costs to further improve the estimations of energy efficiency potentials; synergies among modelling tools to further improve cost-revenue specifications and accuracy of aggregated results; and the possibility to account for and use experience curves of efficient-technologies. Thirdly, we address behavioural determinants and argue that even if modellers are sometimes fully aware of the flaws of modelling tools in this respect, there is still limited empirical work and practical research on how to handle and convert qualitative knowledge about household behaviour into a set of quantitative parameters. To develop comprehensive microeconomic decision-making frameworks, outcomes from social marketing research and social psychology need attention. More research is also needed on the use of discount rates to mimic consumer behaviour and market imperfections. Fourthly, we discuss policy considerations related to models and modelling exercises. We discuss the importance to better represent the portfolio of policy instruments addressing the household sector, including how uncertainties about future policy developments strongly suggest the development of alternative and credible counterfactual situations. Modelling studies should be part of broad multi-criteria evaluation studies.

Finally, we provide overall conclusions in relation to the current situation and recommendations for the future development of models. We address the need to continuously scrutinize the capability of models in relation to the appropriate policy evaluation questions. Quantitative simulation of household behaviour is very limited and complex, but it is nonetheless highly necessary to improve the evaluation and thus design of policies. However, a lack of quantitative evidence of market and behavioural failures also prevents developments in this regard. Agent-based modelling methodology should be investigated as a complementary approach to address multifaceted human behaviour related to technology choice. We stress the significance of ex-post policy evaluation to feedback, not only the design and functioning of policy instruments, but also provide critical information (e.g. transaction and administrative costs, market failures) to improve models and thus modelling studies. Our analysis strongly suggests that there is no single-best method to evaluate energy efficiency policy instruments. Provided that the “right” models are chosen to answer appropriate policy questions, it is concluded that a comprehensive policy evaluation approach requires a portfolio of analytical methods and much greater collaboration across disciplines.

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1. Introduction

The importance of energy efficiency policy in the context of sustainable development has re-gained political momentum (Goldemberg and Johansson, 2004; Metz et al., 2007). Recent years have seen highly volatile oil prices, increased awareness of the need for energy security, and growing energy-related environmental problems—including the threat of human-induced climate change. All these factors are contributing to a re-assessment of society's energy use (Jochem et al., 2000; Metz et al., 2007). A growing body of evidence shows that increased energy efficiency can benefit both society and the environment.¹ (IAC, 2007; Jochem et al., 2000; Laponche et al., 1997; Levine et al., 2007).

In the above-mentioned context, policy evaluation research is commonly, though not exclusively, concerned with the simulation and modelling of the impacts of different policy instruments for increased energy efficiency. In past decades, we have seen an increased use of bottom-up energy models in policy-making to evaluate ex-ante the energy, economic, and environmental impacts of energy efficiency policy instruments. The use of engineering-economic based energy modelling tools for energy efficiency policy analysis has gained widespread recognition at all levels of policy-making in recent years. Energy efficiency scenarios are developed in national and international contexts to explore and evaluate different policy designs and visions of how energy will or should be generated, distributed and used in the future. These scenarios are often developed using bottom-up modelling tools that, only to a limited extent, take into account decentralised decision-making frameworks, such as household decisions regarding energy-efficient technologies (Hourcade et al., 2006). However, the role of energy models and resulting outcomes is paramount because of their effect on policy and decision-making processes. Energy models and modelling studies have historically provided useful policy insights in aspects such as competition of demand-side energy technologies; end-use energy efficiency potentials; and fuel substitution and related atmospheric emissions, among others (e.g. Metz et al., 2007; Scheraga, 1994). While these models are undoubtedly useful, they underestimate the complexities of processes for the adoption of efficient technology. Driven by economic and engineering principles, bottom-up modelling tools often use a traditional and limited 'rational' approach to represent investment decisions and/or technology choice by the end-user. It has been argued that economic rationality is inadequate or too limited to properly represent consumers' technological preferences. Seminal work conducted by, for example, Lutzenhiser (1992) found evidence that consumers lack economic rationality in deciding to forego certain obvious energy-efficient measures. While these models have been helpful in exemplifying potential impacts for alternative technology futures and to support policy-making, several studies have demonstrated the shortcomings of energy models in the field of energy demand and energy efficiency policy evaluation (see e.g. Craig et al., 2002; DeCanio, 2003; Hourcade et al., 2006; Laitner et al., 2003; Moss et al., 2000; Stern, 1992).

Energy use and increased energy efficiency is of prime importance for both energy and climate change policy. In terms of energy use and greenhouse gas (GHG) emissions, the relevance of the building sector is high: it is responsible for one third of all energy-related CO₂ emissions and two thirds of halocarbon emissions (Levine et al., 2007). Thus, there is a need to critically assess energy models/tools² and corresponding modelling exercises in order to identify research areas for further improvements so that policy decision making can be supported more effectively. There is a growing concern among policy makers and analysts regarding representation of consumers' technological preferences and policy aspects in bottom-up energy models (Laitner et al., 2003; Munson, 2004; Worrell et al. 2004). To further enhance the realism of bottom-up energy models and their usefulness for policy design and evaluation, previous research has suggested that such tools need to be improved (see e.g. Craig et al., 2002; DeCanio, 2003; Hourcade et al., 2006; Laitner and Hanson, 2006). In addition, there is limited detailed literature on the

¹ Efficiency improvements can reduce atmospheric pollution; lessen negative externalities resulting from energy production; boost industrial competitiveness; generate employment and business opportunities; improve the housing stock and the comfort level of occupants; enhance productivity; increase security of supply; and contribute to poverty alleviation.

² Note that the terms *energy models* and *energy modelling tools* are used interchangeably in this document.

development and use of bottom-up energy models and corresponding assessments addressing energy demand and policy aspects to increase the energy efficiency of buildings (Levine et al., 2007). In fact most of the modelling tools reviewed in this report were never designed to analyse energy efficiency policy instruments. Therefore, it is not surprising that they may be inadequate to the energy efficiency community. There is need for a comprehensive updated review and discussion of the conceptual and modelling aspects of energy models that analyse energy use and energy efficiency policy options for the household sector.

In this report, we review a number of engineering-economic energy models that could provide useful insights for improving bottom-up models from a multidisciplinary standpoint applied to the household sector. The purpose of the study is threefold. It presents a comprehensive review of various energy models that projects household energy consumption in general, and/or energy efficiency improvements in particular. It identifies and discusses decision-making rules for household efficient technology choice embedded in the reviewed energy models. And it analyses numerous modelling studies that focus on energy efficiency policy instruments for the household sector.

To address the objective, the following research questions were chosen:

- What bottom-up energy modelling tools simulate household energy demand? Which ones were specifically built to analyse energy use and energy efficiency in the household sector?
- What decision-making rules/factors in the energy models determine technology choice for the household sector?
- What are the pros and cons of modelling approaches in addressing energy efficiency policy instruments for the household sector?
- Based on the reviewed case studies, what research areas can be identified/developed to further improve bottom-up energy models that address energy efficiency policy for the household sector?

The research called for data to be collected from a variety of sources to approximate objectivity and reduce uncertainty. Data collection methods included literature review and interviews, including personal communications with model developers and modellers. First, an extensive review was conducted of model documentation, peer-reviewed material, books and grey literature (project reports, workshop/seminar presentations). Interviews played an important role during the research because literature on certain aspects, such as model documentation and data implementation guidance was either limited or not readily accessible. Semi-structured interviews, based on a protocol, were carried out. The objective was to obtain key insights and background information about models and to discuss specific topics in detail. The interviews addressed aspects related to: (i) the model under analysis; (ii) technology-choice issues; and (iii) policy analysis.

Section 3 of this report provides a description of the energy models under review. In addition to general aspects, it focuses on the primary structure or components of the model/tool and on issues of relevance for the household sector. Section 4 describes the drivers behind energy demand and the end-use service coverage under each of the models/tools reviewed. Section 5 provides an overview of the decision-making rules/factors for technology choice embedded in the reviewed energy models/tools. Section 6 analyses a number of case studies that have addressed either implicitly or explicitly energy efficiency policy instruments as applied to the household sector. Section 7 identifies and discusses research from a more multidisciplinary point of view that could further improve bottom-up energy models applied to the household sector. Section 8 comprises concluding remarks.

2. Identified methodological approaches

Following Heaps (2002), Hourcade et al. (2006), Jaccard et al. (1996) and Worrell et al. (2004) four methodological categories of energy-economy models were identified: (i) simulation, (ii) optimisation, (iii) accounting and (iv) hybrid models. They are described below.

2.1 Simulation models

Simulation models attempt to provide a descriptive quantitative illustration of energy production and consumption based on exogenously determined scenarios. The methodological approach aims to represent observed and expected microeconomic decision-making behaviour that is not limited to an optimal pattern. These models try to replicate end-user behaviour for technology choice considering different drivers (e.g. income, energy security, public policies and endogenous energy prices). Thus, and despite that economic data can be of high significance, drivers are often linked to other aspects of energy systems (e.g. CO₂ constraints). Under this category, we found the Residential End-Use Energy Planning System (REEPS); World Energy Model (WEM); Mesures d'Utilisation Rationnelle de l'Energie (MURE); and the National Energy Modelling System - Residential Sector Demand Module (NEMS-RSDM). For a description of these models see section 3.

2.2 Accounting models

The main purpose of *accounting models* is to account for the physical flows of energy. They often use spreadsheets to arrange in tabular form the efficiency in a prescriptive (e.g. impacts from high-efficient technology adoption by end-users) or descriptive manner (e.g. portfolio of technologies resulting from one or various policy instruments). Instead of identifying the behaviour of market agents and resulting outcomes in an energy system, accounting models require users to determine and introduce outcomes beforehand (e.g. technology adoption rates). End-use service demands and change over time due to aggregate macroeconomic and demographic drivers (e.g. population, GDP). Under this taxonomy we found the following models: Long-Range Energy Alternatives Planning (LEAP); National Impact Analysis (NIA); Bottom-Up Energy Analysis System (BUENAS); Model for Analysis of Energy Demand (MAED); and the Policy Analysis Modelling System (PAMS). For a description of these models see section 3.

2.3 Optimisation models

Optimisation models are prescriptive by definition. They attempt to find least-cost solutions of technology choices for energy systems based on various policy and market constraints. Based on the rational model of consumer behaviour, the allocation of energy supplies to energy demands is based on minimum life cycle technology costs at given discount rates and determined by an optimisation approach (linear programming). Constraints can be related, for example, to atmospheric emissions, fuel supply, technological development and capacity utilisation. Under this taxonomy we found, for instance, the following models: Market Allocation (MARKAL) model generator; PRIMES Energy System Model; and the Model of Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE). For a description of these models see section 3.

2.4 Hybrid models

Hybrid models basically merge different methodological components from the above-mentioned types of models. In addition, some hybrid models are also integrated with top-down or general equilibrium models. That is, there is no need for an exogenously determined macro-economic scenario (employment, income effects, economic growth rate, competitiveness, etc.) but endogenous relationships between the economy and energy system take place instead. Some of the reviewed models fall into this taxonomy (see next

section for details of each model). For instance, NEMS combines optimisation, simulation (for each demand sector) and accounting components that provide a general equilibrium system. Likewise, LEAP, PAMS and BUENAS combine elements of simulation and accounting models. In the case of LEAP, the model operates at two levels: (i) built-in basic accounting relationships, such as energy demand and supply, atmospheric emissions, electricity transmission and capacity expansion and costing; and (ii) additional features that modellers can add, such as market penetration of technologies as a function of prices, income level and policy instruments (Heap, 2008).

Modelling tools such MARKAL, MESSAGE, NEMS, WEM and PRIMES can also be coupled with general equilibrium models. For instance in MESSAGE, price-driven energy demands are calculated with MESSAGE-MACRO, which is a macroeconomic top-down module that gives hybrid equilibrium features to the modelling tool. In this case, energy demand curves are given as quadratic functions of energy prices and in two categories: electric and non-electric energy. Energy demands are endogenously determined by MESSAGE-MACRO in a way consistent with the forecasted GDP and energy prices (Messner and Schrattenholzer, 2000) – similar to MARKAL-MACRO (Seebregts et al., 2001).

3. Reviewed energy-economy models

This section provides a description of the energy models under review. In total, twelve different models were analysed. This section focuses on the main structure or components of the model/tool as well as on issues that are of relevance for the household sector. For each category, a sample of modelling tools is given. The sample focuses on the main structure or components of modelling tools; in particular on issues that are of relevance for the household sector. While not comprehensive, the reviewed models attempt to provide a representative sample of these various methodological categories.³ See Table 1.

³ For further details see also Mundaca and Neij (2009).

Table 1: General features of reviewed bottom-up energy modelling tools in which the household sector is included/represented.

Energy modelling tool	Geographical origin	Methodological approach	Household technology representation	Technology-choice decision framework
BUENAS	USA (LBNL)	Simulation/Accounting	Explicit	User-defined
LEAP	USA (SEI)	Simulation/Accounting	Explicit/stylistic	User-defined
MAED	Austria (IAEA)	Accounting	Explicit	Socio-economic and demographic factors
MARKAL	OECD-IEA	Optimisation/Equilibrium	Explicit	Least-cost
MESSAGE	Austria (IIASA)	Optimisation/Equilibrium	Stylistic	Least-cost
MURE	EU (SAVE project)	Simulation	Explicit	User-defined
NEMS	USA (DOE-EIA)	Simulation/Optimisation/Equilibrium	Explicit	Least-cost
NIA	USA (DOE-EIA)	Accounting	Explicit	User-defined/shipment-elastic model
PAMS	USA (LBNL)	Simulation/Accounting	Explicit	User-defined/shipment model
PRIMES	Greece (NTUA)	Optimisation/Equilibrium	Explicit	Least-cost
REEPS	USA (EPRI)	Simulation	Explicit	Ownership, efficiency, use & equipment size sub-models
WEM	OECD-IEA	Simulation/Equilibrium	Explicit	N/A

Before describing the selected energy modelling tools, it is worth noting that the representation of an energy system and the household sector in particular is different under every modelling tool and model as such (i.e. data set). Details of end-use sectors and technology representation depend largely on the energy system under analysis (global, national and regional), the availability of data, and the research goals and questions posed by the research group building the model. While engineering principles and economic information are central to the reviewed modelling tools, the activity representation (i.e. end-use sectors and technology details) can vary considerably across modelling tools and even across data sets using the same modelling tool. Furthermore, the spatial scale, (policy) timeframe and resolution of the reviewed modelling tools can vary significantly.

3.1 Long-range Energy Alternatives Planning (LEAP)

Long-range Energy Alternatives Planning (LEAP) is an accounting framework simulation modelling tool developed at the Stockholm Environment Institute (Boston Centre).⁴ It is widely used in developing countries for integrated resource planning and greenhouse gas (GHG) mitigation assessments. That it is a relevant modelling tool is illustrated by the fact that more than 85 signatories of the United Nations Framework Convention on Climate Change (UNFCCC) use it to report their GHG inventories (Heaps, 2008). As a modelling tool, the main purpose of LEAP is to manage data and results.

LEAP is used to create models of energy system analysis, ranging from energy resources, generation, distribution to end-use across the economy.⁵ It can be used as a database, for simulation purposes and as a policy analysis tool. It can also support historical analysis of energy systems and analyse their economic and environmental impact. LEAP is also a forecasting modelling tool for energy system scenario analysis. It was developed to support studies for time horizons of 20-50 years and can be used to analyse and evaluate the impact of energy/environmental policies. Policies can be modelled to analyse the physical, economic and environmental implications of alternative policy scenarios. LEAP scenarios are based on alternative assumptions on technological progress, economic growth, population, energy prices, environmental constraints, etc. Policy measures can be analysed individually or as a mix of policy measures. For example, modellers can evaluate alternative policy scenarios by comparing the economic and environmental costs of energy demand as a result of a given policy measure.

LEAP is a flexible and easy-to-use modelling tool (Heaps, 2008). Projections of energy and environmental aspects can be made before any cost data are entered into the model under development. Due to its flexibility, LEAP can be used to develop top-down or bottom-up E³ analyses. Thus, the type and depth (i.e. level of detail) of the analysis largely determine the input data requirements for building a given model. Contrary to optimisation modelling tools, which require detailed initial data sets to build models, LEAP data requirements are less intensive. The adaptability of LEAP makes it very difficult to specifically determine input data requirements. In general, input data can be grouped demographically (population, urbanisation rates), economically (GDP, interest rates) and in terms of energy (production, consumption) factors. The modelling in LEAP operates at two levels: (i) built-in basic accounting relationships, such as energy demand and supply, atmospheric emissions, electricity transmission and capacity expansion and costing; and (ii) additional features that modellers can add, such as market penetration of technologies as a function of prices, income level and policy instruments.

3.2 Market Allocation model (MARKAL)

Market Allocation (MARKAL) is a bottom-up optimisation modelling tool developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA). ETSAP supports the use of techno-economic modelling tools at different levels, global, regional, local and assists the development of sustainable economic, energy and environmental strategies. The Second IPCC report acknowledges MARKAL as a modelling tool for evaluating technologies and policies to mitigate GHG emissions (ETSAP, 2005). MARKAL is a widely used modelling tool and its recognition relies on the fact that there are more than 150 teams in more than 50 countries using it.⁶

MARKAL is a model generator that processes the data set(s) that describe a given energy system. As a model generator, it is data-intensive, relying heavily on detailed input to represent global, national, or regional energy systems and their evolution. It is a bottom-up, mostly dynamic linear programming model generator (see Seebregts et al., 2001, for an overview of MARKAL models) with typical projection

⁴ Note that most of the information presented in this section is based on personal communication with Charlie Heaps (January 2009).

⁵ It is expected that LEAP will have capability to support optimisation modelling by 2009.

⁶ For further information visit <http://www.etsap.org/Tools.asp>

capabilities of 40 to 50 years. The source code of MARKAL is written in General Algebraic Modelling System (GAMS), a computer programming language. This source code generates a partial economic equilibrium model as a mathematical programming problem.⁷ In MARKAL, a user-defined Reference Energy System (RES) depicts a network of energy sources, conversion and process technologies (including transmission), energy carriers, demand technologies and end-use sectors. The allocation of energy supplies to energy demands is based on minimum total energy system costs and determined by an optimisation approach. The cost-optimisation process is subject to different constraints, which can be related, for example, to atmospheric emissions, fuel supply, technological development and capacity utilisation, among many others.

