Working paper

Stochastic buildings simulation

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July, 24th, 2012

The following report presents results from a collaboration between the Vienna University of Technology and the Lawrence Berkeley National Laboratory and has been enabled by a research grand of the Austrian Marshall Plan Foundation, Vienna, Austria.

Contents

1 Introduction

The influence of different decision parameters on the energy system in times, where a fundamental system break is needed, can be descripted only insufficiently by black box, top-down econometric models. This is particularly true when long-lasting durable goods such as buildings and their components, with technical lifetimes often exceeding 30-100 years are examined. In such cases techno-economic models provide results that are more robust, since they comprise the functional correlation between cause and effect. When it comes to investment decisions in the built environment, it has to be acknowledged that decision maker in this particular area are not a homogenous but very heterogeneous group. On the one end of the spectrum, there are highly professional institutions. Such investment decisions are the core of their business, but they are often unable to gain fully from higher investment costs and the resulting higher earning or lower costs in the using phase, since in most cases they do not operate and use the building by themselves (investor-user-dilemma). A large number of non-professional decision makers constitute the other end of the range. Decisions taken by this group are characterize by bounded rationality caused by bold lack of information and personal preferences (Braun, 2012, Liao and Chang, 2002). Therefore we can conclude that decision making isn't solely based on a cost driven approach and the neoliberal approach of cost minimization fails.

Within this project, two existing model used by the Energy Economics Group (EEG) and the Lawrence Berkeley National Laboratory (LBNL) has been compared and enhanced. The first model, which is used at the EEG (Vienna University of Technology), is the ERNSTL/EE-Lab Model (Müller and Biermayr, 2011) and the second is the buildings module of the SEDS Model (Stochastic Energy Deployment System), developed at the Lawrence Berkeley National Laboratory (Marnay and Stadler, 2008).

The core decision methodology of both models is logit model, a well-established approach within the discrete choice framework. Discrete choice model are used to describe situation where decision makers must choose between mutually exclusive alternatives. The ERNSTL/EE-Lab model applies a nested-logit-approach (Train, 2003, belongs to GEV models), thus it is not bounded by the independence from irrelevant alternatives (IIA). The SEDS model uses a multinomial logit approach, which requires less data input. The ERNSTL /EE-Lab model applies a probability theoretical approach that deals with distributions as far as possible. The SEDS model uses the Monte Carlo Simulation techniques.

Data related uncertainties arise inevitable when data (e.g. cost data, performance, energy demand profile, solar radiation, etc.) based on drawn samples are projected to the whole building stock or available technologies. In addition, future technological development, future cost and price data are uncertain. Algorithm-related uncertainties arise from the numerous variables that influence decisions makers and the fact, that they are not directly observable and model calibration relies on aggregate data only.

The aim of this collaboration is to advance the used algorithms applied in the models described above, incorporate uncertainties, and thus, increase the robustness of the results and the reliability of the drawn conclusions. The following research questions and aspects are covered in this report:

- Availability and empirical evidence on individual decision criteria and their importance on the decision.
- Major approaches from the field of discrete choice theory, namely the multinomial logit, nested logit and probit approach are discussed and compared.
- An analysis of the arising resulting uncertainties related to the data basis and the decision algorithm with a special focus on stochastic simulation.
- The stability of the model results with respect to the underlining input data and the empirical non-observable model parameters respectively are evaluated.

2 Empirical evidence on individual decision aspects

In this chapter, the empirical evidence of individual decision calculus is investigated. To do so, literature on this issue is reviewed as well as an own survey, conducted within the Lifestyle 2030 project (Bogner et al., 2012) is assessed.

Henning et al. (2011) analyzed based on expert judgments the importance of different decision criteria of various decision agents in the building sector. In the residential building sector, four categories of investor were defined:

- Owners of small residential buildings using the building on their own
- Owners of residential buildings renting out their building(s)
- Community associations of apartment buildings
- Public housing association

Their conclusions are that the first three agents, even though there are some differences, weight their investment decision criteria in a similar way: Most important are the capital needs, furthermore rather stable energy prices and low annual energy costs are preferred. Pay-back-time and the total annual costs including the annuity of investment costs are playing a minor role in the decision process, however they are already covered in the criteria: capital needs and low energy costs which can be transformed into the later ones. Public housing associations apply a different decision calculus, allocating the value of buildings and the possibility to get higher rents a higher importance than the annual energy costs.

At country study on heating systems for Austria, Finland, Sweden and the Netherlands done by Müller et al. (2011) comes to the conclusion that heating systems commonly installed in these countries have similar total heating costs (compared within a country) and belong to those heating systems which have low total annual costs. Thus, the authors conclude, the total heating costs to have a significant influence on the decision, yet costs might not be the not be the sole decision criteria.

Braun (2010) analyzed the decision criteria for new heat supply systems in the German residential building sector using a multinomial logit model. The explanatory variables she used were the income, the number of household members, the average education level of the representative household members, the construction year and type of the building and the location of building. On a brother level the information used was whether or not the building is located in the former GDR; on a region level whether or not the building is located in rural or urban areas. Heating costs were not used as an explanatory variable. Conclusions from her analysis are that neither income, number of household members nor the average education level to have a major impact on the decision. A significant influence on the decision has the location of the building, which can be seen as an estimator of the availability of heating systems, and the construction period of the buildings. The Pseudo R^2 of her model on the full sample (7171 observations) is 0.151[1]. The very low explanatory value of the model reveals that the model misses some important explanatory variables. The author of this report concludes, based on other work done in this field of research, that the costs of heating systems have a major role.

Henkel (2012) asked in an online-survey investor, which recently installed a new heating system in their homes, about the main reasons for their decision for a specific heating system. In case of newly installed conventional heating systems (oil and gas fuelled boilers) about 50% stated that the main reason was that this particular energy carrier has been used already before in the building. Other important criteria were economic reasons, and in case of oil the unavailability of natural gas. In case of alternative heating systems (wood pellets and heat pump with solar thermal systems) one third mentioned the high natural gas and heating oil prices as main reason for their decision. In case of pellet heating systems another 25% based their decision on economic reasons (incl. low operational costs), for the heat pump - solar thermal system combination, economic reasons where decisive for about 45%. 15% to 20% mentioned environmental friendliness as their most important criteria.

[1] The model for the sample subgroup of house owners only (3928 observations) results in a Pseudo R^2 of 0.065 only.

2.1 *Influence of the affinity to a specific lifestyle group on building renovation and heating system decision process.*

Within the *Outlook "Life Style 2030"* project, a survey was conducted, in which the energy consumption and appliances in households and information on the building along with the affinity to a certain lifestyle group of decision makers of those households, using the Sinus-Milieus® cluster (Figure 2.1), were asked (Bogner et al., 2012). The questionary was constituted by the project team groups: Austrian Energy Agency and Energy Economic Group on the Vienna University of Technology. The survey was done online and face-to-face (140 interviews in order to reach the 60-85 year old target group) and was conducted by the market research institute Karmasin. Sample size was ~1000 household representatives within an age of 18 - 85 years.

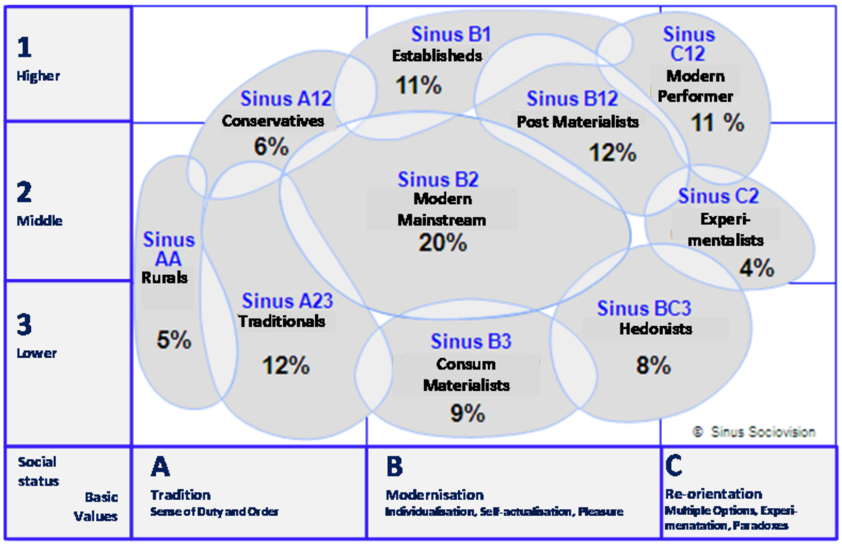

Figure 2.1. Sinus-Milieus® of the Austrian TV-Population in 2009
(source: http://mediaresearch.orf.at/index2.htm?fernsehen/fernsehen_sinus.htm, 5.10.2009, translated)

Based on the original Sinus-Milieus clusters shown above, the clusters condensed in this survey are:

- Incurious group (with respect to energy consumption and environmental conservation) (LSG 1)
- Environmental conservationists (LSG 2)
- Discerning group (LSG 3)
- Traditionalist (LSG 4)
- Established group (LSG 5)
- Alternative lifestyle group (LSG 6)
- Pensioners and sedate lifestyle group (LSG 7)

To assess the decision making process with respect to investments in (thermal) building renovation and heat supply systems, I focus in this work on the current installed systems und use this indicator as an approximation for future decision to make.

Out of the sample of 1053, 94 sample had a valid indication to the age of the building in which they were living, 66 sample included the degree of renovation status of the building. The building age revealed that the groups can be distinguished in two clusters. The milieu clusters LSG 2, 3, 4, and 5 are living in buildings with an average age of 25-35 years, whereas the average building age of the remaining three milieu clusters are in the range of 50 to 55 year and thus almost twice as old. The total share on partly or comprehensive buildings renovation of the sample having a valid answer, is about 80%. The only milieu group that inhabits rather older buildings as well as a lower share on comprehensive or partial renovated buildings is the Alternative lifestyle group (LSG 6). However, since the response rate for this question was very low (5%-7%, except for LSG 6: 11%), the results are not very solid. Therefore the hypotheses: differences in the building renovation status cannot be found, can neither be accepted nor dismissed.

