Internal working paper: literature review of integrating user and investment behaviour in bottom-up simulation models

D4.1 of WP4 of the Entranze Project

Written by:

Jan Steinbach
Fraunhofer Institute for Systems and Innovation Research ISI
Karlsruhe, Germany

Reviewed by:

Carine Sebi, Bruno Lapillonne, Enerdata

Eva Heiskanen, National Consumer Research Centre

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National Consumer Research Centre	**NCRC**	National Consumer Research Centre
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CENER	**CENER**	National Renewable Energy Centre
Politecnico di Milano	**eERG**	end use Efficiency Research Group, Politecnico di Milano
Öko-Institut e.V. Institut für angewandte Ökologie Institute for Applied Ecology	**Oeko**	Öko-Institut
SOFENA	**SOFENA**	Sofia Energy Agency
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Enerdata	**Enerdata**	Enerdata
SEVEn	**SEVEn**	SEVEn, The Energy Efficiency Center

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The ENTRANZE project

The objective of the ENTRANZE project is to actively support policy making by providing the required data, analyses and guidelines to achieve a fast and strong penetration of nZEB and RES-H/C within the existing national building stocks. The project intends to connect building experts from European research and academia to national decision-makers and key stakeholders with a view to build ambitious, but reality proof, policies and roadmaps.

The core part of the project is the dialogue with policy makers and experts which will focus on nine countries covering >60% of the EU-27 building stock. Data, scenarios and recommendations will also be provided for EU-27 (+ Croatia and Serbia).

This report provides an overview of energy-economic models for the building sector and different methodologies of how to consider stakeholder specific investment decision-making in a quantitative analysis. The second part describes the integration of stakeholder behaviour within the bottom-up simulation model INVERT/EE-Lab which is applied within the ENTRANZE project.

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1. Introduction

The major part of the ENTRANZE project is the quantitative scenario analysis of energy demand development and technology diffusion in buildings in the EU Member States. In order to evaluate the impact of different policy instruments on the uptake of energy efficiency measures, an energy-economic model is applied to the building sector. The model needs to incorporate a detailed representation of the building stock including heating and cooling technologies, as well as an explicit representation of various policy instruments. Taking into account the heterogeneity of building owners, who are the decision-makers for refurbishment investments, not only among different Member States but also within countries, the ENTRANZE project has a particular focus on the consideration of stakeholder behaviour and investor-specific barriers in the investment decision process, which also needs to be incorporated into the model.

This paper provides an overview of energy-economic models for the building sector focusing on *bottom-up* approaches and methodologies to simulate stakeholder-specific investment decision-making. There are several existing reviews of building sector modelling, which, however, focus either on different approaches to representing energy demand (Kavgic et al. 2010; Suganthi and Samuel 2012; Swan and Ugursal 2009; Zhao and Magoulès 2012), or on technology choice and decision modelling (Mundaca et al. 2010; Wilson and Dowlatabadi 2007).

Section 2 derives a general classification of energy-economics models for the building sector by explaining different methodologies. The third section discusses technology choice simulation used in existing *bottom-up* building sector models on a national scale and introduces behavioural modelling approaches and case studies of such models with respect to building-related energy efficiency investments.

The INVERT/EE-Lab model, which is applied within the ENTRANZE project, and the integration of stakeholder behaviour (INVERT-Agents) are described in the last section.

2. Models of energy demand and technology choice in buildings

2.1 Overview and classification of energy-economic models for the building sector

Energy-economy models can be differentiated according to their scope and the underlying modelling methodology. The design depends on the respective research question and might focus on a detailed picture of only one specific sector within a country or try to capture the interdependencies among different energy sectors and geographical regions. The main distinction is between *bottom-up* and *top-down* modelling paradigms (IPCC 1995); the former are also referred to as disaggregated and the latter as aggre-

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gated models. However, this classification owes more to the different sectoral and technological aggregation levels than to general differences in the conceptual design and the applied methods (Böhringer and Rutherford 2009).

Fig. 1 shows a general classification of energy-economic models for the building sector. An energy-economic model following a *top-down* approach considers energy demand in buildings as a whole and as one energy consumption sector (Swan and Ugursal 2009). In these models, the main drivers of energy consumption and technology diffusion are macro-economic and demographic indicators - such as GDP and household income, price indices and population growth - as well as the construction and demolition rates of buildings and climate conditions. Swan and Ugursal (2009) categorise *top-down* building sector models according to the explanatory variables into *econometric* and *technological* approaches. Energy prices, technology costs or household income are typical inputs in *econometric* based models, whereas the building stock's characteristics are the main inputs in *technological* based models[1].

Bottom-up models, on the other hand, are used to describe energy systems and demand in greater detail. With regard to the building sector, disaggregated data on reference technologies, building types and consumer groups are used as input which is then extrapolated to represent the whole sector. Possible interdependencies with other energy end-use sectors are generally not considered. *Bottom-up* models are particularly suitable for a detailed system and energy demand analysis of the building sector and individual investment decision-making. *Bottom-up* building sector models can be distinguished by the method used to derive buildings' energy demand (statistical or engineering[2] approach) and by the main modelling methodology (simulation, optimisation, accounting) that determines the dynamic representation of technology choice and energy demand development over time.

[1] A technological based top-down model is presented e.g. by Siller et al. (2007)

[2] The engineering approach is also denoted as *building physics based modeling* (Kavgic et al. 2010)

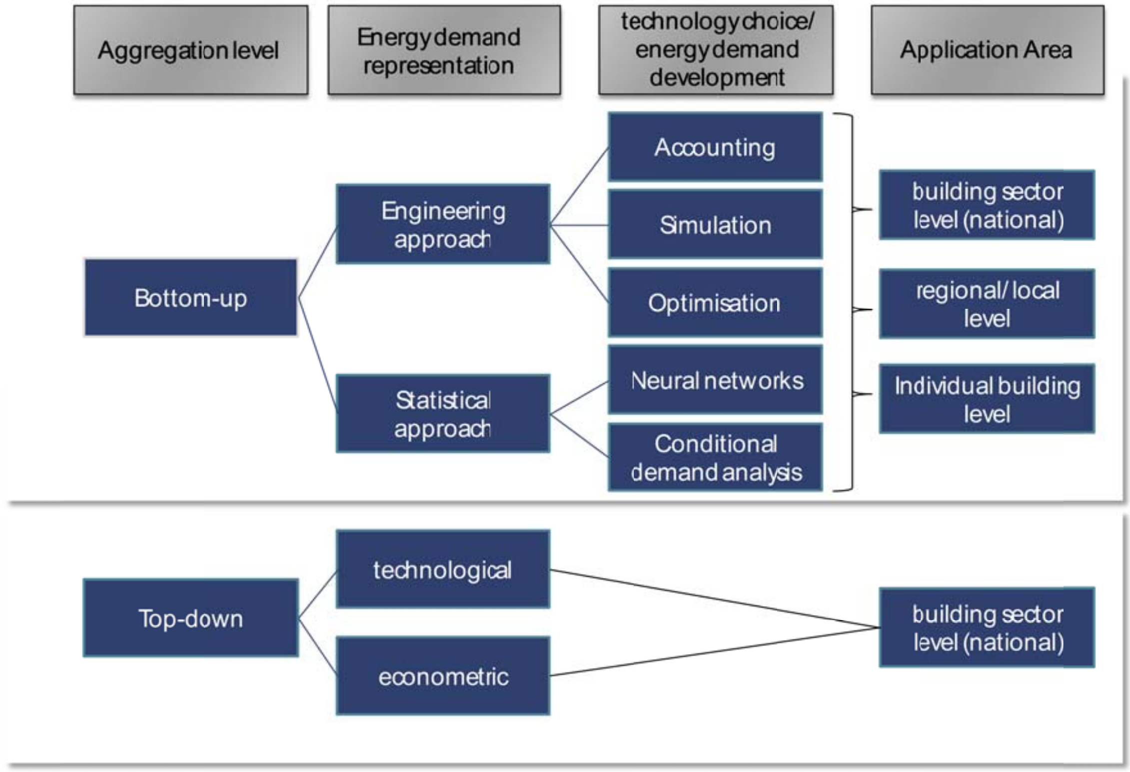

Fig. 1: Classification of energy-economic models for the building sector

2.2 Calculation of buildings' energy demand

In *bottom-up* building sector models, energy demand is represented either based on statistical techniques or on building physics input data (Kavgic et al. 2010; Swan and Ugursal 2009).