The objective function of MARKAL is to find the combination of fuels and technologies that minimises total energy system costs while keeping exogenously determined energy demands satisfied over a given time period. For each time period (t), the model *minimises* the sum of all technologies (k), all pollutants (p), and all input fuels (f) of the various *costs* incurred. In mathematical terms, the *cost minimisation objective function* of the model is formulated as a linear programming problem:

$$\min (TESC) = \min \sum_{t,k,p,f,c} (TechCost_{tk} + OpCost_{tkf} + Imp_{tc} - Exp_{tc} - Salv_{tk} + EmisT_{tp})$$

where *TESC* represents total energy system costs, which are equal to the sum of technology investment costs *TechCost*, operating costs *OpCost* (including fixed and variable technology costs, fuel delivery costs, extraction costs, etc.), import costs *Imp*, revenues from exported energy carriers, *Exp*, the salvage value of technology, *SalV*, and taxes on emissions *EmiT*. Index c refers to the number of energy carriers (imported and/or exported).

3.3 PRIMES Energy System Model

The PRIMES Energy System Model has been under development by the National Technical University of Athens, Greece, since 1993. PRIMES simulates a market equilibrium solution for energy supply and demand within each of the 27 EU member states and seven other European countries. The purpose of PRIMES is to focus on market-related mechanisms that affect the evolution of energy demand and supply, including the framework in which market technology penetration takes place. Similarly, PRIMES serves as an energy policy analysis modelling tool for examining linkages between technology development and energy policy. The EU Commission used PRIMES to support its Kyoto negotiation process in 1997. In the late 1990s PRIMES was also used to generate the EU Energy and Emission Outlook for the Shared Analysis project of the EU Commission, DG XVII.⁸

Driven by engineering and economic principles, PRIMES determines the optimal equilibrium by finding the prices of each energy fuel that match the supply and demand of energy. PRIMES is used for projections, scenario construction and policy impact analysis with a time horizon up to the year 2030, with a five-year time step. The equilibrium generated by PRIMES is static for each time step, but is also found in a time-forward path under dynamic connections. PRIMES is used mainly in the field of energy and environmental policy. This includes analysis of economic impacts of climate change and renewable and energy efficiency policy instruments on energy markets. PRIMES also includes a computable module for the dispersion and deposition of air pollutants (Capros, 2000).

PRIMES is structured around modules that represent different fuel supply (i.e. oil products, fossil gas, coal, electricity and heat production, the so-called ‘sub-system’), energy conversion and end-use demand sectors: household, commercial, transport and (nine) industrial sectors. These modules interact through

⁷ Ibid.

⁸ For further information see Capros (2000).

the exchange of fuel quantities and prices. In turn, this dynamic process leads to global energy system equilibrium. The technological component of the model is explicit and detailed for both the supply and demand sides and also for environmental abatement technologies. The design around ‘modules’ allows the modelling of any single end-use sector or group of end-use sectors. The model is built to generate energy consumption projections for each end-use by fuel.

3.4 Model of Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE)

The Model of Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE) was developed at the International Institute for Applied Systems Analysis (IIASA) as part of its Environmentally Compatible Strategies (ECS) programme. Development of the model was started in 1970 and is continuing. Among many applications, MESSAGE was used to support the formulation of emission scenarios for the IPCC Special Report on Emission Scenarios (SRES). The model describes long-term E3 scenarios (2030-2100).

MESSAGE is a bottom-up engineering optimisation model that addresses primarily the energy supply sector and its economic and environmental impact (Messner and Strubegger, 1995). However, the household sector (along with other end-use sectors) is also represented in the model. Policy scenarios are developed by minimising total system costs under constraints imposed on the energy system. Taking into account this information and other scenario features, such as energy service demand, MESSAGE constructs the evolution of the energy system from the base year to the end of the time horizon in ten-year steps. MESSAGE includes around 400 energy conversion and end-use technologies, covering 11 regions. To find an optimal solution, the model computes all primary energy supply flows that match useful energy demand. This optimisation process is subject to (user-defined) constraints, such as availability of primary energy resources, evolution of energy conversion technologies and a set of useful energy demand in different end-use sectors, including the household sector.⁹ The model calculates an optimal and feasible energy supply technology mix that requires the least total costs and meets a given useful or final energy demand. In other words, MESSAGE determines optimal solution.¹⁰ The combination of resources and technologies that entails the lowest discounted total energy system cost.

3.5 World Energy Model (WEM)

The World Energy Model (WEM) is a simulation bottom-up modelling tool that was developed by the OECD/IEA.¹¹ It has been used by the OECD/IEA since 1993 to provide short- to medium-term energy projections (up to 2030), mostly through the World Energy Outlook publication. Like MARKAL or PRIMES, WEM is a large-scale mathematical simulation tool (containing approximately 16,000 equations) developed to replicate how energy markets work. The main input data come from the IEA’s own statistics and databases. The WEM model has also been coupled with a top-down General Equilibrium Model (GEM) called IMACLIM-R to develop a hybrid modelling framework.¹²

WEM is a partial equilibrium model with a yearly step-based modular structure. As a simulation modelling tool, it generates a quantitative portrayal of exogenously defined scenarios. It requires an enormous amount of historical and economic data which are combined with energy variables. The structure of the WEM model is made up of six modules: (i) final energy demand, (ii) power generation, (iii) refinery and other transformation, (iv) fossil fuel supply, (v) CO₂ emissions, and (vi) investment. In WEM, electricity

⁹ Personal communication with Leo Schrattenholzer (March 2009).

¹⁰ For further information see Schrattenholzer et al. (2004).

¹¹ For further information visit <http://www.worldenergyoutlook.org/model.asp>

¹² For further information see OECD/IEA (2008) and Roques and Sassi (2008).

consumption and electricity prices link both final energy demand and power generation modules. Overall, the activity level of each module is driven by exogenous assumptions regarding economic growth, demographics, international fossil fuels, and technological development (like MARKAL, for instance). Furthermore, primary demand for fossil fuels serves as an input for the energy supply modules.

Overall, WEM was constructed to analyse a number aspects: (i) global energy projections, (ii) environmental impacts of energy use, (iii) effects of policy measures and technological change, and (iv) investments in the energy sector (OECD/IEA, 2008). In this context, it is worth noticing that the reference scenario (i.e. baseline) generated with WEM takes into account several policy instruments already adopted by governments. For instance under the World Energy Outlook, 2007, policies and measures implemented by mid 2007 were included to develop the reference scenario. To support the development of alternative policy scenarios, the IEA has built a database containing more than 3,000 policies in OECD and non-OECD countries.¹³

3.6 Residential End-Use Energy Planning System (REEPS) model

The Residential End-Use Energy Planning System (REEPS) was developed by the Electric Power Research Institute.¹⁴ In general terms, REEPS is a bottom-up simulation modelling tool that allows the evaluation of future energy consumption trends in the household level under various user-defined assumptions and/or for different policy scenarios. REEPS has been mostly used in the USA.

As with many other bottom-up modelling tools, REEPS provides a detailed technology/end-use coverage and is thus very data-intensive. The model offers high flexibility, allowing the modeller/user to modify equations and parameters without changing the source code of the computer programme (Hwang et al., 1994). In turn, the great flexibility offered by REEPS allows the modeller to explore and analyse an extensive range of policies and scenarios with various levels of disaggregation (Kooimey et al., 1995). On the other hand, the flexibility given by REEPS demands that the modeller structures and puts together all the input data. Therefore even if exogenous variables remain the same, a different set of data and parameters generate a different model and projections (McMenamin et al., 1992). In REEPS, modellers work within a common software interface that enables them to concentrate on the analysis as such and evade potential programming errors introduced by changes in the software source code (Hwang et al., 1994), similar to the ANSWER interface when using MARKAL.

According to Kooimey et al (1995) the organization of REEPS model (version 2.1)¹⁵ can be structured in six modules: (i) exogenous inputs (e.g. fuel prices, household income), (ii) housing stock inputs (e.g. number of households, income), (iii) end-use technology inputs (e.g. ownership, efficiency, size, price), (iv) thermal shell inputs (e.g. heat gains/losses, floor area), (v) resulting specific end-use models for technologies based on input data, and (vi) projections (e.g. energy consumption, stock, ownership, purchases). The first four modules listed above form the critical inputs to build the specific end-use models for technologies (i.e. appliances and heating, ventilation and air conditioning [HVAC] technologies).

3.7 Mesures d'Utilisation Rationnelle de l'Energie (MURE)

The Mesures d'Utilisation Rationnelle de l'Energie (MURE) model was developed by a European research team within the framework of the EU-SAVE programme.¹⁶ The model encompasses three main

¹³ Ibid.

¹⁴ For a detailed description of the REEPS model, see Hwang et al. (1994), Johnson et al. (1994) and Kooimey et al. (1995).

¹⁵ Note that the first version of the model (i.e. REEPS 1.0) was based simply on an econometric simulation approach to estimate energy consumption for a given sample of households.

¹⁶ For further information visit www.mure2.com

components. Firstly, MURE entails a comprehensive database of rational use of energy (RUE) measures documented for 15 EU countries and Norway, addressing several end-use sectors, namely, household, transport, industrial and commercial sectors.¹⁷ Secondly, MURE provides a quantitative database that describes the energy system of each country for a base year on a sectoral bottom-up basis level. Third, and in the context of our research initiative, MURE also provides a simulation tool that allows analysis and development of RUE scenarios. The MURE simulation tool aims at estimating potential impacts and costs related to the implementation of policy measures and/or technologies.

An important aspect of the MURE simulation tool is the relationship between measures and technologies. In MURE, the definition of these two terms is crucial. Whereas a ‘measure’ is a policy ‘intervention enacted by the national or local government or energy agency’ to improve energy efficiency, and technology ‘is the means by which energy savings are actually saved’ (SAVE, 1999). The MURE simulation tool calculates the impact of technologies based on two crucial assumptions: (i) each policy measure is associated with one or more technologies and (ii) the impact of the policy measure is the result of the energy performance of the corresponding technologies and their market penetration rate (SAVE, 1999). A given technology can be implemented as a result of one or more policy measures. Therefore, the simulation outcomes are related to the technologies which are driven/triggered by a given policy measure, and not to the measure as such.

The simulation tool was constructed to provide the cumulative effect, starting from a given year, of different energy efficient technologies being triggered by one or more policy measures at a national level. The simulation tool is interactive and contains default values at all stages, with a projections from 2000 until 2025. To generate projections, the MURE simulation tool uses information from the measures, combined with other economic and technical data contained in the database. Key (unitary or cumulative) projections in MURE are potential energy savings and investment costs related to policy measures and technologies. Due to the openness and accessibility of the simulation tool, the modeller can modify nearly all the information contained in the database.

3.8 National Energy Modelling System (NEMS) – Residential Sector Demand Module

The National Energy Modelling System (NEMS) was developed by the Energy Information Administration (EIA).¹⁸ NEMS is an energy-economy modelling system of US energy markets, with a projection horizon until 2030.¹⁹ The purpose of NEMS is to provide projections of domestic energy-economy markets in the long term and develop policy analyses. NEMS is used by the Department of Energy (DOE) of the EIA to produce the Annual Energy Outlook. The model was first used for projections presented in the 1994 Annual Energy Outlook.

NEMS is an integrating hybrid model of the US energy system that generates a general equilibrium solution for energy supply and demand on an annual basis. As a hybrid model, NEMS combines optimisation, simulation (for each demand sector) and accounting components that provide a general equilibrium system. NEMS projects the production, import, conversion, consumption, and prices of energy—all of them subject to a number of assumptions, such as macroeconomic factors, resource availability and costs, technology characteristics and demographics. It provides an inclusive portrait of the energy supply resources and technologies as well as a detailed picture of energy demand across several sectors and end-uses. The organization of NEMS can be divided into six main block and specific

¹⁷ The specific database for the household sector contains approximately 300 policy measures, with a large proportion of command-and-control policy instruments updated to 2002.

¹⁸ For further information see DOE-EIA (2008a, 2008b).

¹⁹ According to the DOE-EIA (2008b), one important and implicit assumption is that there will be no radical changes in technology or consumer behaviour by 2030.

modules: (i) supply modules (i.e. oil and gas, natural gas transmission and distribution, coal market, renewable fuels modules), (ii) conversion modules (electricity market and petroleum market modules), (iii) demand modules (transportation, commercial, industrial and residential) and (iv) a macroeconomic module (i.e. to simulate energy/economy interactions, (v) international energy module (i.e. to simulate world energy/domestic energy interactions and (vi) an integrating model that contains the mechanisms to compute a general market equilibrium among all the modules (DOE-EIA, 2008a). Due to the fact that energy markets are heterogeneous, a single methodology cannot effectively characterize all supply, conversion, and end-use demand sectors. Therefore, the design and development of NEMS involves the flexibility for each component to use the most suitable (regional) methodology (DOE-EIA, 2008a). Thus, the structure of the model entails a system of self-contained modules, each performing a specific and well-defined model function.

Within the scope of our research and as one component of the NEMS model, the Residential Sector Demand Module (RSDM)²⁰ is of prime importance. The NEMS-RSDM is an integrated dynamic modelling system that forecasts energy demand by housing, energy service, fuel and different geographical areas.²¹ In general terms, the NEMS-RSDM is a housing and technology stock energy model. The housing stock and its related set of energy using technologies is tracked for each year of the projection (DOE-EIA, 2008b). The NEMS-RSDM methodology is based on accounting principles and householder consumer behaviour. It consists of a FORTRAN source code with more than 50 sub-routines successively run during the execution of the module. NEMS-RSDM generates forecasts of residential sector energy demand, appliance stocks and technology market shares (DOE-EIA, 2008b). NEMS-RSDM seeks to: (i) provide a disaggregated projections of energy demand for the household sector for the period 2005-2030; (ii) investigate and suggest legislation; and (iii) generate inputs such as the Electricity Market module, the Petroleum Market module and the Natural Gas Transmission and Distribution module. Policy measures might include fiscal incentives for energy efficiency investments, private sector initiatives, such as voluntary agreements and technological developments (new end-use technologies) that have an impact on the household sector. The module outputs generated contribute to the overall estimation of a general equilibrium solution for energy supply and demand (DOE-EIA, 2008b). Furthermore, the NEMS supply modules use the outputs from the residential module to calculate energy consumption patterns and the resulting prices for energy delivered to the household sector (DOE-EIA, 2008b).

3.9 National Impact Analysis (NIA) tool

The National Impact Analysis (NIA) is one the different spreadsheet analytical tools that the DOE-EERE (Energy Efficiency and Renewable Energy) office uses to develop and assess minimum energy efficiency performance standards for specific product types, such as residential appliances) in the USA.²² The NIA tool is part of and supported by a wider analytical framework composed of the following tools: (i) market and technology assessment, (ii) life-cycle costs (LCC), (iii) engineering analysis and (iv) shipments analysis. Market and technology assessment characterises the relevant product markets, existing technology options and prototype designs. Life-cycle costs make an assessment from the consumer's perspective of the LCC of the subject technology with the LCC of the technology chosen in the absence of standards. Engineering analysis determines the relationships between costs and efficiency of the subject technology. Shipments analysis projections estimates of sales of the subject technology and the market shares by product class (DOE-EERE, 2007).

The overall objective of NIA is to support the national rulemaking decision processes concerning Minimum Efficiency Performance Standards (MEPS). NIA provides quantitative assessments of

²⁰ Note that there is a specific sector demand module for each end-use sector contained in the NEMS model.

²¹ Based on the so-called 'census division', the following geographical areas are covered: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific.

²² For further information visit http://www1.eere.energy.gov/buildings/appliance_standards/

aggregate impacts of new standards at national level. NIA generates national energy savings and the net present value (NPV) of efficiency standards of total consumers. Key inputs for determining national energy savings are: (i) annual energy consumption per unit, (ii) shipments, (iii) equipments stock, (iv) national energy consumption and (v) site-to-source conversion factors. Key inputs for determining the NPV are: (i) total annual installed costs, (ii) total annual operating costs, (iii) discount factor, (iv) present value of costs, and (v) present value of savings (DOE-EERE, 2007).

3.10 Policy Analysis Modelling System (PAMS)

The Policy Analysis Modelling System (PAMS) was developed by the Collaborative Labelling and Appliance Standards Program (CLASP), an initiative started in 1996 at the Lawrence Berkeley National Laboratory (LBNL). PAMS aimed at providing an ‘easy-to-use’ modelling tool to support policymakers, in particular those from developing countries, in estimating and evaluating costs and benefits of standard programmes (CLASP, 2006). PAMS was developed to operate over the widest geographical spectrum and with a minimum of detailed input data. PAMS includes basic modelling inputs for more than 150 countries and can be used as an ‘out-of-the box’ tool with no supplementary research needed to perform the analysis (CLASP, 2006). Furthermore, where country-specific data are available, the modeller can customise PAMS in key areas in order to improve the accuracy of projections.

PAMS is a bottom-up tool for modelling the impacts of MEPS.²³ It uses techno-economic specifications for different appliances (refrigerators, room air conditioners, washing machines) to ascertain policy costs and benefits of MEPS. The model analyses one technology and one country at a time. The modelling tool is a self-contained Excel spreadsheet that analyses at (i) household level and (ii) aggregate national level. At household level, PAMS examines the impact of performance standards by looking at costs and benefits based on LCC calculations, taking into account capital and operating costs. At national level, PAMS projects total costs and benefits of the consumer market, which include calculations addressing primary energy savings, the NPV of national policy implementation, and resulting carbon emission reductions (CLASP, 2006). Note that some methodological elements of the NIA tool described in the previous section provide various analytical foundations to PAMS, such as approach to estimate impacts at national level and use of LCC calculations at household level).²⁴

3.11 Bottom-Up Energy Analysis System (BUENAS)

The Bottom-Up Energy Analysis System (BUENAS) forecasting model was developed by the Energy Analysis Department at the LBNL with funding from CLASP.²⁵ BUENAS focuses on energy efficiency standards and labelling programmes. The model takes some components of PAMS, such as uptake of appliances, to look at energy in the building sector and analyse policy programmes covering the whole world.²⁶ Both PAMS and BUENAS were developed in the same analytical framework that focused on MEPS. With a particular emphasis on developing countries, BUENAS integrates known technological opportunities with the experience gained in terms of end-use demand and forecasting markets for end-use technologies (McNeil et al, 2009).