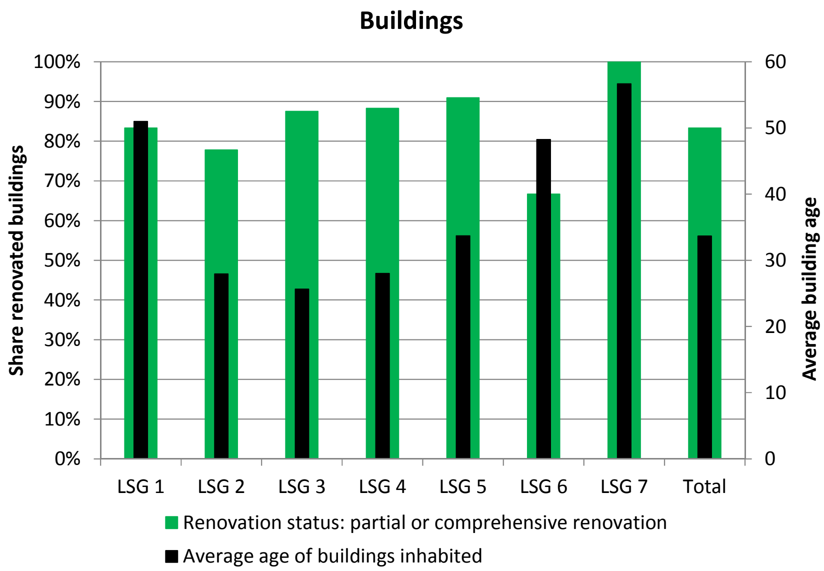

Figure 2.2. Renovation status (black bars) and average age of the inhabited building (green bars).

For the assessment of heat supply systems, a sample of 960 (out of 1053) valid and useful (energy carrier is known and provided) answers is available. Therefore results stand on a solid ground for this analysis. The research hypothesis H0 runs as followed: Currently installed heating supply systems do not indicate that the different lifestyle groups, using the Sinus-Milieu Cluster concept, have individual preferences for the environmental image of the used energy carrier. The counter hypothesis H1 states, that such individual preference can be found in the data sample.

In this analysis I associate heat supply systems using biogenic energy carriers, heat pumps and solar thermal systems with a positive environmental image. In general, the use of district heating, even though associated with a positive environmental image, depends on the availability at the specific site and only to a minor degree on the individual preference of the decision maker. Thus the variance of district heating between different lifestyle groups is used as a reference and is compared against variance of heating systems with an environmental friendly image. If heating systems with an environmental friendly image have a significantly higher variance then district heating systems, it can be concluded that the data reveal some individual preferences for environmental friendly heating systems and hypothesis H0 has to be rejected.

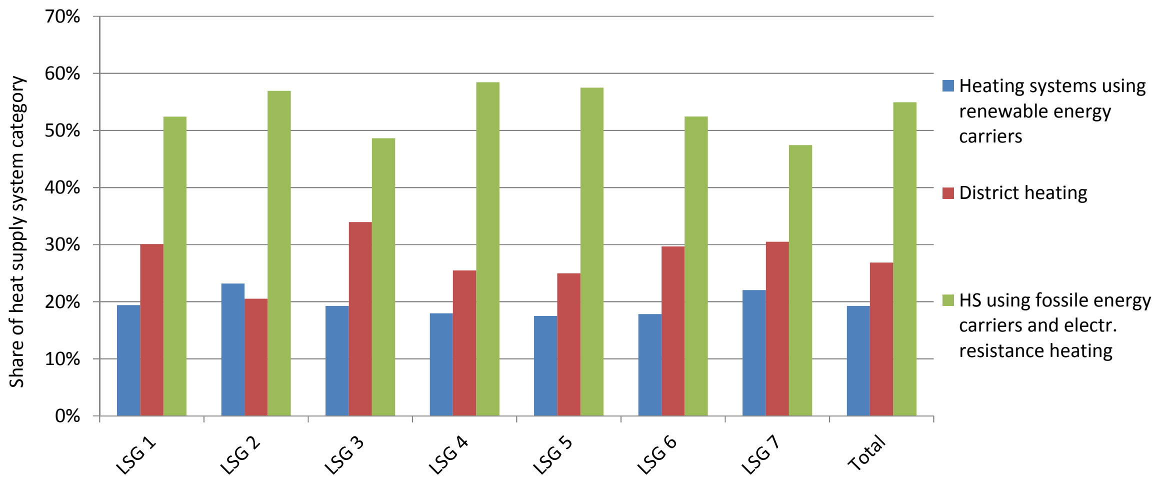

Figure 2.3. Share of heat supply system categories per lifestyle group

The variance of the three heating system categories is calculated as shown in Equ. 1. The market share for district heating systems is based on the total number of observations, whereas the share of heating systems associated with a positive environmental image (PEI) is based on those heating systems, which were freely chosen, which means they do not including the samples were district heating is used.

$$\sigma^2_{HSCat} = \frac{\sum_{i=1}^{G_{SM}} \left(\frac{s_{HSCat,i}}{s_{HSCat}} - 1 \right)^2}{G_{SM} - 1} \qquad (Equ.\ 1)$$

σ^2_{HSCat} ... Variance of heating system categories between Sinus-Milieu Clusters

G_{SM} ... Number of Sinus-Milieu Clusters (7)

$s_{HSCat,i}$ ... Share of heating system category HSCat in Milieu Cluster i

s_{HSCat} ... Share of heating system category HSCat on the full sample

$$s_{district\ heating} = \frac{s_{district\ heating}}{1}$$

$$s_{environm.\ \text{pos image}} = \frac{s_{environm.\ \text{pos image}}}{1 - s_{district\ heating}}$$

The results of this analysis, shown in Table 2.1, do not indicate strong evidence that the shares of PEI heating systems vary to larger degree than district heating systems. If all clusters are considered, the variance of district heating is larger than the one of environmental friendly heating systems. If the environmental friendly lifestyle group (LSG 2), which shows an extra low share of district heating compared to other groups, is not accounted when calculating the variance of district heating, district heating still doesn't have a lower variance. A further correction, in which the share of district heating is corrected by the share of dwellings compared to single and double family houses, gives a variance for district heating, which is slightly lower than those of heating systems associated with an environmental positive image.

Table 2.1. Variance of share of heating system categories between Sinus-Milieu clusters.

	Sinus-Milieu Cluster		
	all Clusters	District heating: all clusters except environmental conservatives	Exclude LSG 2, adjust availability of district heating by the building type: apartment versus single/double-family house
$\sigma^2_{HSCat,environm.\ friendly\ image}$	11.6%^{2}		
$\sigma^2_{district\ heating}$	16.7%^{2}	11.6%^{2}	10.7%^{2}

As comparison, the variance of PEI heating systems has been calculated, assuming a higher share (as a factor of the average share) of those systems in the environmental conservationist lifestyle group (LSG 2).

Table 2.2. Variance of PEI heating system within different lifestyle clusters assuming a higher share of these systems in LSG 2.

	Share of PEI systems in LSG as factor of average share				
	110%	120%	130%	140%	150%
$\sigma^2_{HSCat,environm.\ friendly\ image,\ ref}$	$12.6\%^2$	$14.0\%^2$	$16.1\%^2$	$15.8\%^2$	$21.2\%^2$

Based on the results outlined above, I conclude that the data sample does not reveal a difference exceeding an individual preference of +10% compared against the average for heating systems with an environmental positive image. Therefore the hypothesis H0 cannot be rejected.

3 The ERNSTL/EE-Lab Model

The analyses descripted in the following are based on the ERNSTL/EE-Lab Model, which has been adopted and enhanced within the research grand. The ERNSTL/EE-Lab Modell is a dynamic bottom-up model. The core of the model constitute a module calculating energy demand and final energy consumption for space heating and domestic hot water of buildings on the one hand, and a module that anticipates heating related investment decisions on the other. These modules are connected to a data base, supplying information on relevant data, such as a detailed description of the building stock, heat supply technologies, energy prices, climate data, user behavior, etc.

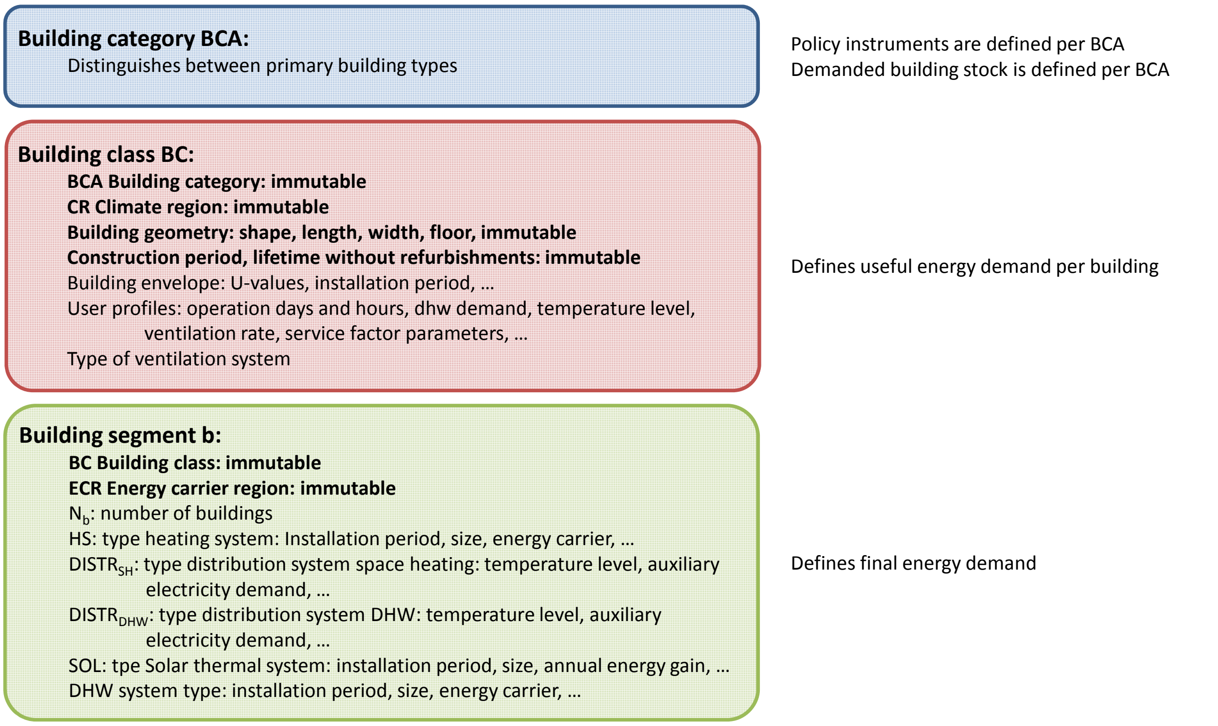

Figure 3.1. Hierarchical structure for the definition of buildings and their main properties