2.2.1 Statistical approach

The statistical approach utilizes sample data for buildings as well as national and regional indicators such as energy prices or income to derive correlations between building characteristics and energy consumption. Typical data sources for these empirical models are historical data from housing surveys or utilities' billing records. The applied statistical methods are similar to those of *top-down models*. Nevertheless, the aggregation level differs in terms of end-uses, technologies or building types.

Existing models based on the statistical approach apply mainly regression techniques to determine buildings' energy consumption as a function of relevant parameters (Swan and Ugursal 2009). The *Conditional Demand Analysis (CDA),* first developed by Parti and Parti (1980), is a well documented method. It regresses the energy demand of buildings (dwellings/ households) to existing appliances, their features and utilisation patterns as well as the user behaviour of occupants related to the respective appliances (Aydinalp-Koksal and Ugursal 2008). The main focus of existing CDA models is on

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the energy consumption of domestic appliances, space heating and hot water in the residential sector, partially in a high time resolution of one hour or less. Most of the models are applied to explain the correlation of energy consumption with climate data, and economic (e.g. gas or electricity tariffs) or socio-demographic variables rather than to provide a comprehensive representation of the energy consumption of the residential sector as a whole. However, Aydinalp-Koksal and Ugursal (2008) do present a *CDA* model at national level for the residential sector of Canada.

(Artificial) neural networks are another approach to calculate a building's energy demand based on historical consumption data (Swan and Ugursal 2009; Zhao and Magoulès 2012). Neural networks are a widely applied machine learning method, which enables pattern recognition within raw data and complex, nonlinear input-output relationships to be modelled. The basic idea is to imitate the brain's biological information processing in a mathematical model. The most common design consists of different layers of information processing units (neurons) which are interconnected with different strengths (weights). In order to determine the relationship between input (explanatory) and output (response) variables, the network has to be trained using a data set of correct input-output pairs. During training, a learning algorithm such as *back-propagation* is applied to change the weights of adjacent neuron's connections until the network converges to a desired performance level. In this way parameters are determined which minimize the mean squared prediction error of the training set. Existing neural networks based on building models mainly predict the energy demand of individual buildings or fluctuating electricity loads (Swan and Ugursal 2009). An energy demand model at national level is suggested by Aydinalp et al.(2004), which applies neural networks to modelling space heating and domestic hot water demand in the Canadian residential sector. The space heating network uses 28 different input units including dwelling characteristics, system and equipment properties, indoor and outdoor temperatures as well as the socio-economic characteristics of households.

Another supervised machine learning method applied to predict building energy consumption are *support vector machines (SVM)*. The major difference to artificial neural networks is that SVMs are not heuristic. Thus, the solution represents a global and unique minimum, whereas neural networks can result in local minima. An overview of SVMs in building energy demand research is described in the review by Zhao and Magoulès (2012). Their paper also describes *grey system theory,* which is able to analyse a building's energy demand using incomplete data; e.g. if energy demand needs to be predicted based on data for only certain weeks in a year. Since the scope of the existing research on grey models and *SVMs* is limited to the individual building level, it is not further elaborated here.

2.2.2 Engineering approach

The engineering approach applies thermodynamic equations together with detailed knowledge about technological parameters (e.g. annual efficiencies, capacities) and systems' characteristics (e.g. heat transfer, solar radiation) to calculate energy consumption. Therefore, there is no need for historical data on energy consumption in these models except those used to calibrate certain input parameters (Swan and Ugursal 2009). In order to model the energy consumption of the building sector at national level, this approach requires reference technologies for heating, ventilation, air-conditioning (HVAC) and representative shares of building types. Engineering models can be further distinguished by the level of detail of the input data and physical calculations. Swan and Ugursal (2009) distinguish between *distributions, archetypes* and *samples.*

Distributions

This approach applies distribution functions of appliance market penetration to derive the energy consumption at end-use or individual appliance level. Distribution-based models do not consider interconnectivity among appliances within the same system boundaries (e.g. within a building/ dwelling). Consequently, influences of the system itself (e.g. buildings' heat transfer) on the performance of the appliance within its boundaries and on the amount of energy demand are also not captured.

Archetypes and samples

To model space heating energy consumption, engineering models based on *archetypes and samples* are more suitable since geometric configurations, thermal characteristics and operating parameters are considered in an integrated simulation of buildings and HVAC systems (Parekh 2005). The classification into *archetypes* and *samples* is more due to the degree of disaggregation of reference buildings and technologies than to a general methodological difference. Both require the application of a thermal load simulation programme. *Archetypes* engineering models represent the building stock by deriving a limited number of reference buildings based, for instance, on building types (single family house, apartment building, offices etc.), vintages and HVAC system configurations. Reference buildings are clustered using average values for certain characteristics such as a typical geometrical configuration for a single family house in a certain vintage class. The number of reference buildings depends on the desired level of detail considering limitations due to data availability and simulation time. The difference to *sample* based engineering models as indicated in the taxonomy of Swan and Ugursal (2009) is that actual building samples are used, e.g. from a representative housing survey, without performing additional clustering.

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2.3 Dynamic representation of technology choice and energy demand development

Mundaca et al. (2010) categorise bottom-up energy-economic models according to their main modelling methodology into (1) *simulation models*, (2) *optimisation models* (3) *accounting models* and (4) *hybrid models*.

Bottom-up simulation models are designed to represent energy demand and supply in a descriptive way (Mundaca et al. 2010), considering microeconomic decision-making based on rational or non-rational patterns as well as different drivers of technology choice. Thus, simulation models try to reproduce a certain system - e.g. the building sector - and predict its development or transformation in the real world under different exogenous scenario variables.

Optimisation models, on the other hand, are designed in a prescriptive way. That is, they derive system states of least total cost deployment under consideration of technical and market constraints as well as certain policy goals, such as CO_2 reduction targets. It follows that optimisation building sector models do not capture individual investment decision-making. Instead, rational consumer behaviour is assumed, which implies the minimisation of discounted life cycle costs as the target variable and main driver of technology choice.

Accounting models are the third methodology type, and manage data and results with either a descriptive or a prescriptive design (Mundaca et al. 2010). The main difference to simulation and optimisation models is the exogenous determination of technology choice by the model's user. For instance, accounting models can be applied to estimate the effect of efficient heating systems' adoption considering life cycle-based replacement rates or the influence of climate change on a building's energy demand (Olonscheck et al. 2011). *Accounting* and *optimisation models* are therefore particularly suited to deriving normative scenarios and development paths, whereas simulation models generally follow an explorative scenario approach.

Hybrid models cannot be allocated unambiguously to any one of the three categories since they combine different modelling methodologies. The term is also applied if top-down models are somehow integrated; for instance, if macroeconomic variables are determined endogenously by a general equilibrium model (Böhringer and Rutherford 2009).

2.4 Synthesis

The overview presented in the previous section illustrates that quite different modelling approaches can be applied to analyse the building stock as an energy economic sector depending on the specific scope and research question. With regard to the analysis and consideration of stakeholder investment decision-making, the prerequisites for a suitable model design are an explicit representation of technologies, endogenous de-

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termination of technology choice and a descriptive rather than prescriptive model design.

Hence, the following section focuses on *bottom-up simulation* models of the building sector and methods to integrate individual investment decision-making and stakeholder-specific barriers in these models. The focus here is on decision frameworks for competing technologies and applications which allow the market shares of space heating and domestic hot water systems to be derived.

3. Analysis and consideration of investment decision-making in bottom-up models

This section analyses different approaches to handling technology choice and its key determinants in building sector simulation models. The focus is on simulation algorithms applied to model the selection of one technology from among competing ones by the different decision-makers. Other important parts of these models such as the derivation of annual replacement rates are not covered in this paper. Firstly, the main determinants of technology choice in existing building sector simulation models are elaborated. Secondly, different approaches of decision-models to addressing stakeholder-specific investment decision-making and barriers are presented.

3.1 Technology choice simulation in aggregated engineering-economic models for the building sector

Existing bottom-up simulation models at national level are based on a techno-economic rather than on a stakeholder-specific perspective. Levelised (annualised) life cycle costs are one of the key determinants of technology choice and incorporate discounted investments, energy costs, operations and maintenance expenses as a function of system- and building-specific characteristics such as efficiency, lifetime or energy load. The difference to an optimisation approach is that market shares are calculated based on a distribution function capturing the relative advantage instead of assigning the total share to the least-cost technology option in each reference building.

A log-linear function is applied by the *Residential Sector Demand Module,* which is part of the *National Energy Modeling System (NEMS)* to determine the market shares of space heating technologies for the *Annual Energy Outlook* of the US Department of Energy (DOI/EIA 2010). The model considers life cycle costs, the current market shares of technologies and aggregated consumer preferences. The latter are used as a bias variable to fit the historical market share.