BUENAS takes an engineering-economic approach that projects energy consumption for each end-use, addressing the household and commercial sectors at global level (McNeil et al, 2008). Like WEM, REEPS

²³ PAMS might be extended to labelling programmes (see CLASP, 2006).

²⁴ Personal communication with Michael McNeil (June 2009)

²⁵ For further information see McNeil et al. (2008, 2009).

²⁶ Note that there are two key elements of PAMS not included in BUENAS. First, BUENAS does not include utility prices—at global level—so the model does not calculate consumer utility costs savings as PAMS does. Secondly, BUENAS does not contain engineering cost data for optimizing MEPS based on LCC (Personal communication with Michael McNeil, February 2009).

or NEMS, the structure of the BUENAS modelling tool is based on a modular approach that contains three modules: (i) activity forecast, (ii) unit energy saving potential, and (iii) stock accounting. Taking into account different macroeconomic drivers, such as household income, the first module estimates current energy demand and forecasts energy demand growth by end-use and by country or region (see next section for details). At the unit level, the second module takes into account the final energy used to supply or satisfy those energy services in the base case, and generates high-efficiency scenarios based on technology meeting a given efficiency target for a given period of time. The third module takes account of market penetration rates and stock turnover of the energy efficient equipment under analysis (McNeil et al, 2008). Finally, as for instance with NEMS, all modules are pulled together in BUENAS. Energy savings are calculated by comparing energy consumption in the base case to energy consumption level under constructed policy scenarios for end-use sectors.²⁷ No financial analysis can be undertaken with BUENAS.

3.12 Model for Analysis of Energy Demand (MAED)

The Model for Analysis of Energy Demand (MAED) was originally developed by the Institute Economique et Juridique de l'Énergie (IEJE) of the University of Grenoble, France.²⁸ Later, the International Atomic Energy Agency (IAEA) took the latest version of the MEDEE model and introduced several changes, such as input data parameters and a module for estimating hourly electricity consumption in order to make it more suitable for developing countries (IAEA, 2006). The MEDEE model was renamed MAED, starting life as a DOS-based system but later upgraded to Windows' Excel.

The MAED model relies on a bottom-up approach. Starting from a base year it projects future final energy demand based on medium to long-term development scenarios driven by socio-economic, technological and demographic determining factors (IAEA, 2006). In MAED, the model outcome (future final energy demand) for each end-use category is aggregated into four main end-use sectors: (i) industry (including agriculture, construction, mining and manufacturing); (ii) transportation; (iii) service; and (iv) household. The methodology embedded in MAED reflects structural changes by associating energy demand for producing various goods/services with key parameters that affect this energy demand (Hainoun et al., 2006). That is, the nature and demand level for goods/services are a function of numerous determinants, which include population growth, GDP, energy prices, market penetration of new technologies or energy forms, number of inhabitants per dwelling, number of electrical appliances per household, peoples' mobility and preferences for transportation modes, efficiency trends for certain types of equipment, etc. (Hainoun et al., 2006; IAEA, 2006). The structure of the MAED model is organized around two modules. The MAED_D addresses the economic sectors, sub-sectors and end-use activities included in the model. It computes all the information involved in the scenarios and calculates the total final energy demand for the analysed period. This module is needed to input all the data and view the results. MAED_EL is used to determine the total electric power demand for each hour of the year (i.e. hourly electric load). This module uses the total annual final demand of electricity for each sector as calculated in MAED_D.²⁹

A critical element in MAED is the internal consistency of the assumptions driving social, economic and technological evolution that frame the development of a given scenario. This is because the model output (i.e. future energy demand and corresponding demand for energy services) is simply a 'mirror image' of the scenario assumptions (IAEA, 2006). The expected future trends for each determining factor, which form the basis to build the scenarios in MAED, are exogenously introduced by the modeller (IAEA, 2006). Therefore, the consistency of the model outcomes depends heavily on the understanding that the modeller has of the interrelation and dynamics of various determining factors (IAEA, 2006).

²⁷ Using the same modular structure, the model developers envision that more end-use sectors and policy approaches - in addition to MEPS - will be developed and included in the model (see McNeil et al., 2009).

²⁸ For further information see IAEA (2006) and visit <http://www.iaea.org/OurWork/ST/NE/Pess/PESSEnergymodels.shtml>

²⁹ See IAEA (2006) for further details.

MAED provides a methodical accounting framework for evaluating the effect on energy demand as a result of changes in the technological and socio-economic system under analysis (IAEA, 2006). As with many other reviewed models, the starting point for using the MAED model is building the base year energy consumption patterns within the model. Not surprisingly, MAED is very data-intensive. Thus, there is the usual and time-consuming task of collecting and bringing together statistical data, calculating numerous input parameters and reconstructing the base year (i.e. calibrating the model).

4. Key drivers of energy demand and end-use service coverage

This section describes the drivers behind energy demand and end-use service coverage for each of the modelling tools under review. Note that the term *energy service* refers to the delivered benefits of useful end-use energy consumption, such as heating, refrigeration, lighting, cooking, transportation, etc., as opposed to the simple provision of units of energy as such (see Blok, 2006; Johansson and Goldemberg, 2002).

In LEAP, the forecasting of energy demand is the result of two variables, (i) activity levels and (ii) energy intensity.³⁰ In the case of the household sector, the number of households can be used to represent the activity level. Then the modeller has to collect historical data and future projections of the chosen activity level variable. In the likely case of future projections being missing or difficult to obtain, LEAP has different built-in tools that allow users to choose the type of forecast trend for making projections (e.g. interpolation, exponential, linear, logistic). When it comes to energy intensity, the data requirements are much more challenging than is the case with activity level, particularly so if a detailed analysis is desired. With statistical information at hand, historical energy intensity values are calculated as the result of total energy consumption of the household sector divided by the chosen activity level. In the case of fuel consumption, fuel intensity values are calculated as the product of total fuel consumption, for example electricity in the household sector, divided by the activity level. To project energy demand, LEAP can be used to project the product of energy intensity and the chosen activity level. Due to lack of information, assumptions are likely to be made by the modeller. Depending on the input data, energy demand results can be estimated for different fuels, time-steps, regions and end-use sectors and sub-sectors of the economy. However, demand forecast might not be consistent with forecasted supply configuration (Heaps, 2002).

A detailed engineering bottom-up input data and analysis is necessary to derive end-use in LEAP.³¹ This approach attempts to describe how different fuels are used across different end-use sectors and energy technologies. Concerning the household sector, the database covers the following categories of energy services: cooking, lighting, space heating and cooling, building shells, water heating, and appliances. Depending on the level of detail of the analysis, the modeller needs to collect data about technical parameters of end-use technologies, such as efficiency level, investment and O&M costs, lifespan and emission factors for each of the end-uses in the household sector. To support this process, and because there are challenging and time-consuming obstacles to the building of an inclusive technological catalogue, LEAP includes a built-in technology and environmental database. This database includes a large number of technologies, providing details about technical features, costs, environmental-related aspects, etc.³²

When it comes to energy demand in MARKAL, the modelling tool requires exogenous projections of energy service demands. Therefore, one can safely say that MARKAL is a demand-driven modelling tool. Input data regarding energy service demands are specific to the model so it is not possible to generalise. For instance, the System for Analysis of Global Energy markets (SAGE), undertaken by the Energy Information Administration (EIA) of the US Department of Energy (DOE), examines a wide range of global energy issues.³³ SAGE integrated a set of regional MARKAL models for the development of the International Energy Outlook 2003. In SAGE, 15 regions are identified, based upon political, geographical and environmental factors. Input data regarding energy service demands have been developed using

³⁰ Personal communication with Charlie Heaps (January 2009).

³¹ Ibid.

³² Ibid.

³³ The entire documentation of the model and a detailed data implementation guide can be found at [http://tonto.eia.doe.gov/ftpoot/modeldoc/m072\(2003\)1.pdf](http://tonto.eia.doe.gov/ftpoot/modeldoc/m072(2003)1.pdf) and [http://tonto.eia.doe.gov/ftpoot/modeldoc/m072\(2003\)2.pdf](http://tonto.eia.doe.gov/ftpoot/modeldoc/m072(2003)2.pdf)

economic and demographic projections.³⁴ The demands for energy services are exogenously determined and grouped into five end-use sectors: household, commercial, agriculture, industry and transportation. The model contains input data from the year 2000 up to a time horizon of 2050. The SAGE model is in five-year steps.

For the specific case of the MARKAL SAGE model for Western Europe, the data are aggregated so figures represent average estimates for a single geographical coverage.³⁵ Projections of energy service demand were estimated by the DOE-EIA in 2003 from information on energy-use patterns, existing and available new technologies and potential sources of primary energy supply for the countries of the EU 15 and Norway. Input information was also supported using economic and demographic projections. Population and GDP projections were based on official data from the United Nations and EIA-DOE (see Table 2).

Table 2: Key drivers to determine exogenous energy service demands for the Western Europe MARKAL model under SAGE

Driver	No	2005	2010	2015	2020	2025
GDP (1997 billions US\$)	1	10,378	11,694	13,125	14,724	16,395
Population (millions)	2	391	391	389	387	385
GDP/Population	3	27	30	34	38	43
Housing stock total (millions)	4	152	155	158	161	164

Data source: DOE-EIA (2003, Vol. II: 101)

For the specific case of energy service demands for the household sector, exogenous-determined values are shown in Table 3. As one can observe, the housing stock was the main driver to estimate exogenous energy service for the household in Western Europe under SAGE.

³⁴ Africa, Australia and New Zealand, Canada, Central and South America, China, Eastern Europe and the Former Soviet Union, India, Japan, Mexico, the Middle-East, the rest of Asia, South Korea, the USA, and Western Europe.

³⁵ The model includes the following countries/regions: Austria, Belgium, Denmark, Finland, France (including Monaco), Germany, Gibraltar, Greece, Greenland, Iceland, Ireland, Italy (including San Marino and the Vatican), Luxembourg, Malta, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland (including Liechtenstein) and the United Kingdom.

Table 3: Exogenous energy service demands (in Petajoules) for the household sector in the Western Europe MARKAL model under SAGE. The final column indicates the key driver used to forecast energy service demands (as shown in the second column in Table 2)

Energy service demand in the household sector	2005	2010	2015	2020	2025	Driver
Cooling	41	42	43	43	44	4
Clothes drying	12	13	13	13	13	4
Clothes washing	2	2	2	2	2	4
Dishwashing	2	2	2	2	2	4
Other electronics	79	97	114	133	152	3
Space-heating	5 152	5 271	5 366	5 462	5559	4
Hot water	720	737	750	764	777	4
Cooking	272	278	283	288	293	4
Lighting	25	26	27	27	28	4
Refrigeration	29	29	30	30	30	4

Data source: DOE-EIA (2003, Vol. II: 99)

When it comes to end-use and related energy services, bottom-up optimisation models such as MARKAL rely heavily on high information needs related to detailed technological data sets. The bottom-up construction of MARKAL requires data to describe how energy is used across different end-use sectors and by numerous technological devices. Thus, a critical input to the model relates to the pool of existing and future technologies and all related technical and cost information. Depending on the extent of the energy system under analysis, the development of a comprehensive data set for MARKAL to determine energy use is a complex and time and resource intensive process, which requires a high level of technical expertise. For instance under the SAGE project, each single technology is characterised using a number of parameters: capacity factor, technical efficiency, fuel input, capital and O&M costs, market penetration rates, discount rate, lifetime, initial year of deployment, etc. End-use and corresponding energy services in the household sector were structured according to the categories shown in Table 3.

In PRIMES, an essential assumption is that producers and consumers of energy respond to changes in fuel prices (Capros, 2000). Consequently, energy demand is a function of energy prices, and commonly evaluated at an EU national level. Prices can be subject to user-constraints resulting, for instance, from the modelling of policy instruments, such as subsidies. The equilibrium condition is that consumer and producer energy prices (use in demand sector plus taxes) are equalised. Prices of purchased fuels depend, among other factors, on cost-supply curves that are exogenously specified, but operate within the equilibrium process embedded in the model.³⁶ Through a continuous process, PRIMES determines the economic equilibrium (and demand) for each fuel. Factors affecting the demand for each fuel can be analysed and provide a basis for an approach concerning the behaviour of energy consumers. By an

³⁶ These fuel cost-supply curves are used for all primary energy supply, including EU gas supply, coal, biomass and even renewable sources to reflect land availability constraints.

optimisation process, costs related to final energy demand consider: (i) endogenous choice of equipment (vintages, technologies and learning); (ii) endogenous investment in energy efficiency (savings); and (iii) endogenous purchase of associated energy carriers and fuels (Capros, 2007).

In PRIMES, the critical data needed to calibrate the model in terms of energy consumption (including the household sector) for a base year and country are: (i) macro-economic data related demographics, sectoral activity, and income variables; (ii) structured energy consumption and activity variables, such as number of dwellings; and (iii) technical and economic data for energy technologies and end-use sectors, such as investment costs, lifetime and efficiency. For the specific case of the household sector, the following variables/indicators are used: (i) household income; (ii) household size; (iii) population; (iv) number of households; and (v) discount rate (E3Mlab, 2005). The basic data source for energy consumption on a sector and fuel basis for PRIMES is Eurostat.

In the case of end-use and associated energy services in PRIMES, the household sector includes five categories of dwellings. In the model, they are defined according to the main technology used for space heating: (i) central boiler household; (ii) electric heating household; (iii) individual gas heating household; (iv) district heating household; and (v) partially heated household. The model further structures end-use and corresponding energy services in the following categories: (i) space heating; (ii) cooking; (iii) water heating; and (iv) air conditioning. It is worth noticing that electric appliances for non-heating and cooling, such as washing machines, dishwashers, dryers, lighting, refrigerators and television sets are considered as a special sub-sector in the household sector. This is independent of the type of dwelling.

MESSAGE is mainly oriented to optimise future energy supply and energy demand in MESSAGE is exogenous. Data input depends on many assumptions regarding energy efficiency improvements and end-use technologies. These are given in an aggregate manner, i.e. overall energy intensity improvements or reduction – lower useful energy demand per unit of GDP (see Schrattenholzer et al., 2004). Therefore, it is assumed that higher economic growth (i.e. assumed GDP trajectory) has a positive impact on energy intensity. Energy demands for six end-use sectors (including the residential) are calculated using a separate spreadsheet model, the ‘Scenario Generator’; which is used to convert quantitative assumptions related to the development of the overall final energy intensity of GDP. This supportive modelling tool is used to combine historical energy and economic data with empirically estimated equations of energy demand trends to determine structural change (Schrattenholzer et al., 2004). This ‘Scenario Generator’ produces forecasts of final energy demand that are consistent with user-defined scenarios and historical trends. Energy demands coming from the ‘Scenario Generator’ are transferred to MESSAGE and remain unchanged. However, in the case of price-driven energy demands, these are calculated with MESSAGE-MACRO, which is a macroeconomic top-down module that gives hybrid features to the modelling tool. In this case, energy demand curves are given as quadratic functions of energy prices and in two categories: electric and non-electric energy. Energy demands are determined by MESSAGE-MACRO in a way consistent with the forecasted GDP and energy prices (Messner and Schrattenholzer, 2000). MESSAGE provides a framework for representing an energy system with the most critical energy relationships, going from resource extraction to the provision of energy end-use services, such as lighting and space conditioning.

In WEM final energy demand is a function of different variables. Firstly, ‘activity variables’ play a significant role. GDP or GDP per capita seem to dominate this type of variable in the model. Secondly, end-use international energy prices are also used. They also include transformation and distribution costs and variable and fixed taxes. Thirdly, ‘other variables’ such as structural and technological change are also taken into account to forecast energy demand. For the specific case of the household sector in WEM, energy demand is estimated for each fuel (coal, oil, gas, electricity, heat and renewables) and end-use as a function of (i) GDP, (ii) fuel prices, (iii) population, and (iv) household stock. For non-OECD regions, WEM determines energy consumption also econometrically by correlating GDP, fuel prices and the lag of energy consumption. The parameters included in the demand side equations are estimated with an econometric model using input data from 1971-2005.

As a common feature for most of the bottom-up energy modelling tools reviewed in this report, WEM's environment is technologically rich and designed to forecast different end-usage, including forecasts for 21 regions of base and alternative policy scenarios. In the model, the coverage of end-uses and related energy services is: (i) space heating; (ii) water heating; (iii) cooking; (iv) lighting; and (v) appliances. For each end-use, energy intensity and fuel shares are forecast econometrically and combined with average energy prices. Key modules that determine fuel consumption by end-use are: (i) per household consumption by fuel and end-use; and (ii) number of households using each fuel by end-use. For the specific case of electricity demand, this is determined by electricity price, household income, and the option to switch to other energy fuel that provides the same energy service. Long-term price elasticities in the model range from 0.4 to 1.3.

The REEPS model forecasts energy demand in terms of how much energy is used for what purposes in the household sector over time (Kooimey et al., 1995). Note that the REEPS model uses a simulation sample of representative households as the crucial element for forecasting. In turn, the sample forecasts are scaled up to generate population forecast (Cowing and McFadden, 1984). Energy consumption is driven by two important input data sets: (i) exogenous input variables; and (ii) housing stocks input variables. Exogenous input variables include fuel prices (oil, gas, electricity, etc.), availability of technologies and household size. This input data set is used to forecast the overall macroeconomic conditions in which energy and technology-related predictions take place (Hwang et al., 1994). When it comes to the housing stock inputs, variables included are, for instance, housing stock as such (i.e. numbers of houses occupied in the base year and by house type), vintage blocks (i.e. houses existing in a given year versus houses built after that given year), decay rates (i.e. rate at which houses are removed from the housing stock), household size and household income. Energy consumption is then forecasted using the technological and behavioural parameters as well. Importantly, instead of using a distribution of values for each parameter, REEPS uses data in the form of an average value within a market segment, such as house type or income. Whereas a distribution of values would better represent the actual situation, the data structure in REEPS could potentially introduce cumulative bias in the forecast (Hwang et al., 1994; Johnson et al., 1994).