3.1 The decision tree structure

Throughout the simulation period, decision anticipated by the model can be structured in a decision tree. For each building class and building segment, the share that undergoes some specific measures defines a new branch.

$$N_{b,t+1} = N_{b,t} \cdot \left(1 - s_{dem}\right) \cdot \left(1 - s_{hs}\right) \cdot \left(1 - s_{ren}\right)$$

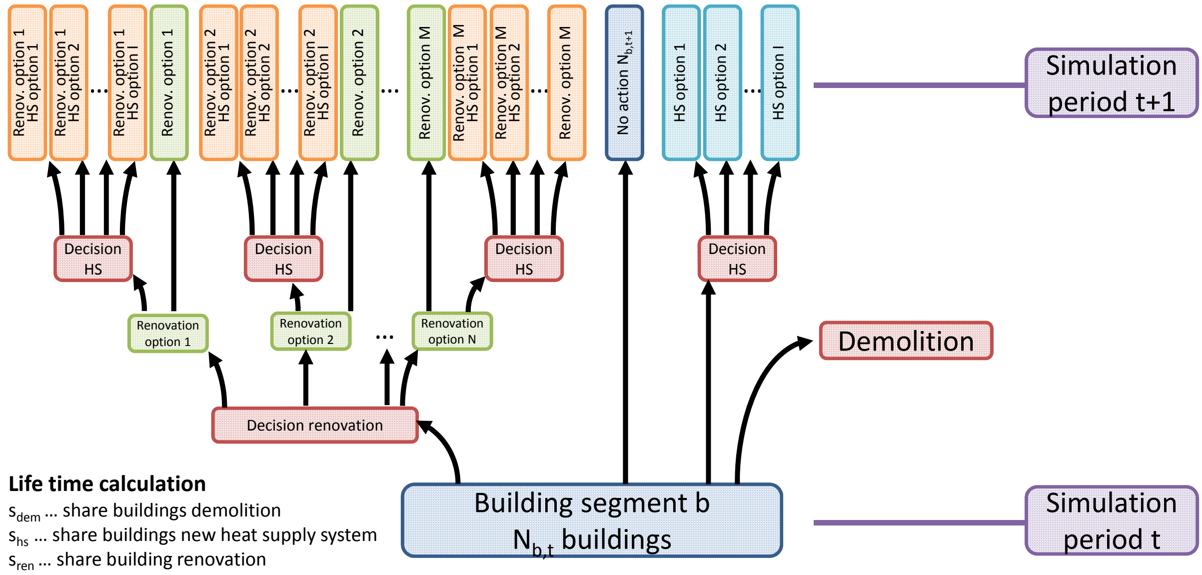

Figure 3.2. Decision tree structure of the ERNSTL/EE-Lab model

Without any restrictions, the number of building classes and building segments would increase exponentially. Given the number of available options and their combinations, such a process would exceed the computing capacity of most computers within a few simulation periods.

$$n_{BC,t} = n_{BC,t-1} \cdot \left(1 + n_{renov\ options}\right) + n_{BCA} \cdot n_{CR} \cdot n_{new\ build\ options}$$

$$n_{BS,t} = n_{BS,t-1} \left(1 + \left(1 + n_{BC,t} - n_{BC,t-1}\right) \cdot n_{new\ hs\ options}\right)$$

$n_{BC,t-1}$ ... Number of building classes in previous simulation period

$n_{BS,t-1}$ ... Number of building segments in previous simulation period

n_{BCA} ... Number of building categories

n_{CR} ... Number of different climate carrier regions

$n_{renov\ options}$ ... Number of available renovation options

$n_{new\ hs\ options}$ ... Number of available options for heat supply systems (and their combinations)

$n_{new\ build\ options}$ ... Number of available options of new buildings

In order to control the number of additional building segments in each simulation period, new segments are only created, if the heated floor areas of buildings that would belong to these segments exceed a predefined minimal share on the total heated floor area.

$$n_{\min,BCA} = \alpha_{\min\,share} \cdot \left(\frac{n_{b,BCA} \cdot \left(2 \cdot A_{hgfa,total} + A_{hgfa,BCA} \right)}{3 \cdot A_{hgfa,BCA}} \right) \quad \forall BCA$$

$n_{\min,BCA}$ ... minmal number of buildings that must be exceeded

$n_{b,BCA}$ ... Number of buildings that belong the a specific building category BCA

$A_{hgfa,total}$ ... Heated gross floor area of the total building stock

$A_{hgfa,BCA}$ ... Heated gross floor area of buildings that belong the a specific building category BCA

$\alpha_{\text{min share}}$ ... Parameter defining the calculation precision (generally $\leq 10^{-5}$)

Besides the defined parameter $\alpha_{\text{min share}}$ which is used to define the calculation precision, the heated gross floor area that a segment must exceed in order to be created depends not only on the total gross floor area of the building stock but also on the gross floor area of buildings which belong to the same building category. This approach represents a compromise between the calculation precision for the total building stock and the precision of the results for each building category and delivers both demands at low computation costs. Neglecting options, which get a low share at all, would mean that the model would underestimate the potential market share of these alternatives. In this case, the final results would not be unbiased approximations of the model core algorithm and results would shift with decreasing calculation precision. To avoid this, in each decision situation, a stochastic algorithm randomly depicts an alternative out of all alternatives that don't meet the minimum floor space threshold.

Three decision situations are distinguished, in which a share of buildings doesn't meet the threshold limit and the minimum floor space threshold applies:

1. The share that undergoes measures doesn't meet the threshold
2. The share that doesn't apply any measures doesn't meet the threshold
3. The average of both doesn't meet the threshold

If the third case applies, the segment is not allowed to be split again. This means that the whole segment will perform a certain measure or none of it will. A segment switches at all if the share that is supposed to perform a measure exceeds a uniformly distributed random number u_b.

$$s_{measure,b} = \begin{Bmatrix} 1 & s_{measure,b} \geq u_b \\ 0 & s_{measure,b} < u_b \end{Bmatrix} \quad \forall b \text{ where } n_b \leq n_{\min,BCA}, b \in BCA$$

If case one or two applies, then at least $n_{\min,BCA}$ buildings must change or remain unchanged.

$$s_{measure,b,t} = \begin{cases} \frac{n_{\min,BCA}}{n_b} & \frac{s_{measure,b,t} \cdot n_b}{2 \cdot n_{\min,BCA}} \geq u_b \\ 0 & \frac{s_{measure,b,t} \cdot n_b}{2 \cdot n_{\min,BCA}} < u_b \end{cases} \quad \forall b \text{ where } s_{measure,b,t} \cdot n_b \leq 2 \cdot n_{\min,BCA}, b \in BCA$$

$$s_{measure,b,t} = \begin{cases} 1-\frac{n_{\min,BCA}}{n_b} & \frac{1-s_{measure,b,t} \cdot n_b}{2 \cdot n_{\min,BCA}} \geq u_b \\ 1 & \frac{1-s_{measure,b,t} \cdot n_b}{2 \cdot n_{\min,BCA}} < u_b \end{cases} \quad \forall b \text{ where } 1-s_{measure,b,t} \cdot n_b \leq 2 \cdot n_{\min,BCA}, b \in BCA$$

The random number u_b is persistent to the building segment once it has been created. This ensures the share at which a segment switches is randomly distributed for all building segments and those not change over time. This is a necessary precondition to guarantee that the results are independent from the number of draws and the chosen time step of the simulation.

Besides defining the share that undergoes measures, also the number of chosen alternatives by the logit model is restricted in a similar way. For each segment, the relative shares of all alternatives that don't meet the minimum floor space threshold are used to define a distribution function for those options. Again a stochastic process depicts randomly an alternative for each segment which then gets the share $s_{b,t,small}$, which is the sum of all alternative not meeting the threshold within its own segment.

$$s_{b,t,small} = \sum_{i=1}^{I} \begin{cases} s_{b,t,i} & n_b \cdot s_{b,t,i} \leq n_{\min,BCA} \\ 0 & n_b \cdot s_{b,t,i} > n_{\min,BCA} \end{cases} \quad \forall b$$

The algorithm descripted above ensures that model results are independently from the chosen calculation precision and simulation step. However, the model outcome is co-determined by a stochastic process. As a result, the model outcomes are not deterministic anymore; multiple model runs are required to define expectation value and variance of the results with respect to the stochastic model algorithm.