(1)

$$\mathrm{ms}_{j,b,g,t} = (1-\mathrm{f}) * \mathrm{ms}_{j,b,g,t-1} + \mathrm{f} \cdot \mathrm{e}^{(c_{j,} + \lambda_{j,} \cdot \mathrm{LCC}_{j,b,g,y,t})}$$

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$ms_{j,b,g,t}$: *market share of alternative j in building type b, regions r in year t*

$LCC_{j,b,g,v,t}$:*levelised life cycle costs of alternative j by building type and vintage v*

c_j : *consumer preference factor of alternative j*

f: weight given to alternative's market share of the previous year

λ_j: *scale parameter of log-linear function*

The building module of the *Canadian Integrated Modelling System (CIMS)* applies a logistic function of levelised life cycle costs and intangible costs - representing the non-economic attributes of an alternative - to determine the market shares of competing technologies (Bataille 2005; Gamtessa 2006). Giraudet et al. (2012) apply a similar functional relationship to calculate the choice shares of retrofitting options within their suggested REF-IF model.

(2)

$$\mathrm{ms_{jt}} = \frac{(\mathrm{LCC_{jt}} + \mathrm{I_{it}})^{-v}}{\sum_{k=1}^{N}(\mathrm{LCC_{kj}} + \mathrm{I_{kt}})^{-v}}$$

ms_{jt} : *market share of technology alternative j at time t*

LCC_{jt}: *levelised life cycle costs of alternative j at time t*

I_{jt} : *intangible cost or benefits (e.g.comfort level) of alternative j at time t*

N: *number of technologies competing to provide the same service as j*

The slope of the market share equation is determined by the scale parameter *v,* which can be interpreted as a measure of market heterogeneity (Gamtessa 2006) or generally the importance of the technology choice variables. In order to determine the factor for the *CIMS* model, Rivers and Jaccard (2006) conduct a discrete choice analysis using a *logit* model. The use of a logistic distribution as the main technology choice function - rather than determining the scaling parameters - is also used in several recent building sector simulation models (Bauermann and Weber 2013; Deforest et al. 2010; Elsland et al. 2013; Henkel 2012; Kranzl et al. 2013; Müller and Biermayr 2011). The methodology is also based on the discrete choice analysis, but applied on a market level instead of the level of different decision-makers. Equation (3 shows the general form of the *multinomial logit* function according to Train (2003):

(3)

$$\mathrm{ms_{j,b,t}} = \frac{e^{-\lambda_b \cdot V_{j,b}}}{\sum_{j=1}^{N} e^{-\lambda_b \cdot V_{j,b}}}$$

$V_{j,b}.: utility\ of\ alternative\ j\ in\ building\ b$

The basic assumption is that the aggregated probability - over all consumers - of choosing a certain technology equals the aggregated market share of this technology.

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The derivation of the function within the context of the discrete choice analysis is presented in the next section (3.2). Existing models for the building sector differ by the type of model – *logit, conditional logit, general extreme value (nested logit)* - and the (weighted) technology choice variables included in the utility value. Deforest et al. (2010) and Elsland et al. (2013) apply a *logit* model with levelised life cycle costs as the only technology choice determinant.

Within the INVERT/EE-Lab model, Kranzl et al. (2013) propose a *nested logit* model with three levels in order to relax the *independence of irrelevant alternatives* axiom of the *logit* model in case of similar alternatives (see Train 2003). The choice utility is also equated to levelised life cycle costs and includes fuel switching costs as well as technology-specific preferences (willingness-to-pay) for heating systems. Bauermann and Weber (2013) apply a two-level *nested logit* model with levelised life cycle costs as the decision parameter.

All the described approaches incorporate - to a different extent - variables reflecting preferences or the non-economic attributes of alternatives when calculating market shares. However, the variables only capture alternative-specific attributes rather than investor-specific ones. Consequently, the market share functions of the presented models are highly disaggregated on the technology-building level but not on the level of investors.

3.2 Empirical models for preference measurement

Empirical or statistical behavioural models explain decision-makers' behaviour based on monitored actions. The discrete choice analysis is a widely applied methodological framework to describe consumer choices and estimate choice parameters depending on the attributes of alternatives as well as decision-makers. The theory originates from mathematical psychology[3], and is motivated by the inconsistent behaviour observed among decision-makers within repeatedly performed choice decisions, whereas the econometrics' perspective justifies a random formulation of utility factors unobserved by researchers (Dagsvik 1994:1180). The behavioural process of choosing among mutually exclusive, commonly exhaustive alternatives within a finite set is described by a function of observed factors x and unobserved factors ε. Since the latter is formulated as a random variable with density $f(\varepsilon)$, a decision-maker's choice is probabilistic. The corresponding utility function of a decision-maker n for an alternative j within a choice set J is decomposed as:

[3] Thurstone's (1927) concept of psychological stimuli - and a later interpretation in the context of utility theory by Marschak (1960), who introduced the random utility models (Train 2003:19).

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(4)

$$U_{nj} = V_{nj}(x) + \varepsilon_{nj} \qquad \forall\, j\ \in J$$

V_{nj} : *observable utility value of alternative j for individual n*

The type of discrete choice model is determined by the assumed distribution of ε which is again motivated by the design of the choice experiment. The latter is crucial since discrete choice models differ regarding their restrictions on the unobservable factors as well as their mathematical convenience. If $f(\varepsilon)$ is assumed to be *Gumble (Type I extreme value)* distributed, it results in a *logit* model. If a choice set with more than two alternatives is analysed, it is denoted as *multinominal*. In the econometric sense, V_{nj} denotes the part of the utility which is captured by the researcher. It depends on the observed attribute vector *x* of alternatives and/ or on the attributes of the decision-maker as well as the scalar parameters β, which represent the weights or importance of an attribute. If a linear utility function is assumed - which is usually the case (Train 2003) - the following *logit* probability results:

(5)

$$Pni = \frac{e^{\sum_i \beta_{ni} \cdot x_{ni}}}{\sum_{j=1}^{J} e^{\sum_j \beta_{ni} \cdot x_{ni}}}$$

A derivation of the function is presented by Train (2003). With respect to the consideration of stakeholder-specific investment decision-making, discrete choice analysis provides both the methods to design suitable behavioural models and the techniques to estimate the relevance of decision parameters from surveys and to derive segments of homogenous taste within a population. The *logit* model is able to capture taste variances by extending the utility function by socio-economic variables. These decision-maker-specific attributes are, by definition, independent of the attributes of the technological alternatives, but there are two ways to achieve taste variation among alternatives by considering variables that differentiate decision-makers: The utility function of each alternative is extended by the decision-maker's specific - socio-demographic - variables as additional attributes which are weighted with the differential effect they exhibit compared to all other alternatives (Train 2003). In this way, decision-maker's variables directly influence the difference between utilities, but are independent of the attributes of alternatives.

(6)

$$V_{nj} = \sum_{i=1}^{I} \beta_i x_{nj} + \sum_{k=1}^{K} \theta_{kj} s_{kn}$$

s_{kn}: *socio-demographic attribute k of individual n*

θ_{kj}: *weight of socio-demographic attribute k for alternative j*

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The other possibility is to incorporate decision-maker-specific variables in the respective attributes of the alternatives or scalar parameters.

$$V_{nj} = \sum_{i=1}^{I} \beta_{n_i}(s_n) \cdot x_{nj} \tag{7}$$

For instance, the importance of initial costs within the investment decision for a space heating system might decrease with increasing income of the investor (Henkel 2012):

$$\beta_{n,\text{initial cost}} = \rho_{\text{initial cost}} / s_{n,\text{income}}$$

The *logit* model exhibits some limitations with respect to the inclusion of alternatives and attributes which need to be considered when designing the chosen model. A detailed discussion of limitations is presented elsewhere (Chipman 1960; Debreu 1960; Train 2003). Especially the proportional substitution patterns among alternatives – "*Independence from irrelevant alternatives" (IIA)* property – as well as the lack of handling random taste variations could be problematic for a behavioural model of heating system choice. The IIA property might be relevant if similar technologies are part of the choice set (Kranzl et al. 2013). In this case, a *nested logit model* is more suitable (see section 3.1). Random taste variations, on the other hand, can be avoided by taking into account preferably all the attributes of the alternatives which are relevant for the decision-makers (Henkel 2012).