In REEPS, input data from exogenous and housing variables are critical inputs for end-uses. They are used as drivers to forecast the size, characteristics, and usage of the appliances and HVAC generic technologies (Hwang et al., 1994; Johnson et al., 1994). As mentioned above, REEPS models in detail technology choices and determines how much energy is used for what end-use purposes over the analysed period. The coverage of end-use and corresponding energy services in the model is large, corresponding to seven categories: space heating, water heating, central air conditioning, room air conditioning, cooking, dishwashing, lighting and other, such as residual (Cowing and McFadden, 1984; Kooimey et al., 1995). Exogenous end-use technology inputs are needed and are specific to each energy service. Likewise, inputs related to the thermal shell are needed and used only in the HVAC model (Kooimey et al., 1995). For each generic appliance and HVAC technology, REEPS estimates, among other things, purchases (for existing households as well as new ones), size/capacity, efficiency, stock, ownership, (unit) energy consumption (Kooimey et al., 1995). In addition, forecasting outputs can be disaggregated per fuel type within end-uses; per house type; and in terms of new homes versus the entire housing stock (Kooimey et al., 1995). REEPS enables users to design tailored models for various energy end-uses in the household sector so each end-use can be developed with its own structure, data, and energy-related relationships, such as capital costs and chosen efficiency (Kooimey et al., 1995).

In MURE, energy demand is driven by the household stock growth rate. On a country basis, the modeller can either use the default figures contained in the database or modify them. For the reference scenario, the household growth rates are used to estimate the energy demand under the assumption that the specific energy consumption per household (i.e. tonnes of oil equivalent per dwelling) by 1995 (base year) remains constant (SAVE, 1999). Dwellings are split into two categories: (i) individual (i.e. single family); and (ii) collective (i.e. multi-family dwelling with four floors and four flats on each floor). Whereas this is the default configuration in MURE, figures can be modified. Then, the stock of dwellings is also split in three

categories in terms of age, with variations according to countries and, in particular, for heating: (i) old dwellings (i.e. built with stones/bricks before 1945); (ii) intermediate dwelling (i.e. built 1945-1950 in reinforced concrete before insulation was required under building regulations); and (iii) new dwelling (i.e. built after insulation was required). For instance, energy demand contained in the database for the reference year is presented in terms of energy consumption per fuel and type of dwelling. Likewise, energy use can be forecasted per type of dwelling. Whereas energy services are not explicitly addressed, end-use is disaggregated in different technology levels on a country-to-country basis. For instance, end-use can be estimated separately for appliances and sanitary hot water – unitary or cumulative figures – so related energy services can be inferred.

As for NEMS-RSDM, key drivers for determining energy demand are the (forecasted) household stock and its geographic location. The latter is a critical factor that determines the intensity of space heating (DOE-EIA, 2008b). In the model, three types of housing are represented: (i) single-family homes; (ii) multi-family homes; and (iii) mobile homes. For the base year (i.e. 2005), figures for the number of houses are derived from EIA Residential Energy Consumption Survey (DOE-EIA, 2008b). Forecasting for occupied households is made individually for each geographical area, following the so-called ‘Census Division’.³⁷ The forecasting approach is based on the combination of the previous year’s surviving stock with forecasted housing starts provided by the NEMS Macroeconomic Activity Module (MAM). In the model, a constant survival rate of the housing stock is assumed (i.e. the percentage of households present in the current projection year but also present in the preceding year) for each type of housing unit (DOE-EIA, 2008b). Thus, the model forecasts housing stock and energy demand per household. MAM’s baseline economic forecast contains the initial economic assumptions used in the NEMS model to support the determination of energy demand and supply, such as population, personal disposable income, and housing starts by geographical location and housing type (DOE-EIA, 2008a). Other drivers for energy demand are fuel prices, population and technology features. The model characterizes energy demand using an algorithm that takes into account the stocks of housing and appliances, technology market share, and energy intensity. Generally, NEMS-RSDM forecasts household energy demand in six sequential steps: (i) forecast housing stock; (ii) choose technology; (iii) forecast appliance stock; (iv) choose building shell; (v) choose distributed generation equipment; and (vi) estimate energy consumption (DOE-EIA, 2008b).

The NEMS-RSDM model allows the examination of end-use in great detail – like many other models reviewed in this report. Energy consumption is forecasted for each energy service, fuel and geographical location. The coverage of end-use services in the model is very comprehensive. It includes sixteen categories: space heating, space cooling, clothes washers, dishwashers, water heating, cooking, clothes drying, refrigeration, freezing, lighting, colour TVs, personal computers, furnace fans, other appliances, secondary space heating, distributed generation (i.e. fuel cells and PV equipment) . In turn, the model also generates disaggregated forecasts for appliance stocks and efficiency for the majority of the appliances used in a household (DOE-EIA, 2008b). The technology characteristics used in NEMS-RSDM include capital costs, equipment efficiency, and corresponding expected lifetimes.

For the NIA tool, national energy savings are estimated as the difference between national energy consumption of the product stock, using average unit energy consumption (UEC) of the stock in the base case (i.e. scenario without minimum standards, and the national consumption in the policy case (i.e. scenario with minimum standards). The product stock depends on the number of sales (or shipments) in past years and a survival function. Technology shipments are forecasted as a function of the capital costs and also driven by fuel costs and the projected housing stock – see next section for more details on ‘shipment model’. The survival component of the product is as a function of equipment vintage or ‘years-since-purchase’ in the model (DOE-EERE, 2007). It is assumed that units have an increasing probability of retiring as they age. To support the annual energy consumption on a unit basis, the characterization of technology used in NIA is mostly derived from the engineering and LCC analyses. These analyses are

³⁷ See footnote #20.

based on the following variables, including technology efficiency/performance, fuel prices, manufacturing costs, capital costs (for purchase and installation), operational and maintenance costs, corresponding technology lifetime, and a (real) discount rate.

The NIA tool has been used to assess minimum energy efficiency performance standards for numerous technologies and related end-uses. For instance, analyses have addressed fridge-freezers, furnaces and boilers, central air conditioners, heat pumps and fluorescent lamps.³⁸ The analyses then address end-use services such as space heating, space cooling, lighting, etc. Within the framework of different analytical tools in which NIA is used, the market and technology assessment provides market structures and product classes, which also address existing and past technologies as well as prototype designs as inputs to establish which technologies can be used to meet higher performance standards (DOE- EERE, 2007).

Similar to various cases described above, the estimation of energy consumption is crucial to determine energy savings in PAMS, i.e. energy savings are calculated by comparing the national energy consumption of the product in the base case to the national energy consumption of the same product in the policy case. Total energy consumption of the technology/product stock is the product of two factors: (i) unit energy consumption (with and without minimum standards); and (ii) the total technology stock – understood as the number of equipment vintage remaining in each year. At the unit level, the UEC is defined as the ‘typical annual energy usage for each class of equipment, according to local patterns and climate conditions’ (CLASP, 2006:5). To determine the technology stock and thus national energy consumption, critical inputs in PAMS are: (i) ownerships estimates; and (ii) shipments, or sales (CLASP, 2006). For the former, PAMS bases its projections of end-use consumption on an econometric-ownership driven model that determines national ownership rates as a function of household income, electrification and urbanisation. In turn, the determination of ownership rates allows the estimation of: (i) product shipments/sales (or likely adoption rates); and (ii) total technology stock in the model. Estimates from the ‘shipment model’ are crucial, as only those high-efficiency technologies sold after the date of the programme implementation generate energy savings. Considering national ownership rates, the total product stock is forecast taking into account the number of products that operate in each year and the rate at which the inefficient and old products are replaced by new and efficient ones as a result of MEPS (CLAPS, 2006). PAMS describes the replacement of an appliance as the probability of retirement, something that varies according to the lifetime of the equipment. Replacements in PAMS are estimated from earlier shipments, a generic time dependence on retirements, and the mean lifetime of technology (McNeil et al., 2006).

The BUENAS model forecasts demand for energy in the household sector through ‘module 1: activity forecast’. To estimate current and future energy demand, BUENAS models demand for energy services (i.e. activity) at the end use level. This is parameterised by appliance diffusion (i.e. average number of a given appliance per household) (McNeil et al., 2008). Along the same lines as the LEAP simulation/accounting tool, an ‘activity’ in BUENAS is understood as a measure for the demand of energy (services) that correlates with economic growth (i.e. GDP growth). In fact, it is argued that the model is well suited to illustrate changes in energy demand as a result of alternative economic scenarios (McNeil et al., 2009). In the household sector, ‘activity’ is depicted in terms of ownership of appliances and lighting technologies. Using a logistic function that depicts the penetration of appliances in households, appliance ownership (i.e. measure of activity) is forecasted according to an econometric ‘diffusion model’ that uses readily-available national data inputs (see McNeil et al., 2009). That is, BUENAS models the diffusion econometrically by associating diffusion rates with macroeconomic variables (GDP, which is exogenously determined) and using linear regression analysis (McNeil et al, 2008). Bearing in mind the similarities with the PAMS model, BUENAS models the diffusion of appliances such as refrigerators and washing machines as a function of: (i) household income (i.e. GDP divided by number of households); (ii) electrification; and (iii) urbanisation. The underlying assumption behind forecasted energy demand is that ownership rates in developing countries will reach similar levels observed in developed countries, as the

³⁸ For further information visit http://www1.eere.energy.gov/buildings/appliance_standards/

income level of the former reaches the level of the latter. Finally, BUENAS covers a wide range of end-use services, ranging from refrigeration, cooling, heating, and lighting—among others.

The MAED model focuses entirely on the projection of energy demand and corresponding demand for energy services across different end-use sectors. In the model, future energy demand is forecasted as a function of a scenario that depicts a given possible development. As mentioned in the previous section, the MAED model projects energy demand based on medium- to long-term development scenarios, which in turn are driven by socio-economic, technological and demographic factors. In turn, each scenario encompasses two components: (i) the socio-economic system that describes the essential features of the social and economic evolution of the country under analysis; and (ii) technological factors that need to be taken into account for the calculation of energy demand, such as equipment efficiency and market penetration rates (IAEA, 2006). For the household sector, the key determinants for energy demand are demographic (population, number and type of dwellings, household size, etc.) and technological (efficiency and fuel penetration for space and water heating and cooking; heat insulation by type of dwelling). Population lifestyle and related economic parameters are also of significance as they affect the type and amount of energy services like penetration of air conditioning and specific electric consumption.³⁹ For instance, increased income increases electricity consumption per dwelling as a result of more use of electronic equipment (Hainoun et al., 2006). All these determinants form the basis for future energy demand under each scenario analysed. The projected future trends for each determinant are exogenously determined (IAEA, 2006). Again, the consistency of the model outcomes depends heavily on the understanding that modeller has of the dynamics and interrelation of various determining factors that conform with the scenarios under study (see IAEA, 2006).

As in the case of other reviewed models, the MAED model allows examination of end-use in great detail. In the model, energy demand is disaggregated into a large number of end-use categories; each one corresponding to a given service. MAED-2 (the latest version) was developed to allow the modeller to enlarge the pre-defined energy demand structure according to needs and/or data availability. According to the model developers, MAED-2 provides a flexible framework to disaggregate energy demand in each economic sector (see IAEA, 2006). For the household sector, the following end-use service categories are covered: (i) space heating; (ii) water heating; (iii) cooking; (iv) air conditioning; and (v) appliances (IAEA, 2006).

³⁹ Personal communication with Ali Hainoun (April 2009).

5. Technology choice and related decision-making factors

This section focuses on the decision-making rules/factors for technology choice embedded in the reviewed energy modelling tools.

As an accounting framework modelling tool, it is worth noting that in LEAP the modeller explicitly accounts for the outcomes of decisions instead of simulating decisions of energy consumers and producers. For example, instead of estimating the market share based on prices and other variables, LEAP is used to examine the implications of a scenario that achieves the given market share or given technology penetration rates.⁴⁰ The modeller relies on expert knowledge for setting likely technology adoption targets resulting from the implementation of policy instruments.

In MARKAL, technology choice is driven by both economic and technical parameters. As is the case with many optimisation bottom-up modelling tools, decision-making rules for technology choice in MARKAL are driven by economic factors, such as energy prices, discount rates, capital and O&M costs; and technological information about the efficiency and emissions of current and future energy-using devices. Technology choice is based on life cycle costs. The allocation of energy supplies and thus an optimal set of technologies to satisfy given energy service demands is based on minimum total energy system costs. In other words, MARKAL finds the least expensive combination of technologies across the energy system to meet exogenous energy service demands. Feasible solutions are obtained as long as all the end-use demands for energy services are met during the time horizon analysed. The optimisation process is performed under user-defined constraints. MARKAL allows the introduction of user-defined constraints that can represent a variety of policy scenarios, such as a cap on CO₂ emissions, limited capital for investment, share of renewable, availability of fuels. Such factors affect technology choice and the way energy is used across end-use sectors.

The degree of technological detail in the representation of the energy system in MESSAGE is flexible and depends on the research topic/area under analysis. The model is constructed by specifying detailed performance characteristics of the technological stock and determining a Reference Energy System that includes all the potential energy relationships in the model (Klaassen and Rihai, 2006) – similar to MARKAL, for instance. The specificities of the technological stock are user-defined and technology choice is also driven by economic, technical and environmental parameters. MESSAGE finds out how much of the available technologies and resources are deployed and used for meeting a particular end-use demand—which can be subject to various user-defined constraints, such as air emissions, while minimizing total discounted energy system costs (Klaassen and Rihai, 2006; Schrattenholzer et al., 2004). As mentioned in the previous section, MESSAGE does not compute energy prices so the model is based entirely on (dynamic) cost information (IPCC-SRES, 2000). This is why the model is linked to the MESSAGE-MACRO module (see Messner and Schrattenholzer, 2000).

In PRIMES energy use is price-driven and the model simulates in detail technology choices. PRIMES entails an explicit representation of end-use technologies, including the current stock of equipment, its expected phase-out, and the option of early replacement. As in any bottom-up model, the explicit technological representation is needed to address the physical constraints on energy conservation and energy use. Technology choice is made on economic grounds, which can be affected by policy instruments, market conditions, and changes in the technological environment, including endogenous learning and the continuous maturity level of emerging technologies. Any technological device operates at the energy use level and uses energy fuel(s).

The behaviour on the demand side in PRIMES, including the household sector, is driven by an optimisation process that aims to minimise total energy and environmental costs related to useful energy

⁴⁰ Personal communication with Charlie Heaps (January 2009).

needs, energy use capacities and technology availability and constrains on environmental emissions. In PRIMES, decisions are represented as a budget allocation problem, in which useful energy is allocated to different uses and processes. In the model, energy use is directly linked to energy service demands that need to be satisfied. These energy services are further linked to changes in energy prices and household income. The methodology for the demand sectors assumes economic agents optimising an economic objective function, which for the household sector is utility maximisation. Or, to put it another way, comfort. Within this optimisation process, the following aspects are considered: (i) the mix of different production processes and/or end uses; (ii) the fuel mix; (iii) capacity replacement; (iv) technological choices; (v) the degree of internal energy conversion; (vi) energy savings; (vii) abatement technologies; and (viii) pollution permits. Decision-making rules of technology choice are based on ‘perceived cost’, which reflects total technology costs, including its supply, and the acceptability of technology by the end-user. These two cost elements can change endogenously in the model. For instance, when an emission cap is applied, end-users may perceive new technologies more profitable than the standard ones. The new technology becomes more acceptable and its market penetration is further facilitated by decreasing technology supply costs. In turn, this process, leads to lower costs for meeting the emission cap. Another example can be related to the likelihood that a given appliance is selected for a household. This probability is calculated as a function of total perceived cost and of the maturity of equipment, so that inter-fuel substitution is constrained. Total perceived costs are a function of capital, maintenance and the fuel (operating) costs of the equipment, as well as of the household’s income. In the model, these dynamic projections represent different conditions over time for technology choice, acceptability and technology supply effects (E3Mlab, 2005). Decision-making rules are subject to end-user/exogenous policy constraints, in the form of taxes, subsidies and new technologies with perceived costs reduced in the eyes of the purchaser.

As regards emerging technologies, PRIMES considers their market potential based on: (i) economic optimality; (ii) constraints on existing capacity; and (iii) gradual penetration and acceptance. By definition, PRIMES treats advanced technologies as significantly more capital intensive. But once the adoption of emerging technologies becomes marginally cost-effective their market penetration triggers technological effects that lead to associated learning curves in terms of capital costs. With due consideration for time limitations for energy system adjustment, this technology supply-side effect contributes to the acceleration of adoption of the new technologies by the end-users. As a result, the mechanism allows for lower adaptation costs for the energy system and higher market penetration for demand-side technologies. According to the model representation, end-users may accelerate (or decelerate) the adoption of more energy efficient technologies, by normal replacement of the device or perhaps its early replacement.

In REEPS, decision-making rules for technology choice (or consumer purchase’ decisions) are modelled based on the so-called ‘state’ of the household/decision-maker (e.g. ownership of technologies, household features). Within this model framework, REEPS uses empirical values. The control year was 1991, in which four decision models forecast decisions made by households during the process of owning and operating household energy-use technologies (Kooimey et al., 1995). These decision models focus on the following aspects: (i) ownership; (ii) efficiency-choice; (iii) usage; and (iv) equipment size. Based on base-year data and numerous parameters, each decision models calculate the corresponding value of these four key variables. These values are then pulled together with exogenous forecasted variables, such as households stock, fuel prices and household income, to provide an estimate of the household sector energy consumption of all of end-use technologies included in the model. Values for numerous behavioural and technological parameters for each decision model must be supplied by the modeller. Each decision model can be characterised as follows:⁴¹

- The ‘ownership decision model’ is a discrete choice model. Within this specific decision model, each generic technology is characterised by utility functions based on exogenous variables,

⁴¹ For further details see Hwang et al. (1994), Johnson et al. (1994) and Kooimey et al. (1995).