3.2 The decision algorithm of the ERNSTL/EE-Lab Model

The basic methodology of the decision algorithm is a logit model, a well-established approach within the discrete choice theory. This approach has already been applied for modeling the heating sectors by other working groups (e.g. Giraudet et al. 2011, Henkel, 2012, Marnay and Stadler, 2008); their results indicate that this approach is also pertinent for the specific research questions of this project. In a very simple form, and if the independence from irrelevant alternatives (IIA) (Marschak, 1960) is not violated, the share $s_{MNLM,i}$ of an alternative i within a building segment b in period t is derived by a multinomial logit model (MNLM):

$$s_{MNLM,b,t,i} = \frac{e^{-\lambda_{b,i} r_{b,t,i}}}{\sum_{i=1}^{I} e^{-\lambda_{b,i} r_{b,t,i}}} \quad \forall b,t,i$$

with

$s_{MNLM,b,t,i}$	market of alternative i in building b at the time period t accoring to the mulinomial logit model
$\lambda_{b,i}$	scaled variance of the decision parameter (assuming that the unobserved parameters are Type-I extrem value distributed)
$r_{b,t,i}$	relative penalty: penalty of alternative i against average penalty of all alternatives in the building b at the time period t

The relative penalty for each alternative are derived based on the average penalty of alternative, weight by their market shares.

$$r_{b,t,i} = \frac{\mu_{b,t,i}}{\mu_{b,t,mean}} \quad \forall b,t,i \qquad (\text{Equ. } 2)$$

$$\mu_{b,t,mean} = \sum_{i=1}^{I} s_{b,t,i} \cdot \mu_{b,t,i} \quad \forall b,t \qquad (\text{Equ. } 3)$$

with

$\mu_{b,t,i}$	penalty of alternative i
$\mu_{b,t,mean}$	mean penalty weighted by market share on installation
$s_{b,t,i}$	market share of alternative i in building b at time period t

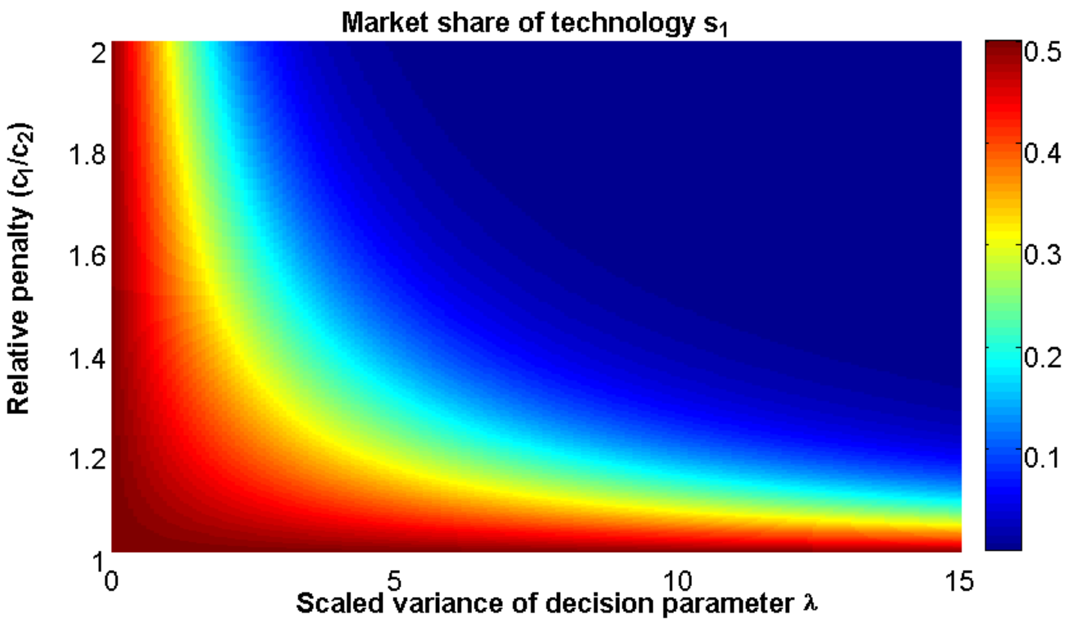

Figure 3.3. Market share of a technology 1 against a technology 2 described by a multinomial logit model, based on penalty ratio 1 against 2 and the scaled variance of the decision parameter λ.

The penalty function used to describe the investors preferences is based on adjusted heat generation costs, thus it is presume that in average, the heat generation costs are the dominant variable. The penalty function (adjusted costs) μ for alternatives is calculated using the long run marginal costs (LRMC) enhanced by monetary and non-monetary barriers for changing the type of heating systems and the willingness-to-pay (WTP) of decision makers. The LRMC include the consumption dependent (energy costs), consumption independent annual costs (fixed annual tariffs, maintenance, etc.) and the levelized investment costs. The consumption dependent energy costs are based on the energy demand presuming the norm indoor temperature in buildings (20°C for the case of Austria). Thus, in the decision making process, behavioral aspects which influence the annual energy demand are not taken into account. By doing so, different alternatives can be compared on the same level of comfort level on the first hand, on the other, especially in the case of building renovation, information on future energy savings due to thermal renovation might come from simple energy performance indicator calculates rather than from more complex methods that incorporate rebound effects. Furthermore it is assumed that the investor does not necessarily have full information about the effects of the supply line temperature of the heat distribution system on the annual efficiency of the heat supply system.

$$\beta_{i,decision} = f_{\mathrm{info},SL} \cdot \beta_i$$

$f_{\mathrm{info},SL}$ ... Information deficit factor for supply line temperature effects

β_i ... Temperatur coefficient factor of heat supply technology i

$\beta_{i,decision}$ ... Coefficient used in the decsion process

Two types of barriers, related to changing the type of the heating systems, are considered in the model. First, non-monetary barriers, basically associated with the comfort level the existing heating system provides, are considered. This means that a significant decrease of comfort level or degree of automation is not allowed:

- If a heat distribution system is available, single stoves are excluded.
- If a building central heating system is installed one-floor heating systems are excluded.
- Coal and wood log boilers are only options in case that either coal or wood log is the existing main energy carrier.
- If natural gas or electricity are the main energy carriers, oil based heating systems are excluded, too.
- If a district heating is used, all other energy carriers are excluded.

Besides these non-economic barriers, economic barriers as they might occur when the energy carrier is changed are also incorporate. Such costs are e.g. natural gas connection costs, oil tank, biomass storage, drilling costs for the bore hole of heat pumps with vertical heat exchangers. All barriers associated with the change of heating system type are summarized in a substitution matrix similar to Cost (2006), yet excluding the LRMC of the basic heating system.

In the ERNSTL/EE-Lab model, the described MNLM approach is extended by the following mechanism:

Decision partly based on Energy prices in previous years

Bauermann (2011) provides empirical evidence, that agents incorporate not only the current, but also energy price of previous periods in their decision making process. Thus running energy costs c of energy carriers en used to calculate the adjusted heating costs $c_{en,t,decision}$ are based on the energy price level of previous simulation periods:

$$c_{en,t,decision} = \sum_{n=0}^{2} c_{en,t-n} \cdot f_n \quad \forall en, t$$

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

Limitation of ultimate market share based on non-tradable restrictions

Non-tradable restriction are considered to be restriction which are associated with the location of the building and are independent from the actual users, decision makers as well as the type of building. By estimating the ultimate market potential for each energy carrier in each sub region (e.g. urban, rural), non-tradable restrictions are taken into account. Such barriers are restrictions on the use of biomass and coal based heating systems in highly populated areas for reasons of transportation logistics and emission pollution, the limited availability of grid-bounded energy carriers such as natural gas and district heat in specific areas or the installation of ground source heat pumps with shallow horizontal heat exchangers in urban regions. In case of solar thermal systems, not only the share of buildings suitable are restricted (Novak et al. 2000) but also the maximum collector area per building is limited on the level of individual buildings, not allowing to use more of 40% of the roof area for buildings with span roofs (or similar) and 70% for buildings with flat roofs.

The diffusion process has been implemented in the decision algorithm as followed. Based on the assumption that the set of buildings b that implements a specific measure in period t is a randomly chosen, statistical independent subset of the set of all buildings B with specific properties, the ultimate share a technology i can get, is described as followed:

$$S_{adapt,max,b,t,i} = \begin{Bmatrix} \dfrac{S_{max,i} - S_{t-1,i}}{1 - S_{t-1,i}} & i \neq tech_{heat,b,t-1} \\ 1 & i = tech_{heat,b,t-1} \end{Bmatrix}$$

$b \in B$

$S_{max,i}$ ...Ultimate market share of technologie i based on all buildings $\in$ B

$S_{t,i}$ ...Market share of technologie i in period t based on all buildings $\in$ B

$S_{adapt,max,b,t,i}$ ... Adopted ultimate market share of technologie i in b

This implies that in those buildings where a different technology is already installed, the ultimate market share for a technology i in building b is reduced by the currently (or previous) market share of this technology. If the same technology has been installed already in the building segment b, the ultimate market share in this case is set to 1 and whole segment b is allowed to reinstall the system again.

Considering the ultimate market share for technologies, the market share for each technology i in building b and time period t can be described, based on the extended MNLM, by:

$$s_{adaptMNLM,b,t,i} = s_{MNLM,b,t,i} \cdot S_{adapt,max,b,t,i} \cdot \left(1 + \sum_{k=1}^{I,k \neq i} \left(\frac{1 - S_{adapt,max,b,t,k} \cdot s_{MNLM,b,t,k}}{\sum_{r=1}^{I,r \neq k} S_{adapt,max,b,t,r} \cdot s_{MNLM,b,t,r}} \right) \right) \quad \forall b,t,i \qquad (\text{Equ. } 4)$$

I ... Set of available options (technologies)

The average market share of a technology i on a set of buildings B derives from:

$$s_{adaptMNLM,Bmean,t,i} = \frac{\sum_{b=1}^{B} s_{adaptMNLM,b,t,i}}{B}$$

B ... Set of buildings

Market diffusion of technologies

The next enhancement of the decision process aims for the change rate in market shares of technologies. Based on historic data, it has been observed, that in many cases, the diffusion process of technologies shows specific patterns, which can be descripted by market diffusion models. Such a well know and widely applied model is the logistic diffusion process (Sultan et al., 1990; Grübler and Nakicenovic, 1991). According to the logistic diffusion model, the diffusion follows an S-shaped curve. Besides the ultimate market potential for alternatives, the curve is described by a parameter ΔT, the characteristic diffusion time. This parameter defines the time span a technology needs to gain a market share of 99%, once it holds a market share of 1%. The big advantage of the model is it simplicity, only one parameter needs to be estimated. The drawback of the model is that it completely predefines the diffusion process based on the single parameter and a symmetric curve. To avoid this behavior, the diffusion process, as implemented in the ERNSTL/EE-Lab model only defines a valid corridor for the rate of change of market shares s for alternatives i in buildings segments b. Based on a logistic diffusion process, the limits for the change rate is defined by the current share an alternative i holds in a considered building category b_j (e.g. single family houses) in a sub-region s_{rk} (e.g. urban areas), the share the alternative i holds in all buildings in the same sub-region s_{rk} and the share the alternative i holds in all buildings of the building category b_j.