There are two methods to collect the input data needed to derive the relevant decision parameters and the segmentation of decision-makers: *Revealed preference* derives respective weights based on observed behaviour – e.g. data on market shares or a survey of homeowners' recently performed energy efficiency measures – whereas the *stated preference* method confronts a consumer with a hypothetical choice experiment. A comparison of the strengths and weaknesses of both methods can be found e.g. in Verhoef and Franses (2002).

Case Studies

There are numerous studies in the field of renewable energies, but most of the empirical literature focuses on the electricity market and the analysis of consumers' willingness-to-pay for renewable electricity. In recent years, more research has been published on the application of discrete choice methods to examine investment decision-making regarding heating systems and energy efficiency measures in buildings. The scope of the applied empirical models covers the determination of relevant decision parameters and the trade-off investors are willing to make between perceived product attributes (investments, energy savings, comfort, sustainability etc.) (Claudy et al. 2011). With respect to a scenario analysis of future energy demand development and technology diffusion in the building sector, the results of these empirical analyses can

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serve as input for suitable technology choice algorithms in bottom-up simulations (see 3.1 and 3.4).

Table 1 gives an overview of discrete choice studies dealing with heating system choice and energy efficiency in buildings. The studies differ with regard to the observed technologies, the considered technological and socio-demographic attributes as well as their scope in terms of geographical region and decision-makers surveyed.

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Table 1 : Discrete choice analysis studies of heating systems and energy efficiency measures in buildings

Choice scope	Decision-makers' scope	Attributes of technologies	Attributes of decision-makers	Reference/ method
Micro-generation systems: ▪ Gas boiler ▪ Biomass boiler ▪ Heat pump ▪ Solar thermal ▪ PV panels ▪ wind turbine	▪ Households in the UK ▪ 1241 respondents	▪ Investments ▪ Energy costs ▪ O&M costs ▪ Convenience in installation and operations ▪ Recommendation by installer/ peers	-	▪ (Scarpa and Willis 2010) ▪ Stated preference
Micro-generation systems: ▪ Biomass boiler ▪ Solar thermal water heaters ▪ PV panels ▪ Wind turbine	▪ Residential building owners in Ireland ▪ 1012 respondents	Perception of ▪ Investments ▪ Sustainability ▪ Fuel independence ▪ Trialability ▪ Complexity ▪ Risk (tech./ social) Subjective norms and knowledge	▪ Age ▪ Gender ▪ Education ▪ Social class ▪ Ownership type ▪ Household size ▪ Region	▪ (Claudy et al. 2011) ▪ Stated preference
Energy efficiency upgrades: ▪ Windows ▪ Facade ▪ Ventilation	▪ 142 owner-occupiers in SFH ▪ 163 tenants in MFH ▪ Switzerland	▪ Retrofit levels ▪ Additional rent per month (MFH) ▪ Investments (SFH)	▪ Tenants ▪ Owner-occupiers	▪ (Banfi et al. 2008) ▪ Stated preference
Renewable heating systems ▪ Gas/ oil boiler + solar thermal ▪ Biomass boiler ▪ Heat pumps	▪ Receivers of RES-H investment grants in Germany ▪ 2985 respondents	▪ Investment ▪ Received grant ▪ O&M costs ▪ Energy costs ▪ Energy savings ▪ Fuel independence ▪ Comfort ▪ Image	▪ Age ▪ Gender ▪ Income ▪ Building characteristics ▪ Spatial characteristics	▪ (Michelsen and Madlener 2012) ▪ Combination of revealed and stated preference
Heating systems ▪ Oil boiler ▪ Electric heating ▪ Pellet boiler ▪ Firewood boiler ▪ District heating ▪ Heat pump	▪ Residential building owners in Finland ▪ 521 respondents	▪ Investments ▪ O&M costs ▪ CO_2 emissions ▪ Fine particle emissions ▪ Required own work ▪ Current heating systems	▪ Age ▪ Gender ▪ Income ▪ Region ▪ Owns forest	▪ (Rouvinen and Matero 2012)
Energy source for heating ▪ Gas ▪ Oil ▪ Electric ▪ District heating ▪ Solid fuels ▪ Oil and solid fuels ▪ Gas and solid fuels	▪ Households in Germany ▪ Representative socio-economic panel of 12000 households	▪ Building type ▪ Dwelling vintage ▪ Retrofit in last 5 years	▪ Owner-occupier ▪ Tenant ▪ Joint ownership ▪ Income ▪ Education ▪ Household members ▪ Children ▪ Region	▪ (Braun 2010) ▪ Revealed preference

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3.3 Social psychological models

To a large extent the literature on energy consumer behaviour deals with models explaining technology choice as a psychological process based on attitudes, norms and habits. The theories attempt to overcome the criticisms of the main assumptions inherit in rational – utility-based – choice models (Jackson 2005):

- Bounded rationality (Simon 1957): Uncertainties about future development and information processing costs contradict the assumption of a decision-maker calculating all the costs and benefits of alternatives.
- Social action: Looking at the individual as the only unit of analysis does not consider technology adoption as a social process (Rogers 2003).
- Moral dimension: Rational choice models only consider individual self-interest as a driver.

The majority of psychological models either refer to the *theory of planned behaviour* or the *value-belief-norm theory* (Galarraga et al. 2011). The former represents a cognitive approach since it is based on rational choice deliberation (Kaiser et al. 2005; Michelsen and Madlener 2010). In contrast, the *value-belief-norm* theory explains consumer behaviour using norms and values and can therefore be described as a normative approach. Psychological theories can be implemented as decision simulation models in the framework of *agent-based modelling* (see 3.4). In the following, the *theory of planned behaviour* is discussed with regard to its application as a theoretical framework of individual investment decision-making in energy efficiency measures and heating systems. A detailed review of the consumer behaviour models suggested in socio-psychological research is beyond the scope of this paper; a comprehensive overview is presented by Jackson (2005) or Wilson and Dowlatabadi (2007).

The *theory of planned behaviour (TPB)* was developed by Ajzen (1991) based on the earlier *theory of reasoned action* (Fishbein and Ajzen 1975). The theory formulates an individual's *intentions* to perform an action (behaviour) – e.g. choose a certain technology from among a set of alternatives – as proximal measures of the probability that this behaviour is actually performed. *Intentions* are determined by three conceptually independent terms, denoted as *attitudes toward a behaviour*, *subjective norms* and *perceived behavioural control.*

Attitudes can be expressed as the sum of an individual's beliefs b_{nj} about the attributes (characteristics) of a choice alternative weighted by the individual's evaluation (importance) e_{nj} of these attributes. This constitutes a simple *expectancy-value attitude* model (Jackson 2005).

(8)

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$$A_{nj} = \sum_{i=i}^{I} b_{inj} \cdot e_{inj}$$

The mathematical formulation does not differ from the preference-based rational choice theory on which discrete choice analysis is based (see 3.2).

Subjective norms represent social factors which aim to capture the influence of relevant other stakeholders or the perceived social pressure of the respective decision-maker. Apart from friends and family members, significant influence on the decision process of energy efficiency investments can be exerted by neighbours, heating engineers, architects or other relevant organisations and institutions (Schulz et al. 2011). The *subjective norm* term *(SN)* is expressed by the normative beliefs n_j each relevant other stakeholder *s* holds with respect to a certain behaviour (choosing alternative *j*) and the motivation of the decision-maker to comply m_{sn} with these values:

(9)

$$SN_{nj} = \sum_{s=1}^{S} n_{sj} \cdot m_{sn}$$

For instance, Bürger et al. (2012) found that a significant barrier to deep renovation measures is the general belief in the need for “breathing” buildings to prevent mould formation disseminated by professional stakeholders such as architects or heating engineers.

The third term – *perceived behavioural control (PBC)* represents the actual extension of the *theory of reasoned action.* It accounts for external factors such as resource availability or skills referring to the decision-maker’s “perception of the ease or difficulty of performing the behaviour of interest” (Ajzen 1991:183). *PBC* is determined by the beliefs (control beliefs) c_i about the presence of external factors influencing consumer behaviour (choice of a certain alternative) weighted by the perceived power of the respective factor.

(10)

$$PBC_{nj} = \sum_{i=1}^{I} p_{in} \cdot c_{in}$$

External factors influence behaviour twofold. On the one hand, technology choice might be directly limited through regulations or infrastructural barriers. On the other hand, even if *attitudes* and *subjective norms* result in a positive evaluation of an alternative, the decision-maker’s perception of a lack of relevant resources will most likely hinder implementation of this alternative (Michelsen and Madlener 2010).

