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"TREATING UNCERTAINTY AND RISK IN ENERGY SYSTEMS WITH MARKAL / TIMES"

«TUMATIM»

W. BENOOT, J. DUERINCK, E. LAES, H. MICHIELSEN, J. MORBEE, W. NIJS, D. VAN REGEMORTER, L. VAN WORTSWINKEL, D. VERCAMMEN

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Energy

FINAL REPORT

TREATING UNCERTAINTY AND RISK IN ENERGY SYSTEMS WITH MARKAL/TIMES

«TUMATIM»

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SUMMARY

Context

Changes in social, political, economic and environmental thinking have led to an increasing amount of questions about prospects of energy use and supply. Techno-economic, partial equilibrium energy models like TIMES have proven their ability to tackle some of these questions. As questions become more and more complicated adequately equipped models are needed.

Objectives

The objectives of this project are twofold: first, a further development of the model and secondly a set of case studies addressing issues important for the development of a sustainable energy system. It will allow a better integration of uncertainty in the evaluation of policy scenarios, where the uncertainty is related to the technologies and their parameters as cost and efficiency, energy prices fluctuations and climate change. The estimation of price elasticities allows to better take into account the reaction of the consumers in a partial equilibrium model as Times.

Regarding the case studies, by looking at issues on the policy table with both the partial equilibrium model and the general equilibrium model, the project can contribute in a rather comprehensive way to the debate and to the definition of specific policies regarding the energy and the environment.

Conclusions

The climate change issue faces different kind of uncertainty. Uncertainty can play a key role within an energy system. The effect of uncertainty depends highly on the possible scenarios and the variance between these different possibilities and on the adaptiveness of an energy system to take these scenarios into account .Uncertainty can cover fluctuating energy prices, future carbon prices and environmental constraints, technology progress and/or security of supply. Besides, there is uncertainty about model parameters like price elasticities which can also influence the cost or the choice of technologies;

Through econometric analysis price elasticities of service demand were estimated. Energy price increase causes energy efficiency improvements. Consequently energy services or useful energy decrease will be less than energy consumption. A pilot study was used to examine the willingness to pay for energy services in residential dwellings. Respondents were able to express their preference via a choice experiment. The analysis showed that the 'rebound' effect could be rather important, i.e. energy saving through investment in more efficient technologies would partly be compensated by an increase in the energy service demand. The estimation of the price elasticities revealed rather low price elasticities for energy services (between 0 and -0.5).

Modelling variability in fossil fuel prices in TIMES has shown that this variability leads to a diversification of the energy mix, and more specifically of the electricity generation mix. It can affect the optimal energy system in two ways. First, technologies not affected by the price variation enter the optimal solution, i.e. coal and renewables, though coal less when a CO_2

target is imposed.. However, with a high risk aversion the relative share of coal generated electricity can increase under a stringent CO_2 policy, when all non-fossil technologies are used up to their maximum availability. Secondly, the cost increases which induces higher energy service prices and thus a decrease in the demand. In general, the effects of uncertainty for the Belgian energy system were limited, especially when a CO_2 policy was implemented, as taking into account the price variability and covariance already induces a shift towards low carbon technologies. Introducing more variability in the prices, e.g. variability in biomass prices might increase the impact.

With stochastic TIMES, a hedging strategy was computed given uncertainty on the availability of carbon storage and the stringency of the carbon constraint. The information on these two issues was assumed to be available only after 2025. With the proposed scenarios, the difference between the hedging strategy and the corresponding deterministic strategy remains small but the lack of information on long term policy measures leads to higher costs of the energy system. For increasing risk aversion, the overall costs of uncertainty increase. However, the information value for the worst case scenario becomes lower as they gain higher relative importance in the objective function.

The policy cases analysed with the TIMES model covered the renewable target for Belgium and the EU proposal of a 30% reduction target in 2030 and of 80% in 2050 compared to 1990 emissions for the EU GHG emissions. The EU target (-30% in 2030 and -80% in 2050) was modelled with the Pan European TIMES model. This gives the cost optimal way to reach the target at EU level, inclusive the cost efficient allocation of the reduction between the EU countries. From this run, the implication for Belgium in terms of CO_2 reduction was derived. Then, with the Belgian model, the impact on the Belgian energy system, on the choice of technologies and on the energy system cost was explored, with a specific emphasis on the availability of nuclear and of carbon storage.