In the current implementation, the upper growth rates as well as upper decline rates (negative growth) are defined based on the market shares in previous periods t-1 to t-n. The corridor spanned by these functions is asymmetrical, since the decline process, defined by ΔT_{dec}, is typically faster than the positive growth process, described by ΔT_{inc}.

The upper growth rate defined by this process for an alternative i in period t is:

$$S_{max,t,i} = \max\left(S_{min}, \frac{S_{max,i}}{1+e^{\frac{-2\log(81)}{\Delta T_{inc,i}} \cdot \left(2t - \frac{-\log\left(\frac{S_{max,i}}{S_{decision,b,t,i,inc}} - 1\right)}{\frac{2\log(81)}{\Delta T_{inc,i}}} \right)}} \right) \qquad (\text{Equ. } 5)$$

S_{min} ... lowest market share allways being allowed

currently used value: $S_{min} = 0.03$

S_{min} defines the lowest market share, which is allowed in any case and is needed by the model to start the diffusion process for new alternatives, not holding shares in previous periods. Consequently, lowest market share an alternative must get is defined by:

$$S_{min,t,i} = S_{max,i}\left(1 - \frac{1}{1+e^{\frac{-2\log(81)}{\Delta T_{dec,i}} \cdot \left(2t - \frac{-\log\left(\frac{S_{max,i}}{S_{decision,b,t,i,dec}} - 1\right)}{\frac{2\log(81)}{\Delta T_{dec,i}}} \right)}} \right) \qquad (\text{Equ. } 6)$$

if $\left\{ S_{min,t,i} < S_{min} \mid S_{min,t,i} = 0 \right\}$

To adjust the market share based on the logit model (Equ. 4) for the diffusion process described by the diffusion corridor (Equ. 5, 6), a correction factor f_{corrLD} is defined:

$$f_{corrLD,t,i} = \left\{ \begin{array}{ll} \min\left(f_{max}, \frac{s_{adaptLM,mean,t,i}}{S_{max,t,i}} \right) & s_{adaptLM,mean,t,i} > \frac{s_{adaptLM,mean,t,i}}{S_{max,t,i}} \\ \max\left(\frac{1}{f_{max}}, \frac{S_{min,t,i}}{s_{adaptLM,mean,t,i}} \right) & s_{adaptLM,mean,t,i} < S_{min,t,i} \\ 1 & S_{min,t,i} < s_{adaptLM,mean,t,i} < \frac{s_{adaptLM,mean,t,i}}{S_{max,t,i}} \end{array} \right\}$$

$f_{max} > 1$ ... upper scaling limit

Finally, the shares are scaled again to account for the changed sum of market shares.

$$s_{b,t,i} = \frac{f_{corrLD,t,i} \cdot s_{adaptMNLM,b,t,i}}{\sum_{r=1}^{I} f_{corrLD,t,r} \cdot s_{adaptMNLM,b,t,r}}$$

By doing so, share reduced to meet the diffusion corridor are eventually scaled up again in this step and vice versa. This allows technologies to growth faster than described by the diffusion model, if the logit model assigns them high shares. This behavior is shown in Figure 3.4 for the case of a simple two alternatives example, and different levels of upper market share in period $S_{max,t,i}$ as an result of the diffusion model for alternative i.

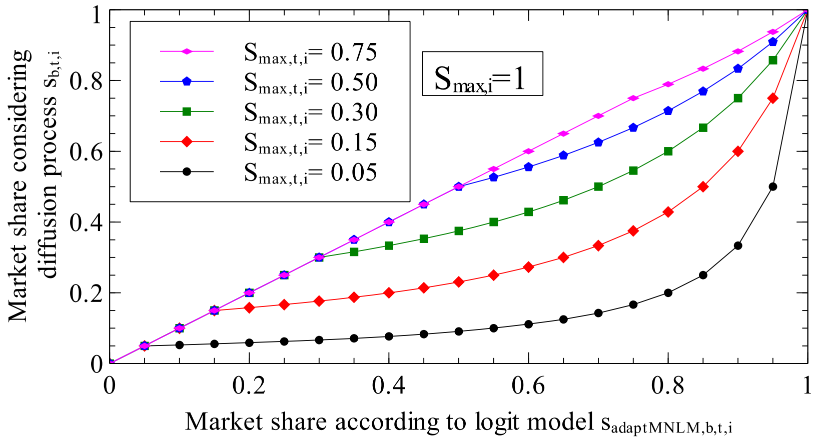

Figure 3.4. Market share $s_{b,t,i}$ of technology i against alternatives for different levels of upper market shares $S_{max,t,i}$ based on to the diffusion model.

Correct market share for previous installations used in the diffusion model $s_{decision,b,t,i,inc}$ and $s_{decision,b,t,i,dec}$

The market share of a specific technology in previous period used in the diffusion model represented by Equ. 5 and 6 is based on the following equation.

$$s_{mean,t-n,b,i,bca,ecr} = s_{mean,t-n,B_{bca,ecr},i} \quad \forall B_{bca,ecr} = \left\{ B_{bca} \mid BCA_j = BCA_b \cup B_{ecr} \mid ECR_j = ECR_b \right\}$$
$$s_{mean,t-n,b,i,bca} = s_{mean,t-n,B_{bca}i} \quad \forall B_{bca} \mid BCA_j = BCA_b$$
$$s_{mean,t-n,b,i,ecr} = s_{mean,t-n,B_{ecr}i} \quad \forall B_{ecr} \mid ECR_j = ECR_b$$

First, for each building segment, that undergoes a change, the historical market shares are calculated for three different set of building. The first set of buildings $B_{bca,ecr}$ consists of buildings, which share the same type of “building category” (e.g. large apartment buildings) and the same “energy carrier region” (e.g. urban region). The two other building sets are the group of building, that do share only one of these characteristics, either the same building category or the same region type with the considered building segment b. This is done, to account for the fact, that the penalty function of a specific technology i compared to the average penalty and thus the previous market shares varies for different types of buildings (e.g. large versus small buildings) and regions (e.g. urban versus rural regions). For the upper diffusion corridor, it is presumed, that a high market share of the specific technologies i in similar buildings B_{bca} in different regions or different building types B_{ecr} in the same region support a higher market share. This consideration is asymmetrical, as it doesn’t mean that the market diffusion holds back if in other building types or regions the diffusion is slower than in the specific building segment.

$$s_{decision,b,t,inc} = \max\left\{\frac{\sum_{n=1}^{t}\left(s_{mean,t-n,b,i,bca,ecr}\cdot(1-f_{bca}-f_{ecr})+s_{mean,t-n,b,i,bca}\cdot f_{bca}+s_{mean,t-n,b,i,ecr}\cdot f_{ecr}\right)^{-n\cdot\delta}}{\sum_{n=1}^{t}\left(s_{mean,t-n,b,i,bca,ecr}\right)^{-n\cdot\delta}}\right\}$$

$$s_{decision,b,t,dec} = \sum_{n=1}^{t}\left(s_{mean,t-n,b,i,bca,ecr}\right)^{-n\cdot\delta}$$

$f_{bca} + f_{ecr} < 1$

f_{bca} ... Weighting factor building category only

f_{ecr} ... Weighting factor energy carrier region only

δ ... Decay rate of the exponential damping function

The following values are currently used:

$f_{bca} = 0.2$

$f_{ecr} = 0.2$

$\delta = 0.4$

Nested logit model

If similar alternatives exist (e.g. gas boiler and gas condensing boiler, single stove versus central an on-floor heating systems, different options of solar thermal collectors against no solar collectors, different options of buildings refurbishment compared to maintenance without effects on thermal losses) the independence from irrelevant alternatives (IIA) doesn't[2] hold. Therefore similar alternatives are grouped together to a so called nest, enhancing the MNLM to a nested logit model (NLM), which is the most widely used generalized extreme value (GEV) model. If all correlations ("similarities") are zero, the GEV converts do a standard logit model. For the choice of heating systems a three-level NLM is applied. The top level nest defines whether or not thermal solar collectors are installed. The second level nest describes different heating systems categories; on the third level subclasses of heating systems (e.g. condensing and non-condensing gas boilers) are grouped together. The distribution of investment costs compared to the value for all technologies are used as a proxy for the similarity of alternatives within each nest.