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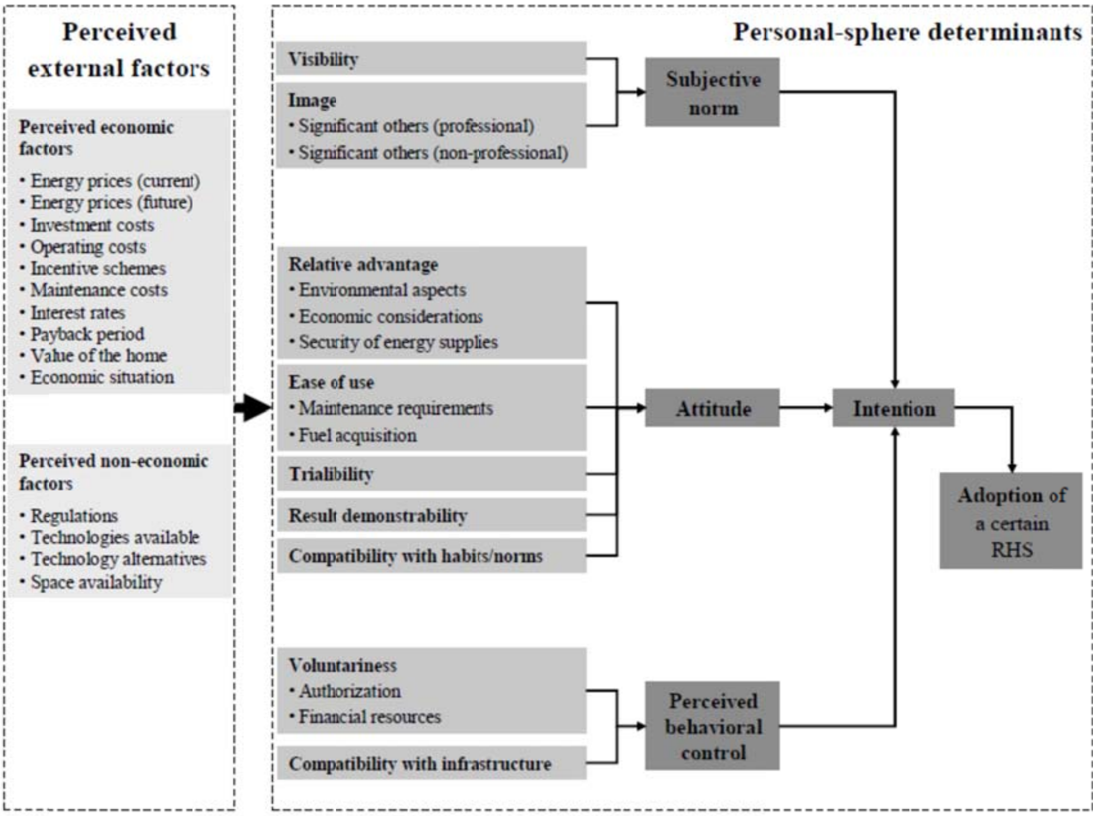
TPB assumes a linear dependency between the three terms and the consumer's behaviour by applying weighting factors (w_x). In the following equations, B_{nj} denotes the behaviour of individual *n* towards an alternative *j.*

$$B_{nj} \approx I_{nj} = w_1 \cdot A_{nj} + w_2 \cdot SN_{nj} + w_2 \cdot PBC_{nj} \tag{11}$$

Case studies

Michelsen and Madlener (2010) propose a theoretical model based on the *TPB* to assess homeowners' adoption of renewable heating systems (Fig. 2). Attitudes, subjective norms and perceived behavioural control are operationalised based on Rogers's (2003) *attributes of innovation* scale (Moore and Benbasat 1996).



Source: Michelsen and Madlener (2010)

Fig. 2: Theory of planned behaviour framework for a heating system decision as proposed by Michelsen and Madlener (2010)

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3.4 Agent based models

Agent-based modelling is one possibility to realise psychological models and their empirical findings in a simulation environment. The term *agent-based modelling* describes modelling techniques which simulate the actions of autonomous individuals or organisations. Its goal is to explain and predict the macro level systems that emerge from micro level behaviour and interactions. *Agent-based modelling* has its roots in three different computational programming methodologies (Epstein and Axtell 1996; Ferber 1999; Hare and Deadman 2004):

1) *Individual based modelling (IBM)*, which was developed to simulate ecosystems, postulates a discrete representation of individuals with different characteristics and spatial distribution (Huston et al. 1988).
2) *Artificial life simulation* aims at modelling living systems on a macro level by capturing micro level behaviours.
3) *Multi-agent systems (MAS),* which are mainly influenced by computer and social sciences (Bousquet and Page 2004), refer to models composed of multiple agents which are "situated in some environment, and that [are] capable of autonomous action in this environment in order to meet [their] design objectives" (Wooldridge and Jennings 1995: 5). In order to be able to perform flexible autonomous actions, an agent needs to be implemented in a software system with the following properties (Wooldridge 2013):
    - Reactivity – perceive their environment and are able to react to changes
    - Pro-activity – exhibit goal-driven behaviour
    - Social ability – able to interact with other agents

Depending on the research topic, agent-based models are attributed to one of the above categories. Hare and Deadman (2004) distinguish the approaches according to the degree of interaction among agents incorporated in the model. IBM focus on the heterogeneity of individuals with simpler interactions, whereas MAS attach more importance to interactions among agents and the decision-making process (Bousquet and Page 2004).

Case studies

Natarajan et al. (2011) propose an extension of the *DeCarb* model (Natarajan and Levermore 2007), which was originally an accounting model for the UK housing stock based on an engineering approach (see 2.2.2). In the resulting *DeCarb-ABM* model, each agent represents 200 UK households. The technical or physical attributes of six different reference dwelling types (vintages) are also part of each agent and are assigned randomly when agents are generated by the model. Agents are placed on a spatial grid with the geographical coordinates of actual locations. However, the model does not incorporate social structure or any interactions between neighbours in the presented scenarios. Consequently, agents are randomly distributed to the grid be-

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cause the locations do not influence the outcomes. However, the paper also presents some results on exploration of agent autonomy. The latter is implemented using a simple theoretical behavioural model for an agent's adoption of double glazing depending on household income, installations by neighbours as well as government policy. Thus, the proposed model does not include much agency in the sense stipulated in the theoretical literature on *agent-based modelling*. The main scenarios, which attempt to reproduce results from the original *DeCarb* model, include neither any heterogeneity in the decision-making process nor interactions among agents. Thus, there is no added value of the spatial grid and the generated agents who exhibit only dwelling attributes rather the individual goals and perceptions. Nevertheless, the exploratory case shows that the design of the model allows indirect influence among agents to be taken into account by considering the neighbours' adoption of technologies (local market shares) as a decision variable.

Wittmann (2008) proposes an agent-based model for investment decisions in urban energy systems. This includes private as well as commercial actors. Private actors represent building owners. A bounded rational decision model simulates investment decision-making in heating systems and energy efficiency options. The agents are distinguished according to their search rules and search domains for alternatives, their goals and decision strategies as well as the metrics applied to measure the goals (Table 2). The design of the decision model is based on the target group typology provided by the *SINUS institute* (SINUS-Milieus) and a classification of different rationality types (Gigerenzer and Selten 2001; Gigerenzer 1999). Commercial actors are energy companies which offer energy services, advertise certain technologies and operate heating and power plants as well as gas and district heating grids. The model allows different companies' strategies to be chosen that define the allocation of capital to different investment options. Furthermore, commercial actors can be differentiated according to their expectations of the development of wholesale energy prices. However, only non-structural decisions are modelled endogenously; these include the decisions to promote certain technologies, alteration of energy prices or offer of micro-cogeneration contracts. Investments in central generation capacity, infrastructure expansion as well as the decisions to enter a new market are set exogenously. Therefore, the interactions between commercial and private owners are only realised by the resulting energy prices as well as by altering the search domain of building-owners in case certain technologies are promoted. A feedback from private actors to the commercial actors in terms of successful contracts is not implemented in the model. Wittmann (2008) presents only an exemplary application of the model. The model has not yet been validated, e.g. using empirical data on building-owner types' allocation and energy companies' portfolios in a certain city.