The analysis showed that it is possible to attain very stringent CO_2 reductions in Belgium. The welfare cost in annualised terms varies from 0.5% of the 2005 GDP when nuclear and carbon capture are available to 1.2% of GDP2005 when none of these options are available. The participation in a global EU CO_2 market is essential for Belgium. Without the possibility of trade and the same EU target of -78% imposed on all EU countries, the cost increase to 0.8% of GDP2005. These costs are the cost within the energy system without considering any potential side benefits and assuming a EU permit system as policy instrument for achieving the CO_2 reduction target..

The CO_2 constraints do not impose major shifts in the energy system in the middle term. The use of more energy efficient technologies and a switch to gas are predominant. It should be mentioned that building insulation and saving lamps are already cost efficient in the reference scenario and because of the many barriers to their use in real life, it is important to address this issue by specific policies. Renewables such as wood and wind on shore are also penetrating rapidly.

In the long term, alternative fuels such as ethanol and biodiesel and electricity are penetrating in the transport sector, offering further reduction possibilities. Their relative cost seems to be rather close and therefore the choice between these different options is very sensitive to the potential of biomass production, the cost of biocrops and of electricity.

Also, in other sectors, the choice of technological options is dependent on the options in the electricity sector and the relative price of electricity when high reduction target are imposed. The availability or not of nuclear and carbon storage are important determinant of the price of electricity and thus of the choice of technological options.

A major contribution is also obtained from a reduction in the energy service demand. This reduction can cover a great number of changes outside the energy system: new production system, change in life style, in urban planning,... Nevertheless, sensitivity analysis showed that a larger reduction in the energy service demand can be very costly. The results indicate that there are reasons to believe that a policy primarily oriented towards deep or uniform demand reductions is questionable for efficient tackling CO_2 emissions. Instead, a climate policy directly oriented to the reduction of CO_2 emissions induces only modest relative reductions of energy services, but it will be more cost efficient and it will induce more technology development.

Focussing on a specific renewables target can contribute to the CO_2 target but the technological choices might not be optimal regarding this last target and not induce R&D in the most appropriate direction. A renewable target is however not sufficient to reach the climate target.

The results from those scenarios show the importance of using a model covering the whole energy system with sector specific technologies to correctly evaluate the trade-off between the options given the overall CO_2 target.

These different conclusions are clearly dependent on the cost and assumptions implemented in the model database and in the scenarios. Therefore this analysis should be complemented by sensitivity studies around the main parameters. Also, though the cost of implementing a complete infrastructure for the penetration of some option is integrated in annualised term in the cost of these options, large resources will have to be mobilised over a rather short period to invest in these infrastructure.

Contribution of the project in a context of scientific support to a sustainable development policy

Climate change and security of supply, along with sustainable development have remained high on the agenda of the policy makers. The energy sector and the development and implementation of new technologies are important elements for the achievement of sustainable development. The contribution of the TIMES modelling framework on this issue can therefore be important. Keeping the model update and contributing to its development within the ETSAP IEA Implementing Agreement is essential. Policy scenario analysis with the model will also contribute in the definition of the Belgian policy regarding sustainable development (energy, environmental, R&D policy) within the EU context.

Keywords;

Energy system modelling, climate change, uncertainty, energy price elasticity

1. INTRODUCTION

The objective of the TUMATIM project is to develop the MARKAL/TIMES modelling framework for a better assessment of energy and climate change policies. Climate change and security of supply, along with sustainable development have remained high on the agenda of the policy makers and this was reinforced by recent oil price crisis. The energy sector and the development and implementation of new technologies are crucial elements for the achievement of the EU and Belgian targets regarding sustainable development. The contribution of MARKAL/TIMES on these issues can therefore be important. TIMES, which is the new generation of the MARKAL family, follows the same paradigm as MARKAL. It is a generic, dynamic optimisation model that represents all energy demand and supply activities and technologies for a country with a horizon of up to 50/60 years. Compare to the previous version it allows for more flexibility and is better suited for policy questions. The model represents all energy uses and energy production as well as the main emissions linked to energy use (N20, CH4, CO_2, SO2, NOx, VOC and PM)[1]. The model produces simultaneously prospective energy and emission balances, tests the potential of new energy technologies and contributes to R&D policy formulation. Besides the Belgian model, a Pan-European version of the model is available now, allowing the integration of the Belgian policy analysis into a European framework.