[2] Hausman test: Hausman, J. (1978): "Specification Tests in Econometrics", Econometrica, 46, S.1251–1271; see also: Hausman, J. und D. McFadden (1984): "Specification Tests for the Multinomial Logit Model", Econometrica, 52, S. 1219–1240

$$\sigma_{Inv,tot,b,t} = \sqrt{\sum_{i=1}^{I} s_{b,t,i} \cdot \left(I_{b,t,i} - I_{mean,tot,b,t}\right)^2} \quad \forall i,b,t$$

$$\sigma_{Inv,R,b,t} = \sqrt{\sum_{j=1}^{J} s_{b,t,j} \cdot \left(I_{b,t,j} - I_{mean,R,b,t}\right)^2} \quad \forall j,b,t\,;\, J \in R$$

$$I_{mean,tot,b,t} = \sum_{i=1}^{I} s_{b,t,i} \cdot I_{b,t,i}$$

$I_{b,t,i}$ ... Investment costs of alternative i in building b and period t

I_{mean} ... Weighted average investment cost

$\sigma_{Inv,R,b,t}$ ... Distribution Sigma of technologies in nest R

$\sigma_{Inv,tot,b,t}$ ... Distribution Sigma of all technologies

$$o_R = \frac{\sigma_{Inv,R,b,t}}{\sigma_{Inv,tot,b,t}}$$

o_R ... Indicator for similarity of technologies within a nest R

Even though the nested logit model is not restricted by the IIA, it still faces two limitations: it can't deal with random taste variations – not all decisions makers have same preference (Hausman and Wise, 1978) – and it cannot be used if unobserved variables correlated over time for each decision maker. Probit models can handle these limitations, however they demand unobserved variables to be normal distributed. In contrast to lognormal distributions, which are the basis for logit and GEV models, the normal distribution has densities larger than zero on both sides of the mean value. For price correlations, this implies that the share of decision makers that prefers higher prices equals the share preferring lower prices. This might be true in some cases, e.g. as more expensive technologies are often associated with better quality or more desirable features. Yet, this line of argumentation might not hold for energy prices. It is difficult to advocate that half of the population has a positive preference for higher energy prices. Mixed logit model finally are able to cope all mentioned limitations. In order to incorporate random taste variations, mixed logit models enhance the probability function for each alternative defined for logit models (Equ. 7) by introducing a density function for the decision coefficients *f*(λ).

$$P_{b,t,i} = \frac{e^{\lambda \mu_{b,i,t}}}{\sum_{j=1}^{N} e^{\lambda \mu_{b,j,t}}} \qquad (Equ.7)$$

Thus the probability function is defined by the integral over all possible decision makers.

$$P_{b,t,i} = \int \left(\frac{e^{\lambda \mu_{b,i,t}}}{\sum_{j=1}^{N} e^{\lambda \mu_{b,j,t}}} \right) f(\lambda)\, d\lambda$$

Mixed logit models constitute a proper technique for implementing individual decision preference. Yet, based on the research briefly outlined in chapter 2, I conclude that the empirical evidence is not sufficient to profoundly calibrate such a model extension.

Limitation of market share of technologies based tradable restrictions

Finally, tradable restrictions for the use of energy carriers are considered by applying cost-resource-potential-curves (CRPC). It is assumed, that the market sets on single clearing price for each energy carrier. Therefore new consumers of an energy carrier pay the same energy price than existing consumers.

Average penalty function per building

Based on the equations depicted above, the mean penalty function used as reference technology (Equ. 3) for each building segment and measure (changing heating system, domestic hot water system or part of the building envelopment) can be calculated.

$$\mu_{b,t,mean} = \sum_{i=1}^{I} s_{b,t,i} \cdot \mu_{b,t,i}$$

4 Results uncertainties arising from calculation precision and simulations step width

4.1 Calculation precision $\alpha_{min\ share}$

As descripted in chapter 3.1, without any restriction on the calculation precision, the computation demand is going to increase exponentially and would exceed available computation power within a few simulation periods. Thus, a control parameter has been introduced to the model, which controls the computation precision and thus the computation demand. The method implemented to cope with market shares below the result precision is based on a stochastic algorithm. This means, that the model results are stochastic results as well and multiple model runs should be conducted to obtain meaningful results. From that, a conflict arises: on the one hand, a reduced computation precision decreases the calculation needs per model run to some extent, the introduces additional uncertainties on the other hand lead to higher number of model runs needed per scenario to obtain the similar low confidence interval of the model results. To get a first estimated of an rational calculation precision, that keeps calculation time and uncertainties low, a series of model runs, using a data set of a baseline scenario for the Austrian built environment from 2009 until 2030 is used.

A necessary precondition for the following analyses is that distribution of results is well distributed. Therefor it was tested whether or not model results resulting from different runs using the same input data are distribute according to a normal distribution or not. This has been done for the results variable energy demand per energy carrier after 22 simulation periods (2030) using a $\alpha_{min\ share} = 4$. The results are shown in Figure 4.1 and suggest that this precondition is satisfied.

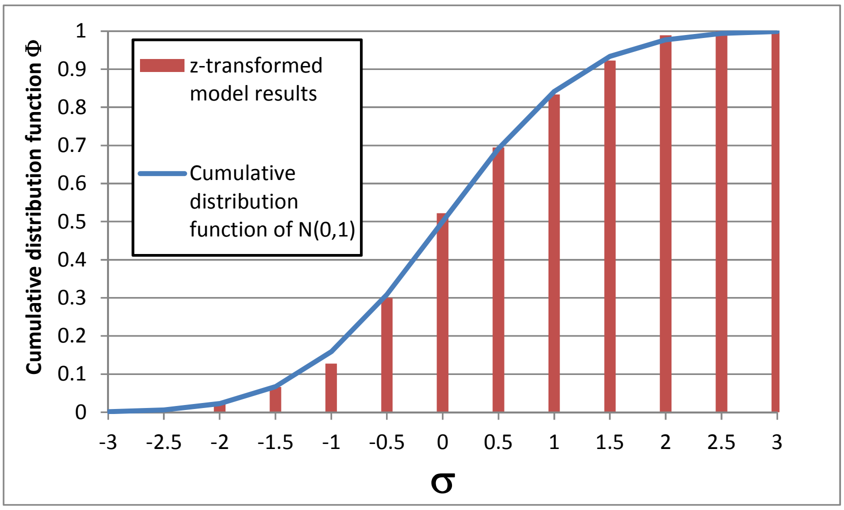

Figure 4.1. Cumulative distribution function (Φ) for z-transformed model results (energy demand per energy carrier after 22 simulation periods, 12 simulation runs, 180 data points) compared to the Φ of the unit normal distribution N(0,1).

As an estimator for the uncertainties arising from the stochastic algorithm the following two parameter ε_{EC} and $\varepsilon_{EC,\ BCA}$ have been defined and their behavior analyzed:

$$\varepsilon_{EC,BCA,\alpha_{min\,share}} = \sqrt{\sum_{b=1}^{BCA}\sum_{e=1}^{EC} \frac{\sum_{n=1}^{\forall B:EC_n=e,BCA_n=b} \frac{(x_n-\mu_n)^2}{(B-1)x_n^2}}{BCA\cdot EC}} \cdot t_{0.1,N_{simrun}-1}$$

$$\varepsilon_{EC,\alpha_{min\,share}} = \sqrt{\sum_{e=1}^{EC} \frac{\sum_{n=1}^{\forall B:EC_n=e} \frac{(x_n-\mu_n)^2}{(B-1)x_n^2}}{EC}} \cdot t_{0.1,-1}$$

$t_{0.1,N_{simrun}}$ ... 5% quantile of the t-distribution

N_{simrun} ... Number of simulation runs per scenario

EC ... Energy carriers

BCA ... Building categories

x_n ... Energy consumption of energy carrier e in building n

μ_n ... Average energy consumption of energy carrier e in building n

$$\mu_n = \sum_{n=1}^{N_{simrun}} \frac{x_n}{N_{simrun}}$$

The parameter ε_{EC} is used as an estimator for results on a rather top level, where only the total the energy demand per energy carrier is considered. In contrast, parameter $\varepsilon_{EC,\ BCA}$ looks at the results on a higher level of details and considers the energy demand per energy carrier for each building category. It is obvious that the confidence interval needs to increase with a higher degree of details. The results of this analysis are drawn in Figure 4.2. It can be seen that, for a specific level of uncertainties, the computation time tends to decrease with a lower calculation precision and a higher number simulation runs.

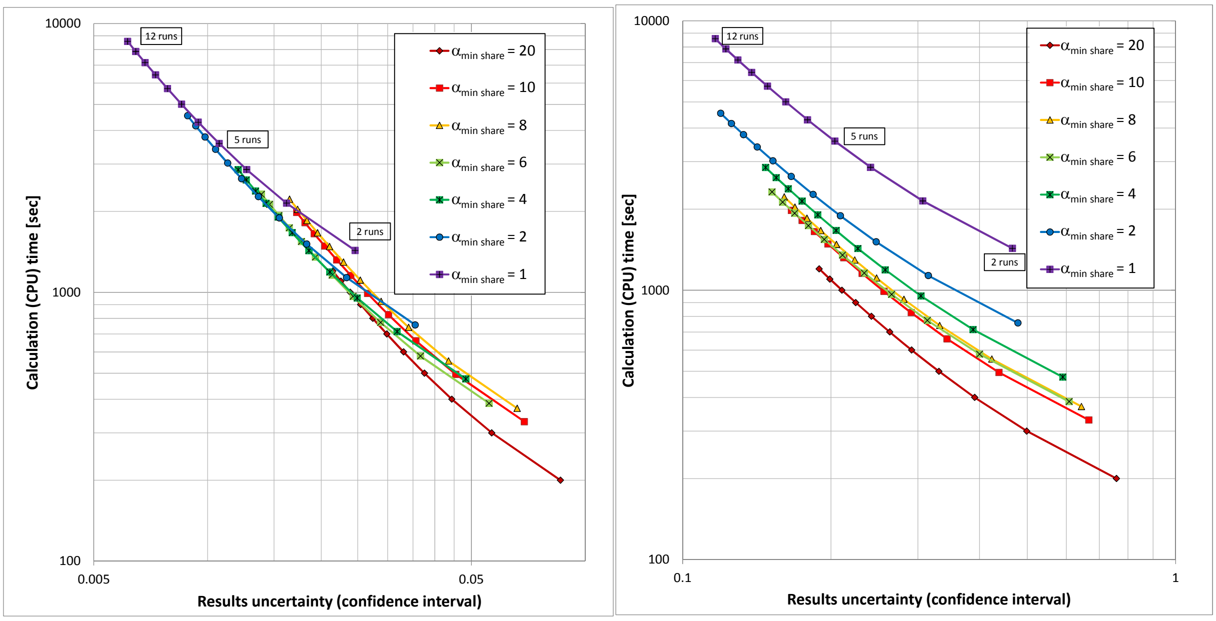

Figure 4.2. Calculation time against the uncertainty indicator $\varepsilon_{EC,\alpha}$ (left graph) and $\varepsilon_{EC,BCA,\alpha}$ (right graph) of results as measured descripted above for the results after 22 simulation periods.