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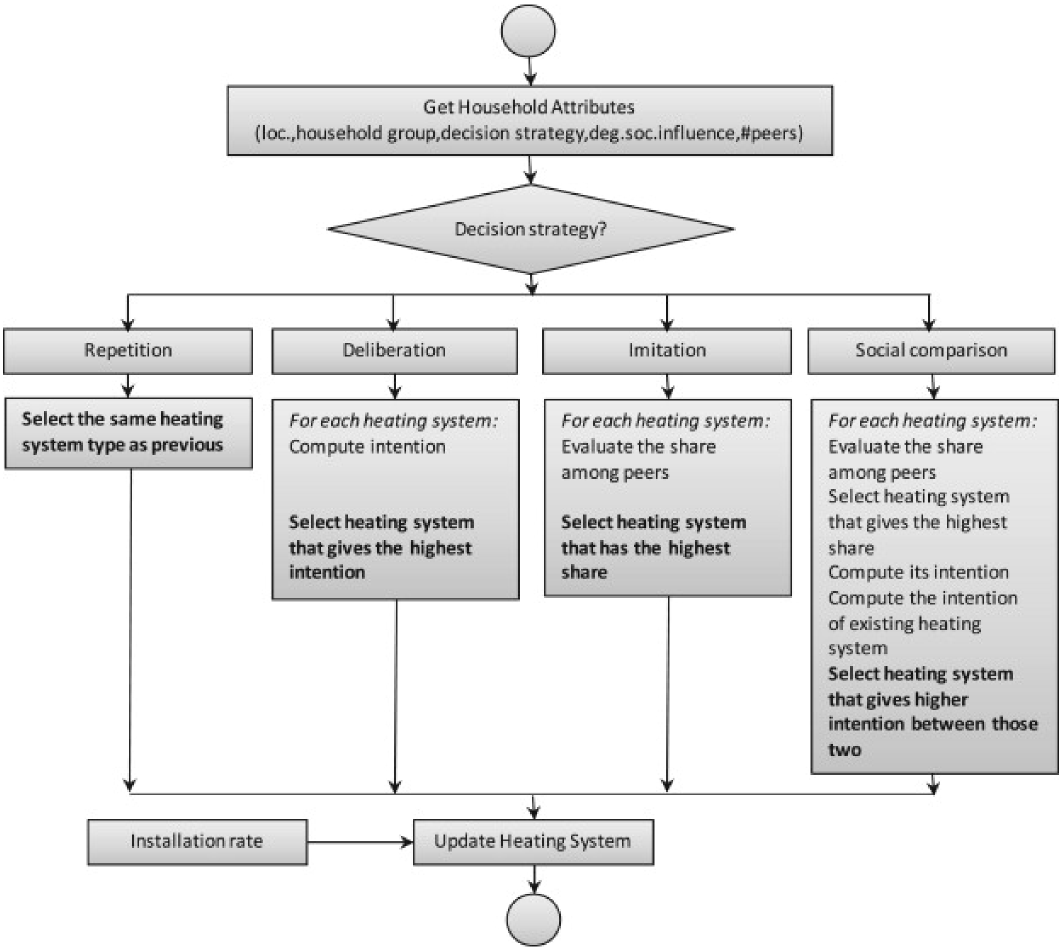
Table 2: Overview of the decision parameters proposed in the private actor model of Wittmann (2008)

Search rule	Search domain	Decision strategy	Goals	Goal metrics
Find all alternatives	Peer group	Goal ranking	Costs	Investments Operational costs Payback Net present value
Find alternatives which satisfy certain constraints regarding the goals	Society	Satisfaction: fulfilment of defined aspiration level of each goal	Environment	Qualitative Energy consumption GHG emissions
Find common alternatives in defined search domain	Location	Lexicographic: setting relative importance of different goals	Comfort	Qualitative
	Topical: new technologies	Weighted adding strategy: utility calculation		

Sopha et al. (2011) suggest an *agent-based* model to analyse the diffusion of wood pellet boilers in Norway. Agents are households which are parameterised using the results of an empirical survey. Agents are spatially distributed in an environment which represents the geographical location of each household in the real world. Heating systems are described by economic and non-economic attributes such as perceived total costs, fuel price stability, and functional reliability. Agents are distinguished according to their decision strategy, degree of social influence, household group, their location and the "number of peers they communicate with about their heating needs" (Sopha 2011:2). The model incorporates four decision strategies: repetition, deliberation, imitation and social comparison (Fig. 3). The deliberation strategy evaluates all the alternatives using a psychological model based on the *theory of planned behaviour* (see 3.3). Here, the heating system with the highest *intention* is chosen. The standard *TPB* model, as described in section 3.3, is extended by the term *personal norm (PN),* which captures the moral obligation to use environmentally-friendly heating systems. *Intention* towards a heating system is determined by a linear equation weighting *attitudes, perceived behavioural control, personal norms* and *subjective norms.* The latter are operationalised by the share of peers currently using the respective heating systems weighted by the degree of social influence in the decision-making of the respective household. This interaction among household agents is implemented by a *small world* *network*; that is each household interacts with each neighbour within a defined spatial radius and with the rest of the population randomly.



Source: Sopha et al. (2011)

Fig. 3: Decision-making algorithm from Sopha et al. (2011)

4. Consideration of stakeholder behaviour within the scenario analysis in ENTRANZE

4.1 Simulation model INVERT/EE-Lab

Invert/EE-Lab is a dynamic bottom-up model for simulating the space heating and cooling as well as the hot water energy demand of a region's or country's building sector. It simulates investment decisions in heating systems and retrofit options under different scenarios and thus allows a scenario analysis of support policies' impacts and the influences of energy price developments on the energy carrier mix, CO_2 reduction and

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overall costs (Fig. 4). With regard to the taxonomy derived in section 2.1, it can be classified as an engineering simulation model on a national scale.

The *Invert* model was originally developed by the *Energy Economics Group* of the *Vienna University of Technology* within the frame of the *Altener* project Invert (Investing in RES&RUE technologies: models for saving public money). This model has been extended during the course of several projects and studies and applied to different countries within Europe (see e.g. Lukas Kranzl et al. 2006; Nast et al. 2006; M. Stadler et al. 2007; Steinbach et al. 2013). Recent modifications include re-programming to improve the run time, usability and flexibility when modelling policy options as well as methodological enhancement of the simulation algorithm (Kranzl et al. 2013; Müller and Biermayr 2011).

In particular, the model has been extended by an agent-specific decision module which takes the heterogeneity of decision-makers in the building sector and investor-specific barriers into account (Steinbach 2013). The following section describes the methodology of the newly implemented agent-based decision module. For a detailed presentation of the other modules, refer to Kranzl et al. (2013).

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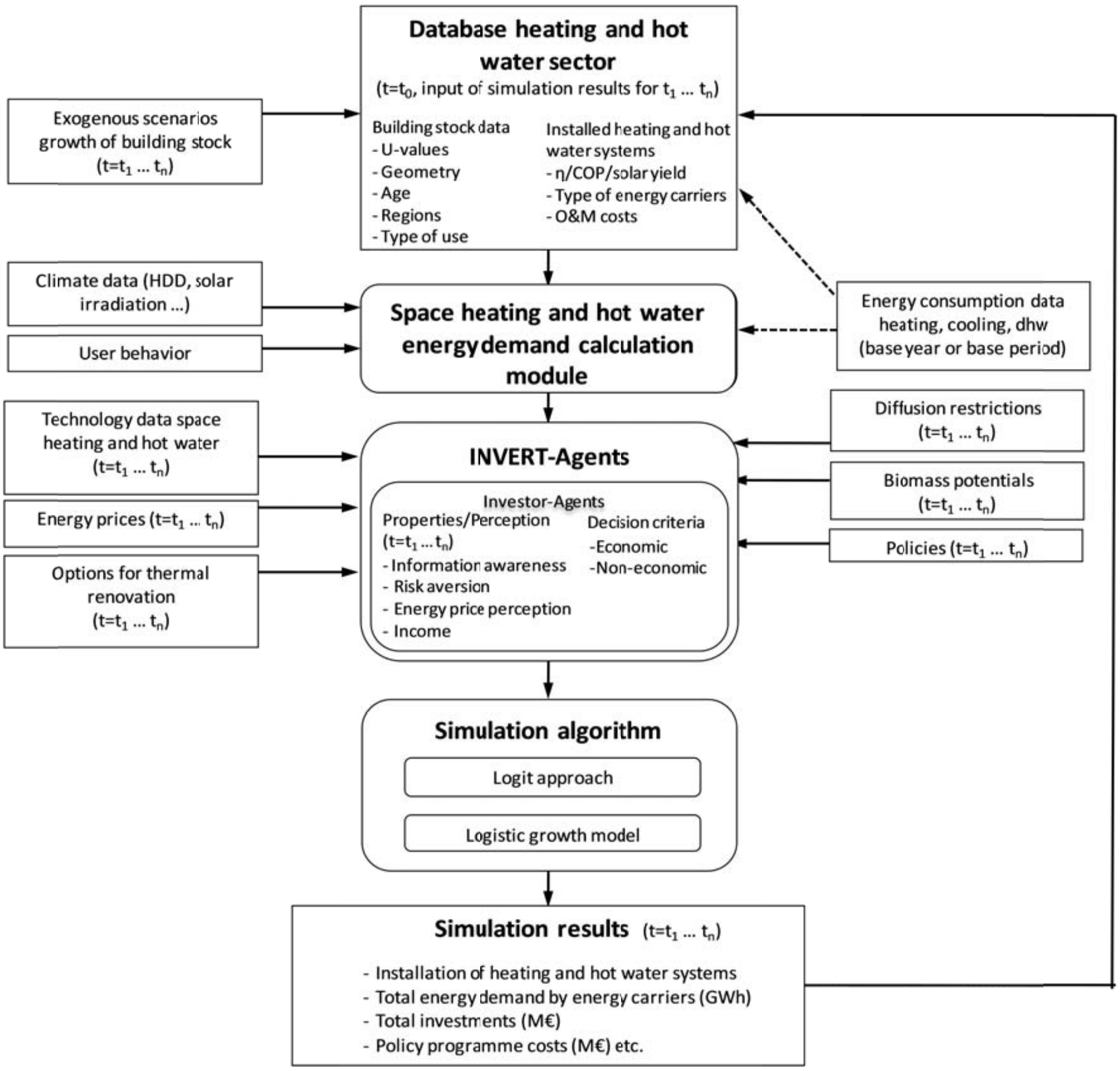