Uncertainty and risk linked to energy technologies, energy supply and climate change increases the difficulty of defining appropriate policies. The first objective of TUMATIM is to explore the portfolio approach to integrate uncertainty about fuel prices in the evaluation of energy and environmental policies and to implement it in the MARKAL/TIMES model. The starting point was to build a small portfolio technology model for the electricity sector. The quantification of the uncertainty regarding energy prices and climate change was done through probability distribution functions. The portfolio approach contributes to a better evaluation of the risk associated with specific technology choices. Its integration in MARKAL/TIMES allows to examine other dimensions than the currently implemented stochastic version which allows to define hedging strategy for waiting till the disclosure of information on climate change risk or on technology breakthrough.

A second part of TUMATIM relates to the price elasticities in the demand components of MARKAL/TIMES. These elasticities are another important source of uncertainty and the objective is to use modern insights of econometrics to estimate price elasticities of service demand or useful energy demand. "Useful energy" or "energy service" can be defined as the service that comes from the consumption of energy in various aspects of daily life, assuming no (or only very limited) preferences for the technological choices. Price increase causes energy efficiency improvements. Consequently energy services or useful energy decrease will be less than energy consumption.

[1] Only CO_2 emissions are used for this report

The integration of the different developments in the MARKAL/TIMES model enhanced the capability of the model to contribute to policy evaluation for a more sustainable energy system and to orient R&D policies on the more promising technologies. The policy analysis used both MARKAL/TIMES for the energy system and GEM-E3, a computable general equilibrium model for the EU (25 countries) for the macroeconomic and sectoral dimensions of the policy cases. Moreover, the European dimension was considered with the Pan European TIMES model.

The MARKAL/TIMES model is a collaborative effort coordinated by the ETSAP network, an IEA Implementing agreement. The Belgian version has been developed by CES-KULeuven and VITO since ten to fifteen years within research programs of the Belgian Science Policy Office and has been used intensively for policy support in Belgium. The collaboration within the ETSAP network for a continuous development and upgrading of the model is one of its main strength.

2. UNCERTAINTY INTEGRATION : METHODOLOGY AND RESULTS:

2.1 Introduction

The climate change issue faces different kind of uncertainty. Uncertainty can cover fluctuating energy prices, future carbon prices and environmental constraints, technology progress and/or security of supply. The liberalization of the EU electricity market increases also the importance of taking into account uncertainty when making investment decisions which are largely irreversible. Private actors on those markets consider the increased uncertainty/risk in their decision process but it is also important to examine its impact from a societal point of view.

Currently, the standard TIMES chooses the technologies on the basis of the lowest expected costs. In reality, the distribution of expected costs is also important. Indeed, each investor has a certain risk aversion: If the expected cost of option A is higher than the one of option B, but with a very high standard, he might choose for option B. Risk aversion is the reluctance to accept a bargain with an uncertain payoff rather than another bargain with a more certain, but possibly lower, expected payoff. An investor can reduce risk by holding instruments which are not perfectly correlated.

This chapter attempts to evaluate the impact of different type of uncertainty on investment decisions with the TIMES. First, a theoretical description of uncertainty estimation is provided. Then, an application in TIMES deals with two different kinds of uncertainty.

In a first part we concentrate on the uncertainty generated by the variability in the fuel prices and its impact on technology choice in the power sector. To analyse this issue, we first built a small power sector optimisation model in which uncertainty about the fuel prices is incorporated. We consider a medium to long term perspective from a societal point of view. The results of this small model are then integrated in the TIMES model. The solution is analyzed for 2 scenarios: a reference without any CO_2 restriction and a scenario with the existing CO_2 targets for Belgium. We concentrate on the investment decisions in the power sector.

In a second part, we use the 'stochastic' TIMES to take into account the uncertainty about technology breakthrough and environmental constraint. Stochastic TIMES allows defining hedging strategies till the disclosure of information around a technology or an environmental constraint. We will apply it to the future CO_2 policy and the availability of carbon capture, with a disclosure of information in 2020 and 2030 respectively.

2.2 Theoretical background

One of the first approaches to include risk in investment decisions in the energy sector - the mean variance portfolio approach - is derived from the financial literature and practices. This mean variance theory for asset investment was introduced by Markowitz (1952).

It proposes how investors can use diversification to optimize their portfolios: holding a diversified portfolio of assets reduces their exposure to individual asset risk. Different other approaches were derived from this technique, but they all focus on the same trade-off between cost and risk in investment decisions. In this chapter, we first discuss the mean variance approach and two alternatives. Then, we review the existing literature on applications of portfolio analysis on fuel price uncertainty. Finally, we look at the stochastic module that is already provided by TIMES, which implements this theoretical approach.