- The ‘efficiency-choice decision model’ is a multinomial logit choice model that forecasts the level of efficiency chosen by the end-user for a specific type of household technology.⁴² On the whole, this decision model represents the relationship between purchase price and chosen efficiency. It improves the estimates of the ownership model by specifying efficiency options that are characterised by utility functions based on purchase price and operating costs.
- The ‘usage decision model’ estimates energy use for each individual technology on an annual basis, i.e. it forecasts the intensity of usage of technologies. For instance, for cooling-related technologies, the usage depends on the following variables: floor area (by housing type), heat gain multiplier, efficiency of cooling equipment type, price of fuel used by cooling equipment, average household disposable income (by housing type), and average number of household members (by housing type).
- The ‘size/capacity decision model’ is used to forecast the size/capacity of refrigerators and freezers and HVAC systems. For all of the other technologies, the size/capacity value is normalised to 1.0 so they are not explicitly modelled. The size of refrigerators and freezers is determined by the specific efficiency choice model but usage is constant.

In MURE, a critical aspect to consider when forecasting cumulative results is the decision taken by the modeller as to how much of the current and future housing stock will implement the technologies analysed. Thus, decision rules for technology choice in MURE are similar to the ones found in the LEAP accounting/simulation tool. That is, the modeller accounts for the outcomes of the decisions rather than modelling the decision of end-users as such. In this context, the simulation methodology encompasses the following steps: (i) the selection of one or more policy measures; (ii) the selection of the technologies being stimulated; (iii) the definition of the energy performance of the selected technologies; and (iv) their respective market penetration rate. Therefore, MURE is used to examine the implications of policy scenarios that stimulate the adoption of one or more technologies that deliver certain efficiency gains and meet a given and exogenously determined market penetration rate. Assumptions regarding the future efficiency performance and diffusion of technologies are thus critical for the simulation outcomes.

Technology choice in NEMS_RSDM is based on a log-linear function and entails the following key variables: (i) capital costs; (ii) operating and maintenance costs; (iii) equipment efficiency and lifetime; (iv) market share of new appliances; (v) efficiency of retiring technology; and (vi) appliance penetration factors. The log-linear function allocates market shares for competing technologies within each end-use service based on the relative weights of capital and operating costs, discounted annually (DOE-EIA, 2008b). In the model, market shares are calculated for: (i) equipment decisions related to new housing construction; and (ii) replacement decisions. A time dependent function calculates the capital cost of technology in new construction based also on a log-linear function. A critical input for technology choice comes from fuel price projections (i.e. operating costs) generated by the NEMS supply module and the technology unit energy consumption (UEC) – as a function of technology efficiency. Both fuel prices and technology UEC determine the operating costs. If fuel prices increase noticeably and stay high over time, more energy efficient technologies are available earlier in the forecasted period than would have been the case otherwise (DOE-EIA, 2008b). The functional form in the model provides flexibility so it allows the modeller to specify/modify a number of parameters, such as retail technology cost and technology switching cost. According to DOE-EIA (2008a), the characteristics of technology are exogenous to the model and

⁴² Note that efficiency-choice is not modelled for certain end-use services such as cooking and lighting.

attempt to reflect Federal standards and expected market changes. Taking into account logistic shape parameters⁴³, a time dependent function estimates the retail cost of replacement technology (DOE-EIA, 2008b).

A complementary approach to technology choice in NEMS was developed by LBNL. In addition to the aspects described above, three different decision components were used to model a tax rebate (more details in next section). In this case, the consumer response to a tax rebate (and resulting shipments) is divided into two components: (i) the ‘announcement effect’, which represents the consumer response to the tax rebate, independent of the rebate level; and (ii) the ‘direct price effect’, which represents the consumer response to the rebate level as such (see Koomey, 2000 and Richey, 1998). In addition to these two effects, one must bear in mind the indirect effect of the ‘progress ratio’ (or so-called ‘increased production experience effect’) which reduces capital costs, similar to the ‘direct price effect’ of the tax rebate (Richey, 1998). These decision components were introduced by LBNL to the original NEMS model.

Due to the nature of the NIA tool, which is focused on MEPS, technology choice of the efficient equipment is determined by the modeller, which accounts for the outcomes of the household decisions rather than modelling the decision of end-users as such. However, the NIA tool requires specific inputs to support adoption rates for given efficient technologies due to the introduction of performance standards. As mentioned in section 3.9, a ‘shipment analysis’ is carried out to forecast estimates of sales and market shares by product class in the presence and absence of new MEPS. To generate projections of shipments, the DOE-EIA developed the so-called ‘shipment model’ that accounts for technology used to replace retired units, technology shipped to new homes, and technology installed due to fuel switching, specifically of residential furnaces and boilers (see DOE- EERE, 2007). The ‘shipment model’ is based on accounting principles that forecast the sales of units and market shares based on the range of lifetimes of the equipment. Two important drivers are found to play a critical role in this specific model. Firstly, outcomes from the model are partly driven by historical shipments. For instance, in the case of residential furnaces and boilers, it is argued that shipments are historically increasing due to: (i) the increased housing stock; (ii) more technologies reaching their retirement age; and (iii) the increased saturation of central heating in new homes (DOE- EERE, 2007). Secondly, the sales of equipment and thus the adoption of technology and the resulting market share are also a function of capital and operating technology costs, including those for installation and maintenance (DOE- EERE, 2007).

In addition, it was found that an ‘Accounting Model with Elasticity’ (i.e. a revised version of the shipment model mentioned above) is also used to forecast market share (or adoption rate) by product class in the NIA tool (e.g. as regards clothes washers). Key parameters in this accounting model include: (i) combined effects of price, operating cost, features and other macroeconomic explanatory variables (income, credit, etc.) on annual U.S. shipments; (ii) market segments (new housing and moves, replacement decisions, non-owner adding a washer); (iii) decisions to repair rather than replace; (iv) purchases of used washers; and (v) age categories of clothes washers (DOE-EERE, 2000). Price-elasticity coefficients are also used. Concerning the ‘decisions’ parameters in the accounting model, they are described in terms of ‘probabilities that typically depend on the type of stock, the age of the clothes washer, the incremental cost of the decision, and market conditions. The probability of two subsequent decisions in the same year is equal to the product of the two individual decision probabilities. The dependence of decision probabilities on price and market conditions is given by a standard econometric logit equation’ (DOE-EERE, 2000:9-8). Thus, a logit purchase probability model is also used to describe consumer decisions and support the calculations of the accounting model.

Technology choice for the PAMS model is similar to the case described for the NIA tool. Due to the nature of the PAMS model, which is oriented towards MEPS, technology choice of the efficient equipment is determined by the modeller/user. First, adoption targets are based on expert knowledge.

⁴³ Note that the logistic function (S-shape) is commonly used in consumer choice models.

Then, and to support technology adoption rates, PAMS uses a ‘shipment model’ that calculates the number of sold high-efficiency products that are affected by MEPS at any given time in the forecasted period. Product sales, or likely adoption rates, are driven by the increase in households owning appliances as in developing countries where the ‘first purchase’ is said to be the dominant driver, or by the replacement of aging appliances, as in developed countries, where equipment ownership is likely to be saturated (CLASP, 2006). Because PAMS is oriented to support policy makers in less developed countries, the ‘first purchase’ is of prime importance and is determined by the number of households in each year and the corresponding ownership rate, as described in Section 4. According to the model developers, the ‘first purchase’ in the less developed world is the combined effect of rapid economic growth, urbanisation, electrification and housing stock (CLASP, 2006).

Technology choice in the BUENAS forecasting model is determined by the modeller.⁴⁴ Due to the fact that BUENAS originated from a research work addressing MEPS, the model relies on expert knowledge of best practices for setting likely technology adoption targets resulting from the implementation of MEPS.⁴⁵ Related information and assumptions come mostly from international work carried out within the CLASP initiative.⁴⁶ It is important to bear in mind that BUENAS models the uptake of high-efficiency appliances, with a strong focus on developing countries. Thus, the modelling of energy demand comes from the purchase of a given appliance rather than technology choices from different equipment models, contrary to the case in developed countries where ownership is already saturated. Unlike PAMS, the estimation of shipments or sales to support adoption rates under BUENAS poses serious challenges (because of its global scope) so it is basically not done. This is because the model is used to analyse all end-uses in all regions around the world – and not on a country-by-country basis as is the case with PAMS. Sales data availability for each country can be taken as a remarkable example of how cumbersome it would be to integrate a ‘shipment sub-model’ in BUENAS to cover the whole globe (McNeil et al., 2008).

Technology choice in the MAED model is determined by numerous parameters. First, two critical elements and corresponding datasets play a critical role: (i) living conditions of the population (i.e. the place or residence; which involves separate calculations for urban and rural areas); and (ii) the type of dwelling – up to 10 different categories can be defined for both rural and urban areas. According to the model developers, this approach allows a better representation of the needs of individuals, including their lifestyle and the definition of potential markets for competing forms of final energy.⁴⁷ Secondly, technology choice is also driven by corresponding market availability of technologies and penetration rates. In turn, market penetration rates are also driven by demographic, socio-economic and technological parameters. For instance, new efficient technologies can be linked to (higher) GDP per capita.⁴⁸

⁴⁴ Personal communication with Michael McNeil (February 2009).

⁴⁵ Ibid.

⁴⁶ For further information visit <http://www.clasponline.org>

⁴⁷ Personal communication with Ali Hainoun (April 2009).

⁴⁸ Ibid.

6. Exploring modelling approaches to energy efficiency policy evaluation

This section analyses the modelling approaches to energy efficiency policy under the energy models described above. In total, 21 case studies were analysed (see Table 4). The cases were randomly chosen based on a literature review which entailed the following selection criteria: a) availability and accessibility of data/information; b) applicability to the household sector; c) recent or updated information; d) material that has undergone some kind of peer review process. Personal communication with researchers involved in these modelling exercises was also undertaken. The case studies illustrate, to some degree, sometimes to a large extent, the application of the reviewed models to the field of household energy efficiency policy evaluation. The following research questions were used to guide the approach:

- What is the main research goal? What kind of evaluation is carried out?
- How are barriers to increased energy efficiency treated in the modelling tool? Are they implicitly considered in some parameters/variables? If so, which ones?
- What energy efficiency policy instruments are modelled? How are they modelled? What are the key elements/determinants used to mimic these policy instruments in the modelling tools?
- Are discount rates used in the model? If so, to what level?

6.1 *Main research evaluation goals*

Basically all the reviewed cases have their own specific research goals. Therefore, no generalisations can be made. On the whole though, three main categories of research goals were identified: (i) to demonstrate use of a given energy modelling tool; (ii) to focus on impact policy evaluation; and (iii) to explicitly evaluate one or more energy efficiency policy instruments.

First, and to a limited extent, one can note that the research goal is to simply demonstrate the use of a given modelling tool to forecast or simulate energy efficiency technologies, such as the MURE and PAMS models. For instance the studies carried out by Eichhammer (2000), Fenna (2000) and McNeil et al. (2006) are quite explicit in this regard. In general terms, these reviewed case studies aim to show the use of the models to forecast the impact of policy-driven efficient technologies. This research goal implies the early development stage of certain energy models and thus the need to test and validate them at the time of carrying out those modelling exercises. Within the context of evaluating models as such, we found the study carried out by Cowing and McFadden (1984). This focuses on a detailed comparative evaluation between the REEPS model and the Oak Ridge National Laboratory (ORNL) model.

Table 4: Reviewed case studies addressing energy efficiency policy in the household sector

Reference	Energy model	Geographical focus	Policy instruments implicitly (I) or explicitly (E) analysed
Morales and Sauer, 2001	LEAP	Ecuador	DSM and IRP programmes (e.g. labelling, audits, technology transfer, financial incentives) (I)
Kadian et al. 2007	LEAP	India	Subsidy removal (on kerosene); subsidies; energy labelling and performance standards (E)
Yanbing and Qingpeng, 2005	LEAP	China	Minimum performance standards, building codes, labelling on household appliances, awareness raising campaigns, etc. (I)
Schulz et al., 2008	MARKAL	Switzerland	Per capita energy consumption cap and CO ₂ emission targets
Kannan and Strachan, 2009	MARKAL	UK	CO ₂ emission reduction targets
Božić, 2007	MARKAL	Croatia	DSM measures, CO ₂ and fuel taxes (E)
OECD/IEA, 2008	WEM	World	N/A
Cowing and McFadden, 1984	REEPS	USA	Minimum performance standards (E)
Koomey et al., 1995	REEPS	USA	No policy instruments as such are explicitly modelled. However, exogenous inputs for baseline development include minimum efficiency performance standards.
Eichhammer, 2000	MURE	Germany	Building codes, minimum performance standards and product labelling (E)
Faberi and Enei, 2000	MURE	Italy	Building codes, minimum performance standards and product labelling (E)
Fenna, 2000	MURE	UK	Building codes, minimum performance standards and product labelling (E)
Richey, 1998	NEMS	USA	Tax credits (E)
EIA, 2005	NEMS	USA	Tax credits, minimum performance standards, and building codes (E)
DOE-EERE, 2007	NIA	USA	Minimum energy efficiency performance standards (E)
DOE-EERE, 2000	NIA	USA	Minimum energy efficiency performance standards (E)
McNeil et al., 2006	PAMS	Central America	Minimum energy efficiency performance standards (E)
Iyer, 2007	PAMS	India	Labelling endorsement programme (E)
Van Buskirk et al., 2007	PAMS	Ghana	Minimum energy efficiency performance standards (E)
McNeil et al., 2008	BUENAS	World	Minimum energy efficiency performance standards and labelling endorsement (E)
Hainoun et al., 2006	MAED	Syria	A variety of policy instruments are assumed, such as standards, labelling, support for micro renewable energy technologies) (I)

Secondly, most of the reviewed case studies have policy impact evaluation as their research goal. Note that *impact* policy evaluation is different from *outcome* policy evaluation (EEA, 2001; Fischer, 1995; Hildén et al., 2002; Vreuls et al., 2005). Whereas an *outcome* is understood as the response to the policy instrument by subject participants (e.g. adoption processes of new technologies, development of new business plans), an *impact* is understood to be the resulting changes generated by outcomes on society and the environment (e.g. emission reductions, energy saving potentials or given energy consumption patterns). In the context of the analysed case studies, research goals in relation to impact policy evaluation range from the quantification of GHG emission reductions as a result of increased energy efficiency to the study of CO₂ emission reductions and resulting economic implications, including the description of future energy use and energy efficiency potential by end-use. For instance, the study carried out by Kadian et al. (2007) with the LEAP model analyses the energy use and quantifies associated emission from the household sector in Delhi, India. Likewise, Morales and Sauer (2001) focus on GHG mitigation for the household sector in Ecuador also using the LEAP model. The modelling exercise carried out by Schulz et al. (2008), with MARKAL, assesses intermediate steps and corresponding implications for achieving the 2000 Watts society in Switzerland. Using REEPS, Koomey et al. (1995) analyse future energy use by end-use for the US residential sector, assessing which end uses grow more rapidly over time. Another example relates to the work carried out by McNeil et al. (2008) with the BUENAS model, which estimates the global potential reductions in GHG emissions by 2030 resulting from energy efficiency improvements in the household and commercial sectors.

Thirdly, and to a much larger extent, the majority of the case studies focus on the explicit research goal to assess one or more energy efficiency policy instruments and related policy scenarios. For instance, the modelling work done by Yanbing and Qingpeng (2005) with LEAP focuses on the impacts related to the implementation of different policy instruments targeting the Chinese building sector. Using MARKAL, the research goal of Bozic (2007) is to evaluate the impacts of DSM measures and taxes, among others energy policy instruments, for a group of islands in Croatia. All the reviewed modelling exercises carried out with NEMS also entail the explicit research goal to analyse a variety of policy instruments in the building sector, such as taxes, performance standards and building codes. Likewise, the reviewed modelling exercises using NIA concentrate explicitly on the research goal to evaluate minimum efficiency standards. Using PAMS, van Burskirk et al. (2007) focus also on standards and Iyer (2007) on labelling endorsement programmes.

When analysing the research goals of the case studies, our findings are consistent with the fact that the limited number of energy efficiency policy evaluation studies has traditionally targeted the narrow, albeit challenging area of impacts, in terms of energy savings, emission reductions and energy savings costs (cf. Boonekamp, 2005; Harmelink et al., 2007; SCR et al., 2001; Swisher et al., 1997). Due to their bottom-up nature, all the reviewed modelling exercises and corresponding models build upon elements of outcome policy evaluation, in particular by detailed analysis of the future competition of energy end-use technologies in the household sector. A good example of this is the modelling work carried out by Kannan and Strachan (2009) which aims to explicitly explore technological pathways and related costs to meet CO₂ emission reductions by 2050 in the UK.

6.2 Modelling approaches to address market imperfections for household energy efficiency improvements

At the risk of stating the obvious these days, energy efficiency improvements are constrained by a number of market imperfections. Among others, information asymmetries, high transaction costs, the ‘principal-agent’ problem, lack of incentives for careful maintenance, external costs of energy production/consumption not included in energy prices, etc. prevent the realisation of energy efficiency improvements (Jaffe and Stavins, 1994a; Jochem et al., 2000; Sanstad, 1994). Within the context of our research project, the question is how and to what extent market imperfections are captured in the reviewed modelling exercises.

When it comes to the case studies, market imperfections are not generally captured in the modelling exercises – at least explicitly. One can assume that market imperfections are at least partly taken into account in the *historical data* used for setting the baseline or a given scenario for analysis. For instance, the work done with the NEMS model considers that ‘the reference case projections are business-as-usual trend forecasts, given known technology, technological and demographic trends, and current laws and regulations’ (EIA, 2005:9). Similarly, the work done with the NIA modelling tool uses a ‘shipment model’ that forecast shipments of efficient technologies based partly on historical trends to set the baseline case. The modelling work done with MURE considers that a given scenario ‘represents the continuation of current autonomous trends with no additional support in terms of legislation, grants or information campaigns’. The work done by Kadian et al. (2007:6200) assumes in the business-as-usual scenario that ‘historical trends will continue’. In other words, one can infer that ‘existing’ market imperfections remain in place under business-as-usual or baseline scenarios. However, no details are given regarding those specific and existing market imperfections or how previous market imperfections have been already reduced or overcome due to the existing portfolio of policy instruments. A more explicit attempt is made by Morales and Sauer (2001), in which several market barriers are mentioned. These include lack of information and high initial cost of technologies. There is an implicit understanding that these are incorporated in the baseline scenario because it is stated that ‘no substantial changes will result from specific measures or introduction of energy conservation programs’ (Morales and Sauer, 2001:51-52). However, no further details are given.