In a further test, the model behavior has been analyzed; determine whether or not, and if to which degree, the results vary with the calculation precision, indicating that the stochastic algorithm introduces some systematic bias. To do so, the average results, based on 12 simulation runs, for simulation using different values for the $\alpha_{min\ share}$ parameter are compared against each other. The behavior of the energy consumption per energy carriers are shown in Figure 4.3. It can be observed, that there appears to be some systematic bias. Yet, using a $\alpha_{min\ share}$ of 10 or less, the discrepancy is less in a range of 3% or less und thus neglect able. Furthermore, it has to be noted that, using 12 simulation runs, results do not tend to stay within the confidence interval, spanned by runs with a different $\alpha_{min\ share}$.

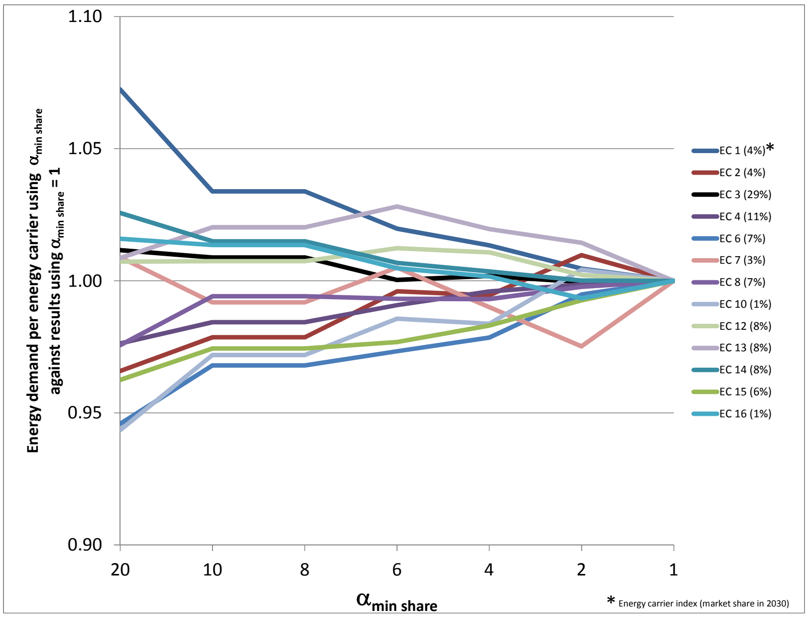

Figure 4.3. Average energy consumption (for 22 simulation runs) per energy carrier against the results of simulation runs with $\alpha_{min\ share} = 1$

In Table 4.1 the results shown above are compared against a simpler, deterministic algorithm, which allows building measures only, if either the number of buildings exceeds $n_{min,BCA}$ or more than half of the buildings within a segment ($s_{measure,b} > 0.5$) perform such a measure. As can be seen from this table, the described deterministic algorithm fails to derive a similar high quality model behavior and the more comprehensive implemented stochastic approach is superior.

Table 4.1. Comparison of results derived from the implemented stochastic algorithm against a simpler deterministic algorithm.

Energy carrier index (market share in 2030)	Energy consumption in 2030 using deterministic approach ($\alpha_{min\ share} = 4$) compared to stochastic algorithm using ($\alpha_{min\ share} = 1$)
EC 1 (4%)	70%
EC 2 (4%)	65%
EC 3 (29%)	96%
EC 4 (11%)	118%
EC 6 (7%)	103%
EC 7 (3%)	51%
EC 8 (7%)	59%
EC 10 (1%)	53%
EC 12 (8%)	103%
EC 13 (8%)	104%
EC 14 (8%)	101%
EC 15 (6%)	92%
EC 16 (1%)	46%

A similar analysis is performed for the variable: *number of buildings undergoing some sort of thermal renovation*. Again, the model results should not shift significantly, if the calculation precision changes. In this case, the algorithm fully meets the requirement, as can be seen in figure 4.4. In addition, the results of a simpler, deterministic algorithm are drawn (dashed lines), which again allows measures only if either the number of buildings exceeds $n_{min,BCA}$ or more than half of the buildings within a segment ($s_{measure,b} > 0.5$) perform such a measure. As it can been seen, the behavior of second algorithm strongly depends on the calculation precision, with results eventually converging (close?) to the stochastic algorithm.

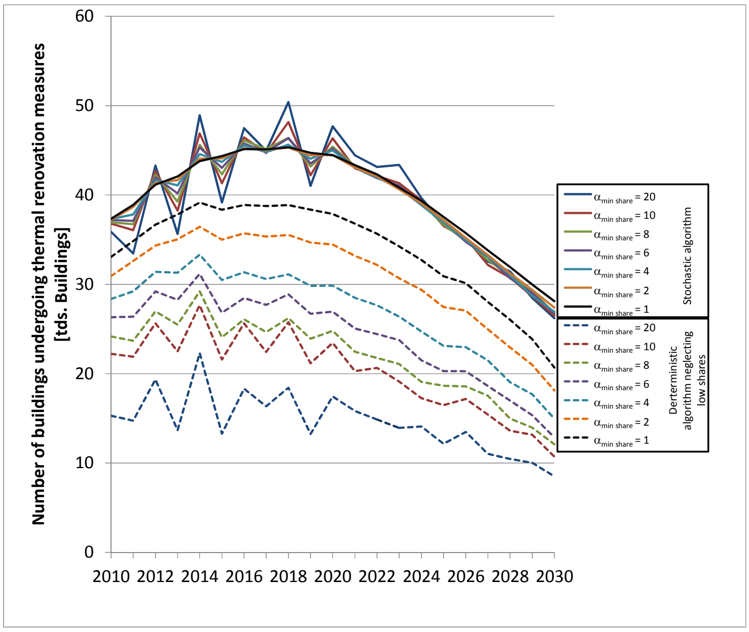

Figure 4.4. Number of buildings performing thermal building renovation. Model results obtained using various calculation precision $\alpha_{min\ share}$. The solid lines represent the implemented stochastic model algorithm. The dashed lines show results using a deterministic algorithm in which measures are only performed, if the number of buildings exceeds $n_{min,BCA}$ or $s_{measure,b} > 0.5$.

4.2 Simulation step width

A different way of decreasing the simulation time is to increase the simulation step width. This means that results are not calculated and obtained for each simulation year but for e.g. every second, third or fifth year only. To validate the results, again it needs to be shown, that the systematic errors resulting from such a simplified calculation tend to be within tolerable range. Again, the average energy consumption per energy carrier (with a market share of 1% or more in 2030), using 12 simulation runs, are compared against the average energy consumption based using $\alpha_{min\ share}$ of 1 and a simulation step width of 1 year.

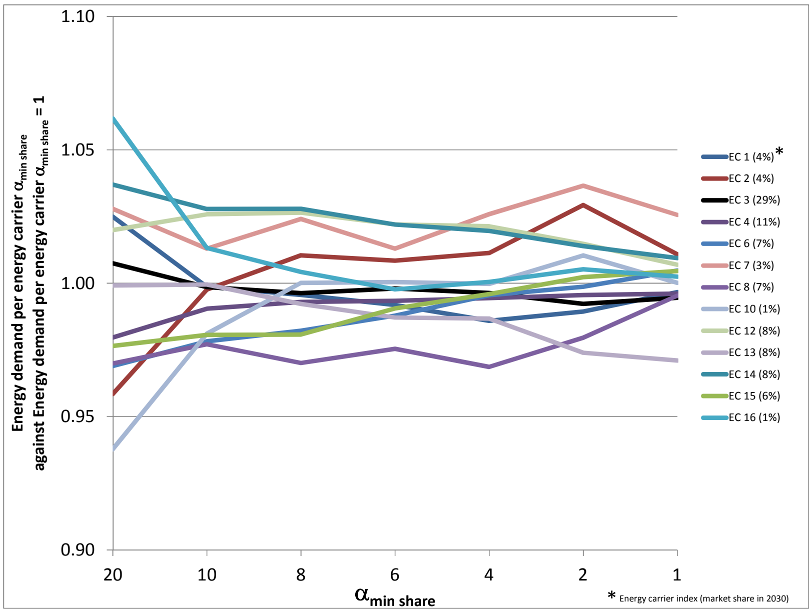

Figure 4.5. Average energy consumption (for 22 simulation runs) per energy carrier using a simulation step width of 2 years against the results of simulation runs with $\alpha_{min\ share}$ and simulation step width = 1

Results obtained from this analysis indicate that the model algorithm delivers data, which basically do not shift with an increasing $\alpha_{min\ share}$. The systematic bias (for the scenario analyzed) compared to scenario runs using an annual step width are in the range of 2,5% or lower, if an $\alpha_{min\ share}$ 10 or less is used. The comparison of uncertainty against simulation time reveals that using a simulation step width of 2 reduces the computation time by more than 50% compared to a simulation step width of 1.

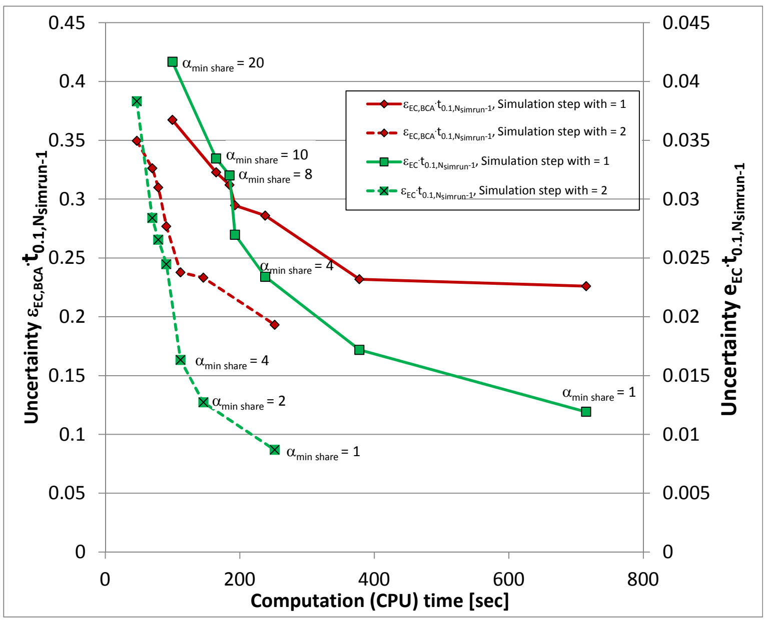

Figure 4.6. Comparison of results uncertainties against simulation time using a simulation step width of 1 (solid lines) and a step width of 2 (dashed lines)

5 Uncertainties of results arising from non-observed model variables

5.1 Scaled variance λ of the decision algorithm

The λ value (scaled variance) of the logit model is responsible for the slope of the selectivity and therefore important to the outcome of the scenarios. To test the sensitivity of the results on this value, we calculate the derivatives of the share of energy carriers with respect to the scaled variance λ. An indicator β has been defined which calculates the sum of squared derivatives for all energy carries.

$$\beta_t = \sqrt{\sum_{i=1}^{en} \left(\frac{\partial s_{FED,i,t}}{\partial \lambda} \right)^2}$$

$s_{FED,i,t}$ ... share of energy carrier i on the final energy demand
in simulation periods t

λ ... scaled variance of the decision parameter

Results derived for the Austria base line scenario after 22 simulation periods (2008-2030), considering all restrictions, indicate a (local)[3] minimum of the β parameter (for the Austrian built environment) in the range of 8-9 (see Table 5.1).