2.2.1. Expected utility and Portfolio theory

The mean variance method is based on the main approach of decision making under uncertainty of maximising the expected utility:

$$Max\, U(F) = \int u(x)\, dF(x)$$

where F(x) represents the cumulative distribution of the outcomes x. The Mean-Variance model, in which the objective function maximizes $\mu - \lambda * \sigma^2$, is an approximation of maximizing the expected utility. μ is the expected return and σ^2 is the variance of the return $\sigma^2 = \sum_i p_i (x_i - \mu)^2$. The variance is an indicator of the risk of the probability distribution and λ reflects the degree of risk aversion of the decision maker. This model corresponds only exactly to the expected utility approach under very stringent conditions on the utility function (quadratic utility function) or on the probability distribution function (normal distribution), but can give a good approximation of the solution that maximises the expected utility (Varian, 1993).

For two assets in a portfolio, the expected portfolio return, $E(r_p)$, is the weighted average of the individual expected returns $E(r_i)$ of the two assets:

$$E(r_p) = w_1 E(r_1) + w_2 E(r_2)$$

Where w_1, w_2 are the proportional shares of assets 1 and 2 in the portfolio and $E(r_1)$, $E(r_2)$ are the expected returns for those assets. The portfolio risk, σ_p, is also a weighted average of the two assets, taking into account the correlation coefficient between the two returns:

$$\sigma_p = \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\rho_{12}\sigma_1\sigma_2}$$

where: ρ_{12} is the correlation between the two return streams, and σ_1 and σ_2 are the standard deviations of the returns of asset 1 and 2 respectively. Lower correlation among portfolio components reduces the portfolio risk reflecting greater diversity.

Applied to investment decisions in the power sector, portfolio optimisation evaluates alternative technologies based on their cost and their risk contributions. In its initial form, it does not take into account the dynamic path of investment decisions. Implementing the approach into an investment model for the power sector which consider explicitly the dynamic of the investment decisions, allows to take both cost and risk into account compared to the least-cost approach implemented in TIMES where only cost is considered.

The objective function becomes then:

$$min\ E\ \ cost\ \ + \lambda\, var(cost)$$

With this objective function, we expect that the optimal investments are not solely based on the production costs, but also on the variance and covariance of price fluctuations of these investments. This can lead to diversification of investment choices, or to 'real options analysis' in which will be invested in capacity that might be used if specific scenarios occur.

2.2.2. Other approaches

The Mean-Variance method is not the only method that is used in literature to incorporate uncertainty on returns in an optimal investment strategy. We discuss one other method the Value at Risk (VaR) and a special case of the mean variance approach, the Upper Absolute Deviation. Both approaches use a parameter of risk aversion to represent the weight of uncertainty in the total cost definition. Each case represents a risk-neutral optimization, when this parameter is equal 0. However, the interpretation of the parameter is different in each case. But as the mathematical set-up is similar in all cases, the influence of the risk aversion parameters on the results should only be regarded as a consequence of different weights attached to uncertainty.

(1) The "Value at Risk" approach

The Value at Risk concept is also derived from finance. It measures the risk of loss on a portfolio of assets: it is a number that expresses the maximum expected loss attributable to changes in the market price of financial instruments for a given time horizon and for a given confidence interval and for a given position or portfolio of instruments. It is the loss level that will not be exceeded with a specified probability. It can be computed for a given assumption about the probability distribution of return on the market variables from which then the probability distribution of the change in the value of the portfolio is derived.

The idea when using it in a power sector investment model is to add a VAR based measure of the risk in the objective function: the objective is to minimize expected cost plus α times standard deviation of cost:

$$min\ E\ \ cost\ \ + \alpha\ \ \overline{var(cost)}$$

The advantage of this approach is that the risk aversion parameter α has a very straightforward interpretation: the case with $\alpha = 1.6$ is equivalent to the minimization of the cost that occurs in the 5th percentile of worst cases, i.e. it minimizes the 95% confidence level of costs, assuming a normal distribution.