At this point, regardless how explicit or implicit market imperfections are taken into account, it is important to consider that household behaviour in relation to efficient technology choice and market imperfections is likely to change over time. Therefore, the explicit or implicit assumption that market imperfections are considered in historical data is part of the evaluation challenge itself. One could argue that historical data is inadequate to evaluate and forecast technology futures in relation to market imperfections and under evolving policy conditions (Kooimey, 2000; Worrell et al., 2004). Furthermore, it is very likely that decision-making frameworks of future generations that are affected by market imperfections will be different or more complex than the ones we are at least partly aware of today. This aspect is very applicable when analysing the role of new household technologies for which no or very limited past data yet exist, such as micro wind-energy turbines.

Another way of representing market imperfections is through an assumed *high (implicit) discount rate*. The use of high discount rates departs from the fact that there is extensive literature showing that consumers use high implicit discount rates for the non-adoption of energy-efficient technologies.⁴⁹ There is compelling evidence that consumers use high implicit discount rates (100 or 200 percent and even much higher), hindering the adoption of efficient technologies (see Gately, 1980; Hausman, 1979; Howarth and Sanstad, 1995; Jaffe and Stavins, 1994a, 1994b; Lutzenhiser, 1992; Metcalf, 1994; Ruderman et al., 1987; Train, 1985).⁵⁰ Consequently, high implicit discount rates cause greater financial hurdles to be set for efficient technologies than for conventional ones. According to the reviewed literature, specific causes of high implicit discount rates include a lack of information about cost and benefits of efficiency improvements, a lack of knowledge on how to use available information, uncertainties about the technical performance of investments, a lack of sufficient capital to purchase efficient products (or capital market imperfections), income level, high transaction costs for obtaining reliable information, risks associated with investments, etc. (Gates, 1993; Metcalf, 1994; Ruderman et al., 1987; Train, 1985). Ownership status is regarded as a relevant socio-economic explanation for high implicit discount rates (Train, 1985). Hausmann (1979) and Train (1985) also argue that implicit discount rates vary inversely with income

⁴⁹ Note that implicit discount rates are estimated by the REEPS model assuming infinite device lifetime. For instance, estimated implicit discount rates are 69 percent for refrigerators, 91 percent for freezers, 120 percent for standard electric dryer, 62 percent for standard gas dryer, from 63 to 200 percent for water heaters (electric, gas and oil), 111 percent for dishwasher, 391 percent for washing machine, from 7 percent to 33 percent for HVAC equipment.

⁵⁰ Implicit discount rates are often estimated by comparing future savings in operating costs with initial capital or purchase costs (see e.g. Hausman 1979; Train 1985; Huntington, 1994).

category.⁵¹ The modelling work done by Bozic (2000) with MARKAL includes discount rates for efficient technologies higher than the overall (social) discount rate of 8 percent used for the whole energy system. For space and water heating the rate is set at 15 percent and for electric appliances 20 percent.⁵² As in MARKAL, discount rates can also be used to approach market barriers within the optimisation components embedded in PRIMES (see Capros, 2000).⁵³

Once policy instruments are modelled, high discount rates are then lowered to reflect 'real' or 'social' rate levels to simulate or mimic household preferences for energy-efficient technologies in response to policy instruments (such as information campaigns and certification programmes). Due to the fact that the use of high implicit discount rates may be a function of asymmetric information, bounded rationality, and/or transaction costs, it is argued that it is possible to assume that policy instruments may affect the implicit discount rate used by consumers by targeting those market imperfections (Howarth and Sanstad, 1995). However, this modelling approach has been criticised. First, the literature points out numerous limitations to infer inefficient behaviour from such high implicit discount rates. These include omitted transaction costs that householders are likely to bear; miscalculation in equipment costs and/or energy savings; and need for compensation for risk (Huntington, 1994; Jaffe and Stavins, 1994a, Sutherland, 1991). Furthermore, it is argued that household investments in energy-efficient appliances might correctly use high discount rates because these investments are illiquid, risky and, for example, in the case of home insulation have long payback periods (Andersson and Newell, 2002; Sutherland, 1991).

On the other hand, the use of high implicit discount rates to represent market imperfections should be compared to the modelling approach of using 'real' or 'normal' discount rates – as also used in other reviewed modelling exercises. Real or normal discount rates are often applied in the modelling studies under the assumptions of 'well-defined consumer preferences' and 'unbounded rationality'.⁵⁴ Consequently, their use generates optimistic penetration rates for efficient technologies. The reviewed cases indicate that the real or private discount rates applied are in the range of 3-20 percent. For instance, the PRIMES model uses a discount rate of 17.5 percent for the household sector and the NIA tool uses discount rates of 3 and 7 percent to assess minimum energy efficiency performance standards.⁵⁵ Once the future costs of capital, operation and maintenance, fuel consumption, abatement control equipment, etc. are calculated and translated into present values using real discount rates, many energy-efficient technologies emerge as profitable and attainable under different policy scenarios. However, this modelling approach has been criticised because of the critical assumptions mentioned above and also because a single ex-ante financial estimate of lifecycle costs embodies the full ex-post social costs of technology choice (Bataille et al., 2006; Jaffe and Stavins, 1994a).

6.3 Policy instruments and corresponding modelling approaches

A large number of policy instruments are evaluated, either explicitly or implicitly, in the reviewed modelling exercises taken as case studies. These include energy taxes, tax-credits, subsidies, building codes,

⁵¹ Train (1985) argues that the relationship between low income category and high implicit discount rates can be explained partly by low-income households having less access to capital markets and less liquid capital to invest than higher-income households. As a result, even given adequate information on investment returns, lower-income households will still be unable to invest in efficient technologies unless complementary economic instruments are in place.

⁵² Personal communication with Helena Božić (March 2009).

⁵³ In addition, PRIMES includes numerous formulations and parameters that can influence technology choice and the growth rate of emerging technologies. For instance, the model includes 'learning-by-doing' curves, parameters that can represent perceived technology costs by end-users, etc. The representation of these non-economic aspects in the model attempts to capture market barriers that prevent the adoption of the cost-effective technologies.

⁵⁴ Note that discount rates are not used in BUENAS as there is no financial and economic analysis.

⁵⁵ To assess the costs and benefits of performance standards, PAMS uses real discount rates for the determination of cost-benefit and social discount rates for the evaluation of national impacts. Both rates are user-defined; however, consumer discount rates are parameterized by PAMS according to the Human Development Index. In addition, the default national discount rate is set at 10 percent.

product labelling, and minimum performance standards (see Table 4). It is important to bear in mind that different sets of assumptions, geographical scope, modelling tools, technological databases, research frameworks and resulting outcomes make the reviewed case studies very case and context specific.

In terms of identified policy instruments being evaluated with the energy modelling tools previously reviewed, the majority of the cases focus, either implicitly or explicitly, on minimum performance standards and building codes. One explanation for this lies in the fact that some of the selected models were specifically developed for such purpose (e.g. PAMS, NIA, BUENAS). In the reviewed cases, they capture most of the research interest. A possible explanation is the relatively simple modelling approach needed to do so. The way the modellers represent or mimic these policy instruments in the models is mainly through modification of efficiency rates, technology market availability and penetration rates (more details below). For instance in the REEPs model, efficiency standards can be modelled by restricting the 'legal' and 'market' availability of given technologies (through exogenous inputs for 1990-2030). In cases in which policy instruments are only implicitly analysed, a lack of methodological details prevented any further judgement.

In addition to performance standards and building codes, the majority of the policy instruments being modelled are economic in nature. This seems to be consistent with the historical development of energy efficiency policy in general, where we have witnessed a substantial use of economic instruments, such as rebates, subsidies, taxes and soft loans (Vreuls et al., 2005). Taxes and subsidies dominate the area of economic policy instruments being modelled. In general, the identified modelling approach for these economic instruments involves the effects on capital and operating costs and the resulting adoption rates. For instance in the NEMS and MARKAL models, rebates used in demand-side management programmes can be modified at the equipment level. Given the economic-engineering orientation of the reviewed models, this seems to be the simplest modelling approach, as economic criteria are used as the major drivers for technology choice. An exception can be found in Richey (1998), in which a tax rebate is assessed using a more elaborated modelling approach. In this particular case, efficiency criteria for technologies qualifying for a tax rebate are set, mostly based on expert opinion. Then current market share of high-efficiency or qualified technologies are estimated/extrapolated, based on current market shipments data for the generic technology. Next baselines of high-efficiency technology shipments are determined based on available data and mostly expert opinion. Capital costs of high-efficiency technologies are estimated based on current installed cost data. Importantly, a 'progress ratio' of 20 percent (based on experience curves) is used to forecast decreases in future capital costs relative to currently installed costs data due to increased production experience. Then the consumer response to a tax rebate is estimated. Here, the tax rebate is calculated in terms of the increase in market share due to the rebate and resulting forecasts of high-efficiency technology shipments. In turn, the consumer response to a tax rebate and resulting shipments is divided into two components: (i) the 'announcement effect', which represents the consumer response to the tax rebate, independent of the rebate level; and (ii) the 'direct price effect', which represents the consumer response to the rebate level as such.⁵⁶ In addition to the 'announcement' and 'direct price' effects, one has to bear in mind the indirect effect of the 'progress ratio' (or so-called 'increased production experience effect') that reduces capital costs—similar to the 'direct price effect' of

⁵⁶ According to Richey (1998:4) 'a 10 year, 20 percent tax rebate is assumed to yield a 10 to 12 percentage point increase in market share (or best case shipment forecast in the case of fuel cells and gas heat pumps) for the high-efficiency technology by the end of the rebate period. As the rebate level and period length change relative to the 10 year, 20 percent benchmark, the increase in market share changes proportionally. For example, a 10 year, 20 percent rebate for electric heat pump water heaters yields a 10 percentage point increase in market share, with the announcement effect claiming 7 percentage points of the increase and the price effect claiming 3 percentage points of the increase. A five-year, 20 percent rebate for electric heat pump water heaters yields a 5 percentage point increase in market share, with the announcement effect claiming 3.5 percentage points of the increase and the price effect claiming 1.5 percentage points of the increase. A 10 year, 10 percent rebate yields an 8.5 percentage point increase in market share, with the announcement effect claiming 7 percentage points of the increase and the price effect claiming only 1.5 percentage points of the increase'.

the tax rebate.⁵⁷ On the whole, the work done by Richey (1998) avoided the modelling approach of simply reducing the capital costs of subject efficient technologies under a tax rebate programme.

Informative policy instruments were identified as being much less modelled compared to economic ones. These types of instruments, include communication campaigns, rating labelling of equipment, educational and advice centres. They work through the provision of information or knowledge as crucial components in accomplishing or preventing social change. The rationale behind informative instruments is that market agents possess asymmetric information, meaning they lack some of the knowledge necessary to reach the right decisions. In some reviewed cases, non-economic/regulatory instruments, such as awareness raising campaigns and labelling endorsement programmes are addressed (see Kadian et al., 2007; Hainoun et al., 2006; Yanbing and Qingpeng, 2005). However, a lack of explicit modelling methodological details prevents any analysis and judgement in this regard. In other cases, the modelling approach is simplified to the extent that technology adoption targets driven by these policy instruments are based on expert knowledge (see e.g. McNeil et al., 2008). Alternatively, higher market shares for qualifying technologies in comparison with standards technologies are set under modelling exercises addressing labelling programmes (see Iyer, 2007). From our review of case studies, one can safely say that the modelling and evaluation of policy instruments addressing consumer behaviour through informative policy instruments remains a challenge for the modelling community. The dominance of economic and engineering determinants for technology choice embedded in the reviewed models gives little room for the representation of these specific policy instruments.

When it comes to the determinants used to model the identified policy instruments, the majority of the reviewed case studies have addressed policy instruments through technical factors and costs of measures for energy efficiency improvements. This simply confirms the economic/engineering paradigm that dominates and drives bottom-up energy modelling tools. Again, this approach departs from the critical assumption that we can mimic policy instruments using economic criteria as the primary driver for decision making and corresponding household technology choice. Here, numerous aspects deserve our attention:

- Most of the reviewed models offer various economic and engineering ‘handles’ that allow the modelling of policy instruments. For all the reviewed cases, technological advancement in equipment design and efficiency, driven by different options, are modified at the equipment level. The so-called ‘policy handles’ in REEPS include a variety of economic and engineering factors, among them energy prices; functional forms and coefficients for choice equations; pre-failure replacement/conversion decision algorithms; restrictions on legal or market availability of specific technologies; and modification of the purchase price and efficiencies of specific technologies. Similarly, the reviewed modelling exercises with MARKAL reveal the usage of technical and economic parameters, such as energy intensity levels or efficiency ratios, O&M costs, emission factors, energy prices, capital costs, discount rates, and technology market shares (more details below). The modeller also has the possibility of modifying a number of parameters in NEMS-RSDM for performing policy analyses. For instance, building shell features can be adjusted in the NEMS-RSDM model to represent building codes or the impact of energy-efficient financial incentives. Once again, this finding confirms that energy efficiency policy instruments and related technology choice in the household sector can only be modelled as functions of economic and engineering variables.
- Taking a closer look at the economic and engineering determinants used to model policy instruments, some generalisations can be made regarding the reviewed case studies. To begin with, there is the common practice of using exogenous determined market penetration rates, usually based on expert judgement, for policy-driven efficient technologies. For instance Morales and Sauer (2001) use market penetration rates of different household efficient technologies, such as

⁵⁷ Note that these decisions components were introduced by LBNL to the original NEMS model.

solar water heaters, heat pumps, compact fluorescent lamps and fuel substitution, for example firewood replaced by liquified petroleum gas (LPG). This conforms a so-called ‘mitigation scenario’ which is then compared to the baseline. In this case, more efficient technologies (relative to the baseline) and corresponding market penetration rates are the key elements used to implicitly model DSM and IRP programmes. Kadian et al. (2007) and Yanbing and Qingpeng (2005) also assumed ‘moderate’ to ‘high’ market penetration rates for efficient technologies when modelling labelling and performance standards. The work done by Bozic (2007) also use high market penetration rates for household technologies when modelling DSM measures. All reviewed cases using MURE use annual penetration rates to model policy-driven technologies, such as space heating, sanitary hot water, equipment replacement/maintenance and appliances. Similarly, the reviewed work of BUENAS and MAED relies on expert knowledge of best practice for setting likely technology adoption targets resulting from the implementation of policy instruments, such as performance standards. For instance, economic and regulatory policy instruments previously noted can be modelled and reflected qualitatively in MAED. However, the quantification of the driven factors to reflect any policy instruments needs expert judgment.⁵⁸

- In relation to market penetration rates, we found cases in which a ‘shipment model’ is used to endogenously forecast estimates of sales and market share by product class in the presence or absence of policy instruments. Technology shipments are forecasted usually as a function of capital costs and are driven by fuel costs and projected housing stock. As mentioned in Section 5, when analysing technology choice for the NIA and PAMS models, forecasted sales take into account the number of products that operate in each year and the rate at which outdated, inefficient products are replaced with the new and efficient ones as a result of policy instruments. The reviewed shipment models generally account for technology used to replace retired units, technology shipped to new homes, and technology installed due to fuel switching.
- Lower energy intensities compared to the baseline are commonly used across the reviewed case studies as another user-defined parameter to model policy-driven efficient technologies. Yanbing and Qingpeg (2005) used lower energy intensities for HVAC systems (relative to the base case scenario) in LEAP as key technical variable to model efficiency improvements in the Chinese building sector. Similarly, all the case studies related to MURE use lower energy intensities to demonstrate the use of the model to assert the impact of numerous policy-driven technologies. For instance, for more efficient policy-driven space heating, the following parameters were modified: (i) average u-value of new buildings; (ii) average u-value of walls; and (iii) average u-value of windows (Eichhammer, 2000; Faberi and Enei, 2000; Fena, 2000). The lower the u-values of external building constructions materials/elements, the lower the energy required for heating purposes. Similarly, the reviewed work with NIA to analyse minimum performance standards involves lower energy intensities of technologies, relative to the baseline of the model equipment, as a key modelling determinant. Another example comes from the reviewed work with PAMS, which also relies on lower energy intensities to model performance standards. In this case, efficiency increases as more features to the baseline technology design are added by the modeller. Thus better design options translate into lower energy intensities. Due to the bottom-up nature of the reviewed models, the use of different energy intensities or efficiency ratios helps to by-pass the development of large and specific technological databases. This is because different and more efficient design options, such as an A++ refrigerator, can be developed by simply modifying the engineering and related economic parameters of a given basic generic technology (e.g. standard refrigerator).
- Only one of the reviewed case studies attempted to address and include non-economic factors influencing household efficient technology choice. Despite the fact that no explicit policy

⁵⁸ Personal communication with Ali Hainoun (September 2009).

instrument was modelled, the work done by Kannan and Strachan (2009) explicitly acknowledges that optimisation tools, in this case MARKAL, do not account for non-economic choice determinants such as design, colour and brand. In this case, the modelling approach to assess CO₂ reductions combines a high discount rate with specific constraints on efficient technologies. In order to capture a non-economic aspect driving technology choice, Kannan and Strachan (2009:423) use a 25 percent rate as an implicit high discount rate for conservation measures and advanced technologies.