Table 5.1. Sensitivity of the model results (share of energy carriers on the final energy demand) with respect to the scaled variance (λ) of the decision parameter.

λ	2.0	2.8	3.6	4.4	5.2	6.0	6.8	7.6	8.4	9.2	10.0	10.8	11.6	12.4	13.2	14.0
β_7	0.15	0.15	0.14	0.13	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.11	0.11
β_{12}	0.20	0.20	0.18	0.16	0.14	0.14	0.13	0.12	0.12	0.11	0.11	0.12	0.12	0.13	0.15	0.14
β_{17}	0.32	0.30	0.25	0.22	0.19	0.19	0.15	0.15	0.13	0.14	0.13	0.15	0.15	0.17	0.19	0.19
β_{22}	0.47	0.44	0.35	0.32	0.26	0.24	0.19	0.17	0.15	0.16	0.16	0.17	0.20	0.21	0.24	0.25

[3] The global minimum of this function can be found at very high λ values (the winner takes it all) with β ~ 0

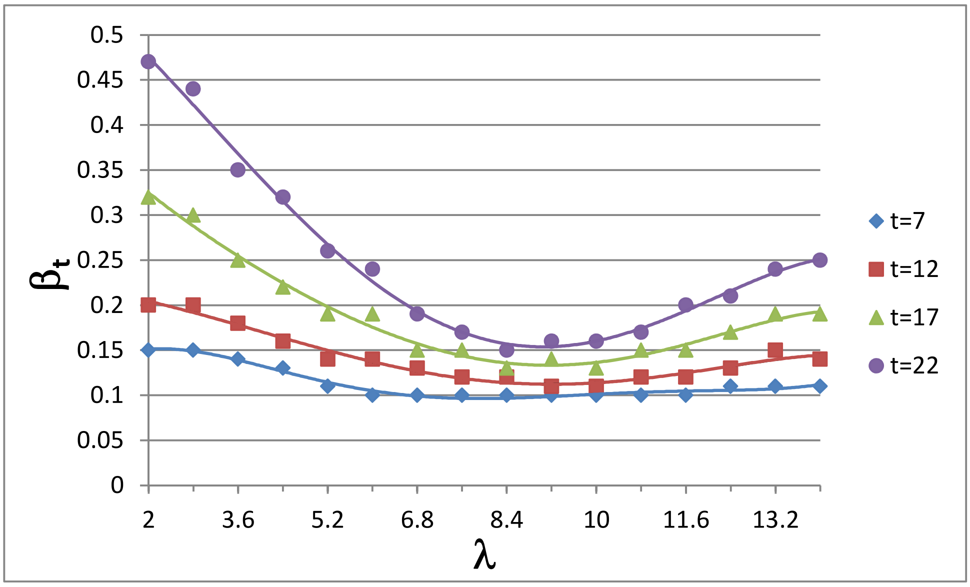

Figure 5.1. Sensitivity (β_t) of the model results to the scaled variance (λ) of the decision parameter.

5.2 Market penetration time of technologies $\Delta t_{inc,i}$

Many scientific publications underline, that diffusion processes often show an S-shaped pattern. This behavior has been introduced in the decision algorithm and is steered by an exogenously defined variable: the market penetration time $\Delta t_{inc,i}$. Since this variable cannot be observed directly and needs to be estimated based on comparable diffusion processes, the question arises, to which extent the model results are determined by this variable, and thus influenced by possible misestimations. A sensitivity analysis, in which this variable has been variety in range of +/- 50%, is used to test the stability of the results. The outcome (shown in Figure 5.2) reveals that the results for 12 and 22 period simulation runs are robust with respect to this variable.

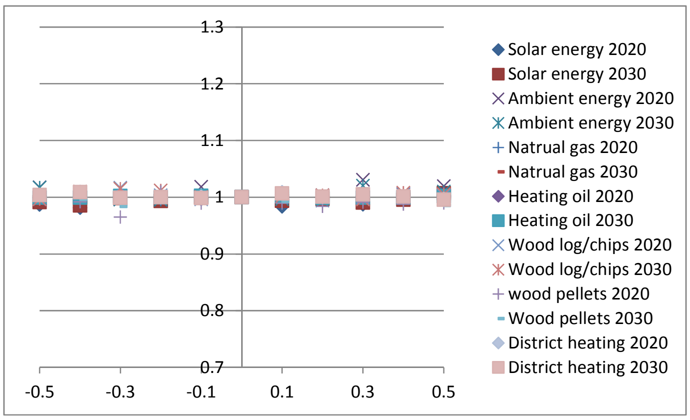

Figure 5.2. Sensitivity of the model results to changes in the penetration time of technologies $\Delta t_{inc,i}$.

5.3 Penalty function $\mu_{b,t,i}$

The decision algorithm of the multinomial logit model assigns market shares of newly installed systems based on penalty function $\mu_{b,t,i}$. This variable derives from annual heating costs, adjusted for the estimated willingness-to-pay of the market for each alternative. Thus it is presumed that in average, the heat generation costs are the dominant decision criteria. As described in section 2, there is not profound evidence to reject this assumption. However, qualitative analyses indicate that costs are not the only decision parameter. In order to analyze the effects of such an altered penalty function, a sensitivity analysis, by modifying the penalty function, has been performed.

$$r_{b,t,n} = \frac{\mu_{b,t,n} + \Delta\mu_{b,t,mean}}{\mu_{b,t,mean}} \quad \forall b,t$$

The results of the variance for the major energy carriers are shown in Figure 5.3. They indicate, that especially emerging (heat pumps, pellet heating systems) and vanishing (heating oil) technologies and energy carriers are sensitive to changes to penalty function.

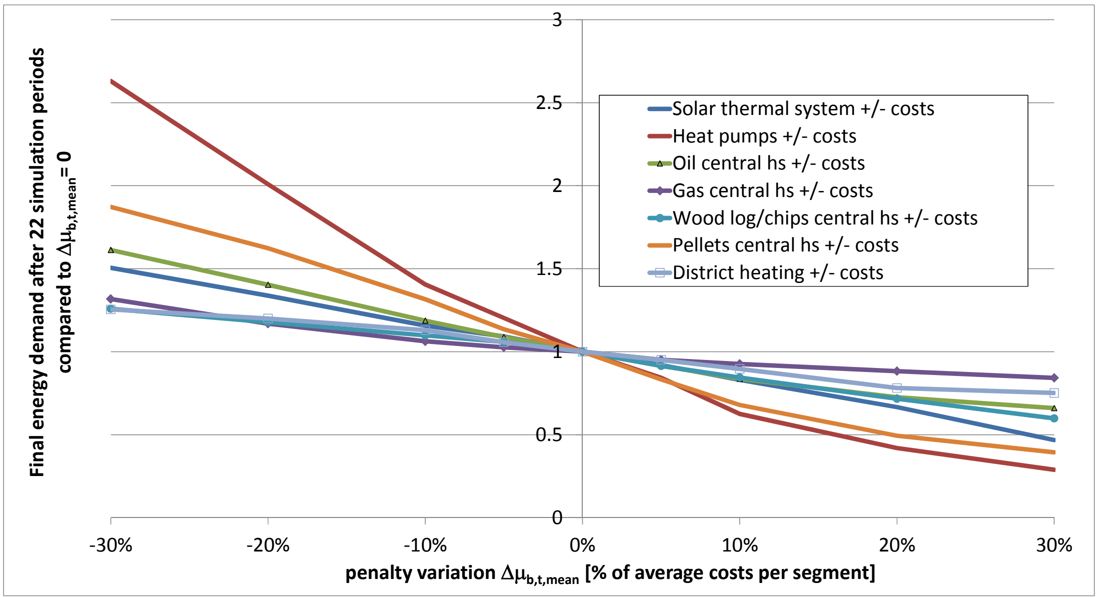

Figure 5.3. Sensitivity of the model results to changes in the penalty function used by the decision process.

6 Conclusions

Gaining insights in the stock changing behavior of the built environment are fundamental for evaluating the effects of policy options and policy framework conditions. This necessary to reach defined energy efficiency and greenhouse gas emission mitigation targets in an effective and efficient way. Computer model are able to improve the understanding of the behavior tremendously. However, it has to be advocated, that models are not able to predict the future. They need to be seen as working tools only, in the same manner as hammers and saws don't build furnitures either. In order to distinguish between results, raised by the individual model behavior (model artifacts) and effects that are inherent to the stock changing behavior, researchers are therefore compelled, to understand the model behavior and its outcome in detail. To do so, a larger number of scenarios, using different input parameter need to be drawn. This goes along with high computational needs. As shown in this report, stochastic algorithms are able to reduce the computation time by a great deal, if the algorithms reproduce the deterministic ones unbiased. Such algorithms have been developed, implemented and tested within this project. By applying them on recent research needs, these algorithms can help to design policy framework conditions, which are suited to reach energy efficiency and greenhouse gas emission mitigation targets, defined and demanded by the society.

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