Fig. 4: Structure of the INVERT/EE-Lab model

4.2 Consideration of stakeholder specific investment decision-making in INVERT/EE-Lab

The agent-based decision module allows the definition of different investor types and the simulation of investment decision-making as a function of investor-specific variables reflecting barriers and perceptions. Fig. 5 shows the structure of the module.

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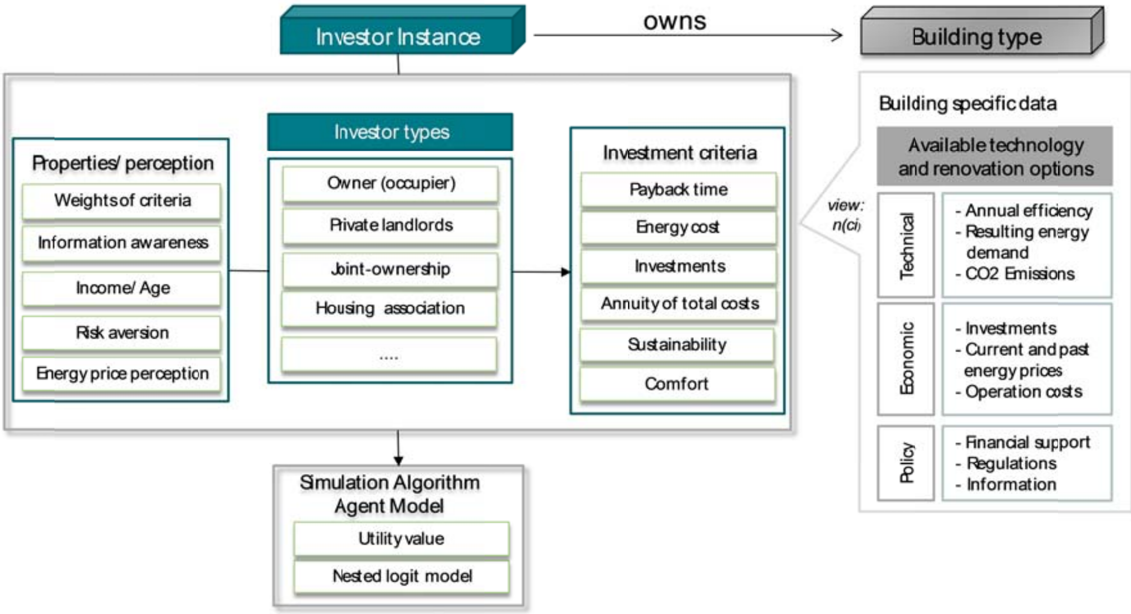

Fig. 5: Overview of the agent-specific decision module (INVERT-Agents)

The simulation of investment decision-making in this model is based on different economic and non-economic criteria which are then calculated for each combination of technologies, buildings and investor types. The defined properties of an investor determine how an investment decision is made (relevance of different criteria) as well as the perception of investment options and influencing parameters. The latter might result in different values of the decision criteria if the same technology is considered by different investors. For instance, dissimilarities of criteria values among investors can result from unequal knowledge of subsidy schemes and their consideration in the investment decision-making process. With respect to regulative policies, such as the minimum efficiency standards defined by building codes, the model allows agent-specific compliance rates to be defined. The usage of the building by the investor is also considered as a parameter in the decision process. Thereby, the model differentiates between investors occupying the whole building, collective ownerships, private landlords and housing associations. Energy cost savings through an energy retrofit or a different heating system are only a relevant parameter for owner-occupiers, whereas the refinancing of an investment through additional rents is considered for private landlords and housing associations.

Using the investor-specific criteria values, total utility values are calculated for each technology option. Economic and non-economic values are normalised to utility values using a linear transformation (norm(x)). The total utility value of a technology option j in a building b is determined using weights for each criterion which are defined individually for each investor type n.

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$$V_{njb} = \sum_{i=1}^{I} \beta_{in} \cdot \mathrm{norm}(x_{inj}(\mathrm{inf}_n, \mathrm{risk}_n, \mathrm{pcalc}_n, \mathrm{invc}_n))$$

β_{in}: *weight on attribute i by investor n,* $\sum_{i=1}^{I} \beta_{in} = 1, \forall n$

x_{inj}: *attribute value i of alternative j as perceived by investor n*

inf_n: *information awareness, [0,1]*

risk_n: *risk aversion, [0,1]*

pcalc_n : *energy price calculation*

invc_n : *usage of building - owner-occupier or landlord*

The perceived attribute values depend on the investor-specific variables:

- *Information awareness* denotes whether the share of agents within an investor instance perceive regulatory policies (e.g. building code requirements) within the investment decision and whether existing financial support instruments are considered.
- The *risk aversion* sets the share of agents within an investor instance willing or able to raise a credit in order to finance energy efficiency investments. This variable is relevant if the impact of credit-based support schemes (soft loans) is analysed. These are the major support policies for the energy-related retrofitting of buildings in most EU Member States.
- *Energy price calculation* defines if energy costs are calculated based on current prices, the weighted average of prices observed in the last three simulation periods (years) or considering energy price increases in the last three periods.

Based on the resulting utility values, investor- and building-specific market shares of technologies are determined using a *nested logit model* (see section 3.1)

(12)

$$ms_{njb,t} = \frac{e^{-\lambda_b \cdot r_{njb}}}{\sum_{j=1}^{J} e^{-\lambda_b \cdot r_{njb}}}$$

$$r_{njb,t} = \frac{V_{njb,t}}{\sum_{j=1}^{J} ms_{njb,t-1} \times V_{njb,t}}$$

ms_{njb}: *market share of alternative j in building b for investor type n*

r_{njb}: *relative utility of alternative j in building b for investor type n*

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5. Conclusion

This paper presented an overview of energy-economic models for the building sector and methods to integrate individual decision-making in such models. Energy-economic models are differentiated according to how energy demand in buildings is calculated (engineering or statistical), the main modelling methodology (simulation, optimisation, and accounting) and the scope (building, regional or country level).

An engineering approach allows buildings' and technologies' characteristics to be captured on a highly disaggregated scale. However, it requires the same level of detail in the input data and does not account for behavioural patterns. Statistical models, on the other hand, have the advantage of using measured energy consumption data in combination with available macroeconomic and socio-demographic variables. Thus, user behaviour is directly captured within these models.

The dynamics – in energy demand development and technology diffusion – is determined by the applied modelling methodology. Optimisation models are able to derive cost optimal scenarios in terms of refurbishment activity, energy carrier mix and infrastructures (gas and district heating grids) given a certain energy or CO_2 emission saving target. Normative scenarios can also be calculated with accounting models. Diffusion and refurbishment rates are defined exogenously. Simulation models aim to capture real world dynamics which facilitates, for instance, the evaluation of the impact of different policy instruments.

Since the building sector exhibits a heterogeneous investor structure with different non-economic barriers and supporting factors, integrating stakeholder-specific investment decision-making in simulation models is crucial for the quality of the results. Building sector simulation models on a national scale consider non-economic barriers only on an aggregated level, if at all, and do not differentiate between different stakeholders. On the other hand, there are modelling approaches which focus on the investment decision process itself and the interactions among stakeholders. However, these models are usually not designed to represent the whole building sector or exhibit a higher aggregation level in terms of techno-economic inputs.