Some aspects can still be elaborated for those case studies in which no specific information was found about energy efficiency policy instruments under evaluation but in which the household sector is still under analysis. The use of 'quantitative targets', in the form of CO₂ or energy consumption reduction targets are used as a key modelling departure point. For instance the work done by Schulz et al. (2008) analyses primary energy reductions combined with CO₂ emission caps applied to the Swiss MARKAL energy system. As concerns the household sector, the focus is on heating-related technologies and modelling results show that heat pumps and district heating systems start to dominate the market to a greater extent once the targets are applied. The modelling work by Kannan and Strachan (2009) also uses an emission cap as a central element in its modelling framework approach. The authors explore technological pathways in the household sector for achieving an economy-wide CO₂ emission reduction target by 2050 of 60 percent in the UK MARKAL energy system. In this case study, the household sector plays an important role to meet the imposed emission caps and reductions in the household sector are achieved mostly through appliance efficiency improvements.

Finally, from the documentation of the WEM model, one can easily infer that the model includes an economic and environmental policy analysis for the investments on efficient demand-side technologies. For instance, the policy analysis addresses how investment costs to end-users relate to the monetary savings as a result of lower energy bills. If an alternative policy scenario, such as one on efficiency performance standards, increases the demand for more energy efficient technologies, then the WEM model accounts for the capital investment needed to cope with the increased investment demand level. The policy analysis addressing energy efficiency improvements considers: (i) the level of energy efficiency under the reference scenario; (ii) the policy-driven energy demand reductions resulting from the alternative policy scenario; (iii) the costs of the more energy efficient technologies; (iv) the useful lifetime of the equipment; and (v) the ownership levels (OECD/IEA, 2008).

7. Discussion on dimensions to advance energy modelling tools

In the light of outcomes of the previous sections, the aim of this part of the report is to identify, discuss and suggest aspects to further advance energy modelling tools in relation to energy efficiency policy evaluation for the household sector. It seeks to provide a basis for the discussion and advancement of the feasibility and appropriateness of the energy modelling tools used to evaluate these policies. Some aspects might be applicable to bottom-up modelling tools in general but discussion here focuses on energy efficiency and the household sector in particular.

7.1 *The modelling dimension*

To begin with, a transparent modelling effort that provides all the necessary information to its target group (e.g. the research community or policy makers) is highly critical. In fact, during the development of this project report, our research was sometimes challenged by limited access to related-model documentation and/or modelling exercises. Publicly available model documentation, detailed data implementation guide, including data quality and related uncertainty, and explicit model assumptions are central to provide a key foundation for policy makers and the research community to better evaluate the superiority and significance of the energy model and modelling results as such. For instance, technology databases are sometimes kept by modelling groups who are not willing to share this critical modelling input with the rest of the research community. Undoubtedly, the development of such databases is highly resource-intensive so this practice might be sustained by economic and strategic arguments. However, sources of information, parameters and assumptions contained in those databases should be publicly available in some form so they can be duly scrutinised and further improved. Certainly, the ever-growing complexity of environmental and energy policy issues makes difficult the appropriate selection of energy models for answering different policy questions (Levine et al, 2007; Worrell, et al., 2004). At all events, much more effort is needed to openly recognise the strengths and weaknesses of energy modelling tools. Limitations or flaws in modelling tools must be provided explicitly. All these aspects have to be clearly communicated to policy makers and other researchers to better understand and judge whether the ‘right’ model has been selected or used to answer the appropriate policy questions. What we sometimes see in reality is that policy makers seem to be frustrated because the same modelling tool is used to answer all policy questions, or the wrong tool is chosen to answer a given policy evaluation question (Hourcade et al., 2006; Scheraga, 1994).

A second critical modelling aspect relates to an explicit elaboration of the methodology to model and represent energy efficiency policy instruments. It has been argued that there is still a lack of robust, comprehensive, and detailed bottom-up evaluation studies of energy use/efficiency and related GHG reduction prospects in the building sector worldwide (Levine et al., 2007). Based on our analysis, it is first necessary to provide clear information about the methodological details on how a policy instrument under analysis is actually modelled. In other words, studies focusing on energy efficiency policy targeting the household sector need to show what is the model ‘language’ (e.g. variables, parameters, assumptions) being used by the modeller to represent the policy instrument in the model being used. Furthermore, this form of ‘idealistic’ policy instrument representation needs to be compared with the most likely form that the same policy instrument is supposed to take in reality and under different policy circumstances (Worrell et al., 2004) – see Section 7.4 for more details. Modelling studies should provide this comparative exercise to transparently reveal the gap between most-likely real policy implementation and the modelling approach undertaken to mimic the policy instrument. In addition, the justification for such an abstract representation – perhaps highly necessary – should be provided. This allows a suitable and transparent basis to judge the appropriateness of the modelling approach. Likewise, methodological details are needed concerning how the policy instrument(s) under analysis is supposed to reduce or eliminate market imperfections that prevent increased energy efficiency in the household sector. Again, a clear identification of the variables and parameters being used to mimic the effect of the reduced market imperfections is of prime importance. Critical assumptions and simplifications can aid a better understanding of the complexity and related advantages, limitations and uncertainties of such a modelling approach.

As a result of the reviewed modelling tools, and in particular the case studies, we also identify that there is a great need to better translate modelling outcomes into policy language. Complex and rich modelling results can be of limited value if no guidance is given to policy makers or users regarding the interpretation and policy implications of the obtained results. Besides transparency and openness, lessons from the reviewed case studies tell us that there is a need to enhance the interpretation of modelling outcomes by explicitly linking the advantages and disadvantages of the model and the modelling approach undertaken, with guiding research questions, scenario development, assumptions and input data concerning quality and related uncertainty (cf. Worrell et al., 2004). These relationships should be clearly communicated to policy makers. This means that modelling exercises need to put more effort into translating and condensing complex modelling results into a set of concrete policy recommendations. Due to the relevance of the building sector in terms of energy use and GHG emissions – responsible for one third of energy-related CO₂ emissions and two thirds of halocarbon emissions – there is a great need for sound policy recommendations to effectively support related decision-making processes. This panorama offers an opportunity to further enhance the contribution of modelling exercises addressing energy efficiency policy evaluation for the household sector.

Based on our review, there is no doubt that energy models and modelling studies do provide useful policy insights and they should be complemented with other qualitative and quantitative methods of research for policy design and instrument choice. Modelling tools can contribute to improving our understanding of policy instruments – provided that the right models are chosen to answer appropriate policy questions. However, there is no single best energy model that can answer every single policy question (Hourcade et al., 2006; Scheraga, 1994). It has to be recognised that complementary research methods (surveys, agent-based modelling, cost-benefit analysis, intervention theory, systems analysis approach, Delphi method, interviews and statistical analysis) are likely to be needed to better comprehend the broad effects and attributes of energy efficiency policy instruments. Therefore, and from the methodological point of view, the appropriateness of *triangulation* is confirmed throughout this review. That is to say, a variety of methods for analysis are needed to address the empirical and normative understanding of energy efficiency policy instruments applied to the household sector. In other words, no single best method is relevant in providing a comprehensive analysis of policy instruments. In turn, broad policy evaluation studies underscore the triangulation research approach for data collection. A wide evaluation exercise needs to define its purpose and research questions. It has to match a number of conditions, including the resources available and the dissemination and effective exploitation of the findings. Results from broad evaluation studies can provide an extensive foundation for balanced discussions and may contribute to improved communication among stakeholders. A broad evaluation also gives policy makers stronger grounds on which to assess the performance of policy instruments and on which to justify these instruments to stakeholders. Based on the research findings, it can be said that the objectives and design of the policy, as well as an understanding of how the instrument should be implemented and function within a portfolio of instruments, are also likely to frame the challenges encompassed by broad energy efficiency policy evaluation studies. What is usually needed in policy analysis is a portfolio of methods for data collection and analyses to perform the overall evaluation and comparison for alternative policy instruments. More in Section 7.4.

The modelling community should engage much more on agent-based modelling exercises. The economic/engineering paradigm that dominates the reviewed modelling tools falls short of capturing the multi-agent system nature of energy efficiency technology choice and also the interactions and complexities of household behaviour. Agent-based modelling appears as an appropriate modelling paradigm to address the complexities of human behaviour and technology choice at the household level. This modelling approach deals with the simulation of dynamic social systems. It addresses the forms in which social structures come into view from complex interactions amongst individuals and how those structures affect and limit individual behaviour, including feedback processes to the identified social structures (Moss et al., 2001). There is a need to identify all the decision-making entities (i.e. the agents) and consider the rules or processes governing the interactions among the agents. The household should be the key decision-making entity within an agent-based model that deals, for instance, with the diffusion of

energy efficiency technological innovations. However, we should bear in mind that technology choice is usually affected by a number of intermediaries (e.g. project developers, construction companies, equipment dealers). These actors also take many critical and strategic decisions on behalf of householders so they should also be considered as important decision-making entities. Lately, agent-based modelling approaches are becoming very popular amongst electricity market modellers and a number of studies can be identified (Ma and Nakamori, 2009; Sensfuß et al., 2007). Lessons learnt from these modelling exercises should be taken as a point of departure to support and complement studies carried out with other optimisation, simulation or equilibrium bottom-up models.

7.2 The techno-economic and environmental dimension

Due to the fact that increased energy efficiency can benefit both society and the environment, one can safely argue that model specifications for the integration of co-benefits should become a central research component within the modelling community. Efficiency improvements can benefit both society and the environment by: reducing atmospheric pollution; lessening negative externalities resulting from energy production; boosting industrial competitiveness; generating employment and business opportunities; improving the housing stock and the comfort level of occupants; enhancing productivity; increasing security of supply; and contributing to poverty alleviation, among other aspects (see e.g. IAC, 2007; Jochem et al., 2000; Levine et al., 2007). The number of (potential) ancillary or co-benefits is substantial but they are not usually included in energy efficiency (modelling) evaluation studies, underestimating the economic potential of increased energy efficiency (Levine et al., 2007; Ürge-Vorsatz et al., 2009). The fourth IPCC assessment report explicitly acknowledges the need to integrate co-benefits in GHG mitigation studies, and into related policy decision-making processes (see Levine et al., 2007). Furthermore, it has been noted that one of the weaknesses of the ‘Integrated Impact Assessment’ carried out for major EU policy proposals lies in the exclusion of long-term environmental and social benefits (see Pallemarts et al., 2006). Even though there is a great need for their integration in the evaluation policy studies to better support decision-making processes, yet very little progress is identified in modelling studies to introduce and represent them. The inclusion of a wider set of co-benefits resulting from increased energy efficiency is very likely to simply strengthen the socio-economic attractiveness of higher levels of energy efficiency improvements. Certainly, a broad and explicit quantification (including monetary aspects) of co-benefits poses a serious challenge for a thorough modelling evaluation exercise. Initially, specific methodological aspects need to be developed for integrating workable co-benefits into the modelling tools, as well as providing guidelines on how to address more subtle and product-specific co-benefits, such as noise reduction and comfort. Empirical research addressing the order of magnitude of non-energy benefits is a central building block to support this research task (cf. Levine et al., 2007).

Another area for further research relates to the analysis and introduction of transaction costs (TCs). TCs are for investment involve expenditure that is not directly involved in the production of goods or services but is essential for realizing the transaction (Coase, 1960). There is extensive literature on the theoretical and empirical aspects of transaction costs and their negative impacts on energy efficiency policy instruments (Mundaca, 2007; Ostertag, 1997; Reddy, 1991; Sanstad and Howarth, 1994; Sioshansi, 1991). However, most modelling exercises ignore or underestimate this critical issue (Worrell et al., 2004). Transaction costs usually arise from due diligence, the search for and assessment of information, negotiation with business partners, acquisition of legal services, measurement and verification of the actual level of improvement, etc.⁵⁹ The problems regarding imperfect and asymmetric information may prohibit the purchase of equipment that aims to increase end-use efficiency. It is argued that end-users face high costs to get reliable, inexpensive, and opportune information when buying more efficient technologies (Sioshansi, 1991). Furthermore, the presence of transaction costs can decrease the financial gains of increasing energy efficiency (Sanstad and Howarth, 1994). By making new measures seem more expensive than conventional ones, transaction costs can thus favour inefficient or standard household technologies,

⁵⁹ For an extensive discussions on the concept and the components of transaction costs see Ménard (2004).

making potentially profitable investments completely unattractive. As transaction costs are also present in the interface among market agents, they are often assumed to be part of the variety of market imperfections undermining the further penetration of more efficient technologies (Jochem et al, 2000). In all, we can safely argue that the presence of transaction costs can overshadow the financial gains from increased energy efficiency. All these arguments call for a better analysis and understanding of transaction costs in modelling exercises to further improve the estimations of household energy efficiency potentials. An improved modelling tool in this regard will allow better simulating policy instruments attempting to reduce or eliminate sources of transaction costs affecting the adoption of efficient household technologies. We argue that continuous research is needed in order to feedback modelling efforts and thus the design and evaluation of policy instruments.

Following on from the economic aspects of increased energy efficiency; there is a need to explore synergies among modelling tools to further improve cost-revenue specifications and the accuracy of aggregated results. It has already been argued that bottom-up modelling tools provide an insufficient specification of cost-revenue ratios for efficient (industrial) technologies (Worrell et al., 2004). As known, one important market barrier to uptake energy efficiency technologies refers precisely to the lack of information about the technical and financial performance of household technologies. With only a few exceptions (MURE, NIA, PAMS), energy-saving costs and energy-cost savings on a technology-basis are critical aspects for which details are difficult to obtain or identify in modelling studies, in particular when a stylistic representation of technologies is given. From the end-user perspective – an important analytical and policy-decision component – a utility maximisation approach or cost-revenue analysis has to be carried out, usually outside the model. In fact, synergies among different modelling tools further enhance cost-revenue ratios and related results were not found in the reviewed case studies. The combined use of tools that are also project-oriented evaluation in nature (MURE, PAMS, RETScreen⁶⁰) with those that are more energy-system-oriented (LEAP, MARKAL, MESSAGE) should be further explored. Features or components of the former group of modelling tools allow the analysis of the effects of policy instruments at the household level, which can be aggregated and then fed into energy system-oriented modelling tools when analysing policy-driven efficient technologies at the aggregated level. At all events, one has to acknowledge that maintaining and updating databases is also highly resource-intensive. If human and financial resources are not devoted to support this crucial activity, it should come as no surprise that we continue relying on uncertain modelling results, even where sophisticated models are used.

The reviewed case studies show that there is the possibility to further account for and use experience curves of household energy-efficient technologies. The use of experience curves offers a research method to study past cost developments that in turn allows analysis of future cost development. Learning rates are derived based on the results of experience curve analysis (Neij, 2008). Experience curves and associated learning rates (with due uncertainties) have been used already and adopted in bottom-up modelling studies that explore future energy systems; however, most of the attention has focused on energy supply technologies (Neij, 2008; Pan and Kholar, 2007). It is known that energy-efficient technologies have a marginal market share once they are introduced. However, cumulative production can increase rapidly during early stages of commercialisation, bringing with it sizeable opportunities for cost reductions related to increased production. In our case, the modelling exercise performed with the NEMS model for tax credits shows that it is possible to apply experience curve analysis for end-use technologies. Capital costs of high-efficiency technologies were estimated based on current installed cost data and a learning ratio of 20 percent; which is in turn based on experience curves. This was used to forecast decreases in future capital costs relative to current installed costs data as a result of increased production experience. In addition, PRIMES includes learning-by-doing curves and parameters that can represent perceived technology costs by end-users. There is compelling literature about experience curves and learning rates for supply technologies (Neij, 2008) and the very same research efforts that have been made to collect data for these technologies should be done for household technologies in order to approach (endogenous) technology cost development in modelling exercises (Koomey, 2000; Worrell et al., 2004). For instance, research work done by Weiss et al. (2008) in this area can be taken as a departure point.

⁶⁰ For further information see <http://www.retscreen.net/>

7.3 The human-behavioural dimension

To begin with, there is a need to further improve microeconomic decision-making frameworks for household energy-efficient technologies. It has been long argued that bottom-up energy models provide an unrealistic portrait of microeconomic decision-making frameworks for technology choice/investment. Whereas economic factors are used as key determinants for technology choice in the energy modelling tools, there is compelling evidence that shows a variety of determinants that need to be taken into account when analysing the process of (non-)adoption of efficient technologies by households (Moukhametshina, 2008) – more below. Furthermore, as previously mentioned, it is also important to take into account the fact that technology choice is often strongly affected by intermediaries such as developers, construction companies, installation companies and vendors (Lutzenhiser, 1993; Wilhite and Shove, 1998). These actors take many important and strategic business decisions – sometimes on behalf of end-users – influencing subsequent household energy use. Several studies show that intermediaries' incentives to pursue energy efficiency are few, while their disincentives are many (Blumstein et al., 1980; Brown, 2001; Stern and Aronson, 1984). Shortcomings such as these are usually omitted in modelling efforts. Undoubtedly, these aspects pose a challenging but necessary research task, because a more realistic portrayal of decentralised and dynamic microeconomic decision-making frameworks is crucial to improving the design and evaluation of policies for the household sector. We acknowledge that quantitative simulation of household behaviour is very complex but it is nonetheless necessary. Even if modellers are sometimes fully aware of the flaws of modelling tools in this respect, there is still limited empirical work and practical research on how to handle and convert qualitative knowledge about household behaviour into a set of quantitative parameters (Worrell et al., 2004).

Following on from a better representation of technology adoption frameworks, our findings about decision-making factors and rules affecting and driving technology choice in modelling tools confirm that a larger representation of determinants for technology choice is highly needed. The limited number of determinants driving technology choice in the reviewed models confirms the long-standing criticism of bottom-up modelling tools. Whereas household decisions addressing energy-efficient technologies are far more complex and depend on multiple parameters, the reviewed case studies confirm the dominance of economic drivers affecting those decisions. Undoubtedly, the number of determinants affecting influencing household's choices regarding efficient technologies is extensive (Moukhametshina, 2008). For instance, a combination of factors, including design, comfort, brand, functionality, reliability and environmental awareness is likely to influence consumers' decisions regarding energy-efficient equipment.⁶¹ Those determinants can be relevant to different types of technologies (Lutzenhiser, 1993; Stern, 1986; Uitdenbogerd, 2007). It can be safely argued that a great variety of determinants that frame and drive consumer's energy-related decisions regarding technology choices is needed to further enhance modelling tools for energy use scenarios and support energy efficiency policy evaluation. The key question now is to what extent a better representation of empirically estimated determinants of choice is actually feasible in energy modelling. Which determinants are more workable than others in improving such tools? How can one assess the specific influence of certain parameters on technology choice? Importantly, the estimation of technology-related market response parameters is usually based on historical data. This can become of limited or no value once policy instruments are actually implemented to modify technology markets. As already discussed, this issue is of prime importance when analysing the role of new household technologies in relation household behaviour for which no or very limited past data yet exist.

To support the development of comprehensive microeconomic decision-making frameworks, outcomes from social marketing research and social psychology need much more attention (Worrell et al., 2004). Whereas the latter discipline focuses largely on aspects related to individual/group behaviour and critical factors behind it, the former discipline aims for the systematic application of marketing strategies to influence those factors and attain specific behavioural goals for a social cause. These social disciplines can provide important insights into household preferences for efficient technologies; broadening the narrow

⁶¹ For an extensive and recent literature review see Moukhametshina, (2008).

economic approach that dominates in modelling tools (Costanzo et al., 1986; Stern, 1992; Worrell et al., 2004). Modelling studies addressing household energy efficiency and related policy aspects need inputs from these disciplines. By drawing on research outcomes, a better understanding of influence processes can be achieved. This can help identifying and improving mechanisms to effectively target the household sector through better designed, modelled and analysed policy instruments.

Much more research is needed on the use of discount rates to mimic consumer behaviour and market imperfections. Our review of case studies and modelling approaches for policy instruments and market imperfections suggests that more research is needed to understand the decision-making processes of consumers. Even if purely economic parameters are examined in modelling exercises, there is still a gap between the revelations of ex-post analyses and the discount rates used in ex-ante modelling exercises. As already pointed out, the literature shows numerous limitations to infer inefficient consumer behaviour from such high implicit discount rates, e.g. omitted transaction costs that householders are likely to bear; miscalculation in equipment costs and/or energy savings; and need for compensation for risk (Jaffe and Stavins, 1994a, Huntington, 1994; Sutherland, 1991). Implicit discount rates also illustrate that the “economic rationality” applied by householders is different for different types of measures and technologies. At the risk of oversimplifying, even though high implicit discount rates and related causes have been the most common and frequently mentioned evidence for the non-adoption of efficient technologies by consumers (see Huntington, 1994), the debate regarding the use of appropriate discount rates in modelling exercises continues (Anderson and Newell, 2002; Bataille et al., 2006). Whereas the importance of (implicit) discount rates in the context of the ‘energy efficiency gap’ has been long debated (see Jaffe and Stavins, 1994a, 1994b; Howarth and Sanstad, 1995; Scheraga, 1994), most of the reviewed cases ignore the possible scale of the effects of discount rate uncertainty. Our findings confirm that the debate in the mid-1990s on consumer discount rates and energy efficiency technology choice is still very much present. In turn, this evaluation challenge tells us that more research is needed in order to better understand how current energy efficiency policy instruments have actually reduced or overcome the market imperfections that they are supposed to target in the household sector. Research outcomes from this area could better support methodological efforts addressing the way market imperfections are represented in energy models. Together with social marketing research and social psychology, behavioural economics also has a role to play here.

Another lesson arising from the research involves the need for a far greater focus on outcome evaluation to improve diffusion processes that can complement impact policy evaluation. As previously elaborated, an outcome is understood as the response to the policy instrument by subject participants, for example in adoption processes of new technologies or development of new business plans. In contrast, and building upon certain elements of outcome evaluation, the majority of the reviewed case studies focus their research goals on impact policy evaluation. Research has already indicated different approaches/modalities deployed by households for adopting efficient technologies. For example the decision might not be about whether to purchase a technology as such but rather which version of the technology should be chosen and which parameters influence that decision-making process (Ashdown et al., 2004; Brucks et al., 2000; Nowlis and Simonson 1997; Oxera 2006; Uitdenbogerd 2007). Although technical change is often limited to the dissemination of mature efficient technologies, the involvement of multiple market agents seems to be critical in encouraging households to take a front-line position and act proactively on energy efficiency (Wilhite and Shove, 1998). A better understanding of technology diffusion patterns and processes should effectively provide dynamic feedback to modelling studies (cf. Arentsen et al., 2002). It is unlikely that by focusing solely on impact evaluation aspects mentioned above could be captured. Non-modelling evaluation efforts addressing outcome evaluation have been made and should be further developed and integrated in modelling studies. They stress the importance of outcome evaluation for policy design and the development of specific indicators.⁶²

⁶² See Neij and Åstrand (2006) for examples of outcome indicators applicable to new energy efficient technologies.

7.4 *The policy dimension*

The review of the case studies also stresses the importance of careful scenario development. Whereas some of the justification for our research builds upon the concerns regarding the mechanisms for simulating/forecasting the choice of efficient household technologies, one should not underestimate the relevance of careful scenario development, in particular when policy makers and analysts scrutinize modelling tools, approaches and resulting outcomes (cf. Koomey, 2000).⁶³ Even if we attempt to predict the impacts of energy efficiency policy instruments in the household sector with very complex modelling tools, such as NEMS or REEPs, inherent limitations and uncertainties remain. According to Lindgren and Bandhold (2003) scenarios are an effective way of reducing an enormous amount of information into a controllable format without over-simplification. Although one can ascertain several weaknesses in the reviewed models, it has to be recognised that most of them do provide a very useful and concrete framework for organising complex and extensive end-use household-related input data. The specific analysis of modelling approaches to energy efficiency policy strongly suggests the need to perform careful scenario analysis. For instance, while many of the reviewed case studies do acknowledge limitations in terms of access and sources of data, no methodical examination of the impact of uncertainties on scenario results was found. In most of the cases, the limited focus is narrowed to the costs of policy scenarios. Ringland (1998) argues that the purpose of scenario development is to manage uncertainties and risk. According to Strupeit and Peck (2008), the purpose of scenarios and scenario development encompasses four areas: (i) changing thinking and creating a common vision; (ii) decision support; (iii) managing risk and uncertainty; and (iv) learning and understanding. In our context, a set of scenarios has to be used to explore different technology futures and explicit (exogenous) assumptions about the effectiveness and efficiency of the existing and future portfolio of policy instruments have to be made (cf. Nakicenovic and Swart, 2000). The conclusions of our report are consistent with Koomey (2000). While the author argues that modelling studies and related quantitative analysis can provide consistency and add credibility to scenario development exercises by clearly elaborating on the outcomes of future events, he emphasizes that energy modelling tools should not steer but support research and the learning process.

The review also reveals the need to better represent policy instruments in modelling tools. As argued in previous sections, the reviewed cases show that energy efficiency policy instruments tend to be modelled in an idealistic or perfect manner. However, this form of idealised policy instrument representation needs to be compared with the most likely real form of the same policy instrument, in particular under different policy circumstances (Worrell et al., 2004). The implementation and functioning of policy instruments is much more complex, with strong dependence on institutional and market conditions (Greening and Bernow, 2004). To support a better representation of policy instruments ‘intervention theory’ can be used to describe how a policy instrument is likely to work in reality. Intervention theory can guide this process and support the overall policy analysis (Mickwitz, 2003; Vedung, 1997). Intervention theory is usually understood as all the empirical and normative beliefs underpinning public policy interventions (Vedung, 1997). For instance, this approach can be used to develop a conceptual model addressing how a given policy instrument could or should affect consumers’ technology choice of decision-making frameworks. Supported by empirical evaluation research, all potential mechanisms to simulate or mimic household preferences for energy-efficient technologies in response to the modelled policy instrument should be identified and guide the type of model ‘language’ (e.g. variables, parameters) that the modeller uses to represent the policy instrument. A key challenge in this area is represented by informative policy instruments. All methodological aspects, including assumptions and limitations, should be given explicitly.

Following on the above-mentioned aspect, the reviewed case studies also stress the importance to model and better represent the portfolio of policy instruments addressing the household sector. Even though a number of policy instruments were modelled in some reviewed cases, synergies and overlaps among them were omitted. Thus, one could argue that modelling studies address, to some extent (possibly a large extent), the combined effects of the portfolio of policy instruments. However, only very minor

⁶³ Personal communication with Leo Schrattenholzer (March 2009).

methodology details were found regarding their representation in the model – see also paragraph above. In contrast, what we see in practice is a portfolio of policy instruments. The effects (i.e. impacts and outcomes) of a single policy instrument cannot be added with other instruments in an ideal form in modelling studies (Worrell et al., 2004). Policy instruments do not function in isolation, so it is necessary to posit and analyse the interaction among policy instruments in order to identify synergies and avoid overlaps. Furthermore, research is also needed to de-link the effects from various policy instruments – the so-called ‘impact problem’ (Scriven, 1991). It is also relevant to consider how the additionality of efficient technologies implemented under a given instrument can be ensured if a variety of policy instruments exists. The way a given instrument functions and performs in relation to a portfolio of instrument functions (and vice versa) is likely to frame the challenges encompassed by broad energy efficiency policy evaluations in modelling studies. On the whole, research efforts in this area should aim for a better representation and modelling of the entire portfolio of policy instruments.

The existence of the current portfolio of policy instrument and uncertainties about future policy developments calls for the development of alternative and credible counterfactual situations. Modelling studies should bear in mind the so-called ‘regulatory capture problem’. The term refers to the situation in which (environmental or energy) targets reflect business-as-usual trends (see OECD, 2003). This means that if an energy saving target is set, energy efficiency improvements would have taken place regardless, so the regulatory capture and the free-riding effect can seriously affect the integrity of the policy instrument. Thus, the current portfolio of policy instruments needs to be taken into account when addressing the key issue of baseline scenario. In turn, the regulatory capture underscores the importance of having alternative and credible counterfactual situations. The development of alternative counterfactuals can be critical in ascertaining the robustness and sensitivity of the modelling outcomes to the assumptions and limitations embedded in different counterfactuals, such as in the SO₂ cap-and-trade programme in the USA (see Ellerman et al., 2000; OECD, 2002). This indicates the necessity to define meaningful additional criteria when eligible technologies, driven by policy instruments, are modelled. Due to the fact that energy efficiency is a moving target, additionality, assumptions and data related to eligible technologies need to be carefully scrutinised and periodically updated. The development of alternative counterfactuals also needs to be supported by careful scenario development. One has to note that most of the reviewed modelling tools and corresponding databases represent historical know-how through relationships that are obtained usually from statistical analysis. However, as Koomey (2000) argues, the statistically-derived relationships embedded in modelling tools are precisely the ones that (modelled) policy instruments aim to change. Thus, those relationships must be modified in the modelling exercise; otherwise it is argued that modelling outcomes are likely to be biased. Here, the development of alternative scenarios can be critical in ascertaining different institutional and also behavioural changes if relationships change under different policy scenarios and levels of uncertainty.

Consistent with the lesson elaborated on above, energy efficiency modelling studies should be part of broad multi-criteria evaluation studies. The traditional but narrow single-criterion evaluation approach based on cost-effectiveness seems to dominate the limited number of evaluation studies on energy efficiency addressing the household sector (cf. Harmelink et al., 2007; Vreuls et al., 2005). However, it is argued that the cost-effectiveness criterion is inappropriate to comprehensively address the attributes of energy (efficiency) policy instruments and the institutional and market conditions in which they work (Greening and Bernow, 2004; Gupta et al., 2007). Research shows that multiple attributes are related to or can be attached to energy efficiency policy instruments (Gillingham et al., 2006; Vreuls et al., 2005). The case for a broad evaluation is further justified when policy instruments explicitly address multiple policy objectives (social, environmental, economical and technical). In fact, we very often see that one policy objective can be maximised only at the expense of others. Conflicting policy objectives can arise in the interplay of energy and other public policy fields. Thus, a multi-criteria evaluation framework; addressing for example economic efficiency, political flexibility, administrative burden, and transaction costs, can give us the opportunity to better comprehend the complexity of the instruments’ effects and to identify inevitable trade-offs. Furthermore, a multi-criteria evaluation policy framework can allow us to better understand the broad effects, attributes and complexities of energy efficiency policy instruments. As

previously argued, whereas modelling tools do provide useful policy insights, the complexity of policy instruments suggests that they should be complemented with other methods using a variety of qualitative and quantitative research methods.

Another research area that can further improve modelling tools from the policy perspective is the account of administrative costs. This specifically addresses the workload that public authorities face when a policy instrument is implemented and enforced (Harrington et al., 2004; Rist, 1998). It also focuses on the administrative outcomes that the implementation of policy instruments can generate for the public authority, with regard to the internal response to implementation. Such costs can be related to the design features of the instrument and policy objectives and to the human and financial resources incurred by the authority administering the instrument. While administrative costs do matter in public policy, they are often overlooked in evaluation studies and most modelling exercises simply ignore or underestimate this critical issue. Nonetheless, ignoring such costs can generate biases towards the evaluation of policy options (Tietenberg, 2006), leading to an overestimation of energy efficiency potentials. Supported by empirical research, attention should be given to the costs of implementing, monitoring and enforcing a given policy instrument. Modelling studies should bear in mind that these costs are likely to be a function of the complexity of the institutional framework, the number of regulated firms or subject participants, and the accessibility of necessary data about these firms (Nordhaus and Danish, 2003).

8. Concluding remarks

The aim of this report was to analyse a number of engineering-economic energy modelling tools and modelling approaches and to provide an understanding of how these models are used for energy efficiency policy evaluation for households. Most of the findings presented in this report have confirmed criticism and flaws related to bottom-up energy modelling tools. The identified shortcomings prevent these modelling tools to effectively support a fast-evolving demand for policy evaluation addressing complex energy and environmental problems. At the risk of oversimplifying, the findings stress the need to scrutinize the capability of the modelling tools in relation to the appropriate policy research questions. However we do acknowledge that, albeit imperfectly, well-formulated energy modelling tools provide valuable frameworks for organising complex and extensive end-use household-related data. This is a critical issue in effectively supporting and developing careful scenario analysis.

A number of case studies and corresponding modelling approaches were analysed. However, different sets of assumptions, geographical scope, modelling tools, technological databases, research frameworks and resulting outcomes make the reviewed case studies very case and context specific. Generalisation is difficult, but we conclude that the majority of the reviewed case studies focus their research goals on impact policy evaluation through implicit or explicit assessment of various energy efficiency policy instruments. In terms of identified policy instruments being evaluated with the energy modelling tools, the majority of the cases focused, either implicitly or explicitly, on minimum performance standards and building codes. This may be explained by the relatively simple modelling approach needed to do so. In addition to these specific instruments, the majority of the policy instruments being modelled and identified were economic in nature. This finding is consistent with the increasing use of economic instruments in energy efficiency policy. On the contrary, informative policy instruments were identified as being much less modelled compared to their economic counterparts. This can be explained by the dominance of economic and engineering determinants for technology choice embedded in the reviewed models. The economic/engineering 'policy handles' used in bottom-up energy modelling tools for policy evaluation gives little room for the representation of social change as a result of the provision of information or knowledge. In fact, the majority of the reviewed case studies modelled policy instruments through costs of measures for energy efficiency improvements and corresponding technical factors.

Based on the reviewed models and modelling approaches, we have attempted to provide a wide basis for the discussion and advancement of the feasibility and appropriateness of the modelling tools used to evaluate policies influencing energy-efficient technologies in the household sector. The background that laid the basis for this report concerned various dimensions: (i) modelling issues; (ii) techno-economic aspects; (iii) human-behavioural factors; and (iv) policy considerations. Within each dimension, we have discussed and elaborated on several research areas and insights that could take a multidisciplinary approach to the improvement of bottom-up models applied to the household sector. To summarise, the following potential improvements and research areas were identified:

1. The modelling dimension

- Develop explicit methodology to model and represent energy efficiency policy instruments
- Need to better translate modelling outcomes into policy language
- Complement modelling studies with other qualitative and quantitative methods of research for policy design and instrument choice
- Develop an agent-based model

2. The techno-economic and environmental dimension

- Integrate of co-benefits should become a central research component within the modelling
- Introduce transaction costs
- Explore synergies among modelling tools to further improve cost-revenue specifications
- Account for and use experience curves of household energy-efficient technologies

3. The human-behaviour dimension

- Improve microeconomic decision-making frameworks for household energy-efficient technologies & develop a larger representation of determinants for technology choice
- Introduce outcomes from social marketing research and social psychology
- Further analyse the usefulness of using discount rates to mimic consumer behaviour and market imperfections
- Focus on outcome evaluation

4. Policy dimension

- Develop careful scenario development
- Represent the portfolio of policy instruments addressing the household sector
- Develop of alternative and credible counterfactual situations
- Combine and support modelling studies with multi-criteria evaluation studies
- Account for administrative costs

Taking into account critical challenges such as household behaviour, methodological aspects, decision-making rules, uncertainties and data gaps, the identified research areas and challenges attempt to support a more comprehensive foundation for improving the significance and orientation of modelling exercises. However, note that by no means we argue that the suggested research areas are accurate or have been validated. On the contrary, as in any rigorous research work, they have to be further developed, implemented and duly evaluated and scrutinized. Potential next steps in the research project could involve more analysis of hybrid models working with empirically-estimated household behaviour parameters. Alternatively, the conceptual development of an agent-based model could also represent another research area for this project. The findings also stress the need and significance of ex-post policy evaluation. Empirical evaluation can feedback not only the design and functioning of policy instruments, but also provide critical information to improve modelling tools (e.g. in relation to transaction costs and market imperfections).

Even if we use sophisticated modelling tools, there are inherent complex challenges to overcome and that demands new foundations for future advancements and support from other research methods and disciplines. Our analysis strongly suggests that there is no single best method to evaluate (residential) energy efficiency policy instruments. A portfolio of research methods (e.g. surveys, agent-based modelling, cost-benefit analysis, intervention theory, Delphi method, interviews, statistical analysis, hybrid models) can allow us to better understand the broad effects, attributes and complexities of energy efficiency policy instruments. Whereas a comprehensive policy evaluation can sometimes be a complex, challenging and resource-intensive process, it is a doable exercise that provides a continuous learning process. Progress in modelling tools is unlikely to be made if other parallel suggested improvements do not materialise.

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