Therefore, INVERT/EE-Lab attempts to combine an energy-economic simulation model, which is highly disaggregated in terms of technologies and buildings, with an agent-based investor decision module. The latter enables the definition of different investor agents with different goals, knowledge and perceptions.

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Annex: Transformation of investor-specific decision criteria and barriers in INVERT/ EE-Lab

A.1 Description of input data on stakeholders

The model setting of decision criteria and investor-specific barriers are based on the qualitative analysis conducted by NCRC (see deliverable 4.2). This analysis is based on a comprehensive literature review as well as expert interviews in each of the target countries. Based on the literature review's evaluation of the respective project partners in each of the target countries, the relevance of the decision criteria has been rated on *a 5 point scale* separated according to the defined stakeholder groups. Barriers are rated if they are relevant (A, (B)) or not (-).

Stakeholder-specific decision criteria

Decision criteria are clustered in five categories.

Table 3: Decision criteria considered in the qualitative analysis

Decision categories	
Financial	Initial cost
	Payback time
	Return on investment
	Energy savings
Ease of renovation	Quality service available
	Quick instalment
	Turnkey solutions available
Lifetime and risk considerations	Timing vis-a-vis previous renovations
	Ease of maintenance
	Widely used solution
Other benefits	Improved comfort
	Improved value of property
	Social approval/status
Environmental/societal motives/pressures	Environmental considerations
	Expected future regulation
	Recommendation by experts

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Stakeholder-specific barriers

Stakeholder-specific barriers are clustered in five categories:

Table 4: Barriers considered in the qualitative analysis

Decision categories	Criteria
Genuine uncertainties regarding cost effectiveness	Conflicting information, mistrust of information
	Heterogeneous outcomes
	Uncertainty concerning measurement & verification of savings
Financial barriers	High initial costs
	Long payback time
	Access to/cost of capital
	Unwillingness to incur debt
	Occupant take-back
	Low/uncertain resale value of property
Organisational problems	Tenant-owner dilemma
	Collective decision problems
	Short timeframe of decisions
	Public budgeting practices
Lack of information and skills	Lack of customer attention and interest
	Lack of customer knowledge
	Lack of reliable advice
	Unsophisticated financial analysis
Transaction costs	Lack of skilled service providers
	High information search costs
	Switching costs, concerns over disruption
	Risks of failures in renovation

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A.2 Decision criteria barriers in INVERT/EE-Lab and diffusion algorithm

Since the model is still only a reflection of the real decision processes, a one-to-one transformation of the specific barriers and relevant decision criteria gained in the qualitative analysis is not possible..

As described in section 4, the agent-based decision module of INVERT/EE-Lab allows different investor types to be defined with respective shares in each building class. Each investor type is characterised by specific variables which are relevant for the investment decision process. Variables can be differentiated by agent properties which define the perception of investors (Table 4) and by weights on decision criteria which define the decision process. The choice of heating systems and energy efficiency measures is calculated separately. Firstly, the perceived criteria values of each alternative are calculated specific to each investor and building and linearly normalised on a 0 to 100 scale. Secondly, utility values are determined by applying investor-specific weights. In the case of energy efficiency measures, which are always limited to four different options, the alternative with the highest utility value gains the whole market share within the building of the respective investor. In the case of heating systems (an arbitrary number of systems can be defined), utility values are used to calculated market shares by applying a *logit* function. Basically, the alternative with the highest utility value gains the highest market share while the other alternatives gain market shares equivalent to the difference in utility value.

The following criteria can be set to be investor-specific in the decision process:

1. Economic criteria
    a. Investments (initial costs)
    b. Payback time
    c. Profitability (net present value based calculation)
    d. Energy cost savings
2. Non-economic criteria
    a. Sustainability
    b. Comfort
    c. (Existing heating system)

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Table 5: Investor-specific input variables

Perception/ property variables:	Description	Variable settings
Investor class	• Energy savings are relevant for decision (in case of owner-occupier) or • Additional rent (in case of landlords)	• 1: owner-occupier • 2: private landlord • 3: joint ownership (owner-occupied MFH) • 4:Housing association • 5: Owner of non residential buildings
Information awareness	• Share of investors within investor type group with knowledge about financial support instruments • Investor-specific compliance rate with regulation	• Float number between [0,1]
Risk aversion	• Indicates if credit-based support instruments are considered in the investment decision	• 1: risk averse (no consideration of soft loans) • 0: not risk averse
Energy price calculation	• Indicates how the development of energy prices is considered	• 1: Weighted average last three periods • 2: Energy prices of current period • 3: Calculation according to standards: discounted price increase over lifetime
Interest rate	• Investor-specific interest rate if net present value based on *profitability criterion* is considered	• float number between [0,1]

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A.3 Transformation of qualitative results into model settings

Calculation of decision criteria weights

The weights within each group are calculated by dividing the assigned value by the total sum of assigned values within the group. Each group is weighted by its sum divided by the total sum of criteria values considered. Thus, each criterion weight is calculated as follows:

$$weight_j = \frac{value_j}{\sum_j^J value_j}$$

value: assigned relevance on a 5-point scale

j: index of criteria

Transformation into model variables

An explicit transformation of all the decision criteria as investor-specific variables is not possible due to the algorithms implemented in the model. Furthermore, decision criteria are grouped in economic and non-economic variables within the model rather than the five groups suggested in the qualitative analysis (see Table 3). There are several criteria which are not incorporated as investor-specific variables but which are considered implicitly in the model. The following criteria describe the influences of the timing of a renovation or a heating system change rather than the choice among alternatives:

- Timing vis-a-vis previous renovations
- Quality service available

Since the trigger for a renovation or a heating system change is implemented in INVERT/EE-Lab via an age-dependent distribution which describes the breakdown probability of components, these variables are only considered on a aggregated level and not differentiated by specific investors.

Another group of criteria describe the maturity stage of alternatives or the market itself:

- Quick instalment
- Turnkey solutions available
- Widely used solution
- Ease of maintenance
- Recommendation by experts
- Expected future regulations

These variables are also considered only implicitly in the model by means of the diffusion restrictions which set the maximal diffusion of an alternative depending on its current market share.

With regard to economic variables, all the “financial” decision criteria are considered explicitly.

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The variable *comfort* is coded by the decision criteria:

- Improved comfort
- Improved value of property

The variable *sustainability* is coded by the decision criteria:

- Environmental considerations
- Social approval/status

Transformation of barriers into investor-specific properties

Most of the barriers are either already reflected in the respective decision criteria or represent general obstacles to changing the heating system or conducting any renovation. As already discussed, these barriers influence the rate of renovation or heating system change, but not the choice between the competing options.

The investor-specific variable ***risk aversion*** is coded by the following barriers derived in the qualitative analysis:

- Access to capital
- Unwillingness to incur debt

An investor agent is assumed to be risk averse if any of these two barriers are relevant – assigned an “A”.

The ***information awareness*** variable is coded by the following information-relevant barriers *(barriers$_{inf}$)*:

- Conflicting information, mistrust of information
- Lack of customer attention and interest
- Lack of customer knowledge
- Lack of reliable advice

The share of agents within the investor instance with knowledge about financial support schemes and regulative requirements is calculated as follows:

$$inf_n = \frac{card(barriers_{inf} = A)}{card(barriers_{inf})}$$

Energy cost calculation is assumed to be based on the weighted average of energy prices of the last three periods for private investors (Kranzl et al. 2013):

$$p_{sn,t} = \sum_{i=0}^{2} p_{s,t-i} \cdot f_i$$

$$f_0 = 0.3.\ f_1 = 0.5,\ \ f_2 = 0.2$$

$p_{s,t,n}$: *price of energy source s at time t as perceived by investor n*

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For non private investors, energy price calculation is assumed to be according to *VDI guideline on economic efficiency of building installations* taking into account energy price development over the lifetime of the respective installation (VDI-The Association of German Engineers 2000).

$$p_{sn,t} = p_{s,t} \cdot \frac{1 - \left(\frac{r}{q}\right)^T}{q - r} \cdot a$$

$$r = 1 + \frac{1}{2} \cdot \sum_{i=0}^{2} \frac{p_{s,t-i+1} - p_{s,t-i}}{p_{s,t-i}}; \qquad a = \frac{q-1}{1-q^T}; \qquad q = 1 + i$$

q: annual price increase

a: annuity factor

q: Interest rate factor with rate i

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