(2) Linear Approach: Upper Absolute Deviation

In both methods described in the previous section, the variance that is computed to measure the cost of uncertainty implies that a nonlinear, non-convex model is used to compute a final solution. As non linearity imposes computational restrictions on the model size, one can replace the variance by a model using upper absolute deviation:

$$UpAbsDev\ \ cost\ \ = \sum_{j} p_j\ \ cost_j - E\ \ cost\ \ ^{+}$$

Where $y = x^{+}$ is defined by the following two linear constraints: $y \geq x \text{ and } y \geq 0$. The objective function becomes then

$$min\ E\ \ cost\ \ + \gamma\ \mathrm{UpAbsDev\ (Cost)}$$

The advantage of this approach is that this linear system decreases the computation time of the model, so that complex systems are solvable within a reasonable time. However, there are two important consequences of using the upper absolute deviation: First, the average variation of the model is lower when only upward deviations are taken into account. As a consequence the cost of uncertainty is lower compared to the VaR and the Mean-Variance method, if using the same risk aversion parameter. This underestimates the total uncertainty effect. Second, possible profits resulting from lower than average cost are never taken into account. In literature, this is referred to as adaptiveness. These profits might decrease the incentive to diversify or to invest in certain technologies. The two effects together might over- or underestimate the total cost of uncertainty. It is thus important to take these limitations into account.

In the remainder of this chapter, the two approaches are implemented: For the small numerical example, we use the VaR method as the limited model size allows using a non-linear approach. For a full integrated approach in TIMES, we use the upper absolute deviation method to incorporate uncertainty in the Belgian optimal energy strategy.

2.2.3. Portfolio theory in Electricity sector

In literature, we find a first application of portfolio theory to fossil fuel procurement in the US electricity industry carried out by Bar-Lev and Katz (1976). However, no follow-up research was conducted. Only recently, portfolio analysis is applied on the determination of an optimal mix of electricity generating technologies. Risk analysis for the energy market has first been studied for the US (Humphreys and McClain, 1998) and the European Union (Awerbuch, 2000). While Awerbuch focused more on electricity generation and the optimal electricity mix, Humphreys and McClain developed a regional model for the US, incorporating different industries and energy services. Further papers of Awerbuch and Berger (2003) and Awerbuch (2006) add refinements to the original paper. An overview of these early attempts can be found in Bazilian and Roques (2008) and Fuss (2010).

Applications of portfolio analysis in the energy sector were made for The Netherlands (Jansen et al., 2006), for Switzerland (Krey and Zweifel, 2006) and Taiwan (Huang and Wu, 2008). Recent contributions discuss both the effect of uncertainty in prices and availability of electricity generation (Delarue, 2010).

2.2.4. Uncertainty in TIMES

As we pointed out in the introduction, an energy model faces different kinds of uncertainty. For the uncertainty in some model parameters, there is the stochastic version of TIMES. For a detailed description of the stochastic TIMES formulation, we refer to Loulou and Lehtila (2008). This module provides two possible approaches to deal with uncertain parameters: a Minimax regret criterion with respect to the objective function or the mean variance approach but where the variance is approached through the upper absolute deviation method as discussed before. We focus on the second approach in this chapter. An application of these approaches can be found in recent literature (Loulou et al., 2009) for the global TIMES model TIAM. In section 2.4, we provide another application of this approach in TIMES to investigate some effects of uncertainty on the Belgian energy system and its optimal long term strategy.

One limitation of the in TIMES implemented stochastic module is that only uncertainty for a limited number of parameters can be included and uncertainty on fuel price variations are not considered. In the next section we show the approach used to include the fuel price variations and co-variation. In section 2.3.3, these fuel price scenarios are incorporated in the Belgian TIMES.

2.3 The effect of fuel price uncertainty

2.3.1. Fuel price scenarios

To model the price volatility of fossil fuels, fuel price scenarios are constructed for oil, coal and gas. The stochastic process retained for the fuel prices takes into account that the price processes are correlated. Oil, coal and gas prices are modelled as a multivariate geometric Brownian motion. The covariance matrix of oil, coal and gas log returns is estimated based on annual prices 1988-2008 as reported by BP (2009), see Table 1. The variance shown corresponds to an individual annual volatility of 21-22% for each of the commodities. The covariance between two and the same commodities is not 1 , because it is log returns; an increase of exp(oil_price) with 10% is an increase of oil_price with 4.8%).

Table 1: Covariance matrix of annual log returns of oil, coal and gas price processes

	Oil	Coal	Gas
Oil	0.047666		
Coal	0.015483	0.046052	
Gas	0.022898	0.018412	0.046349

Fuel prices were then generated for the period 2010-2050 through Monte Carlo simulations, given the covariance matrix above. For the small numerical example, 1000 simulations were created. Various examples of prices generated by this model are shown in **Figure 1**.

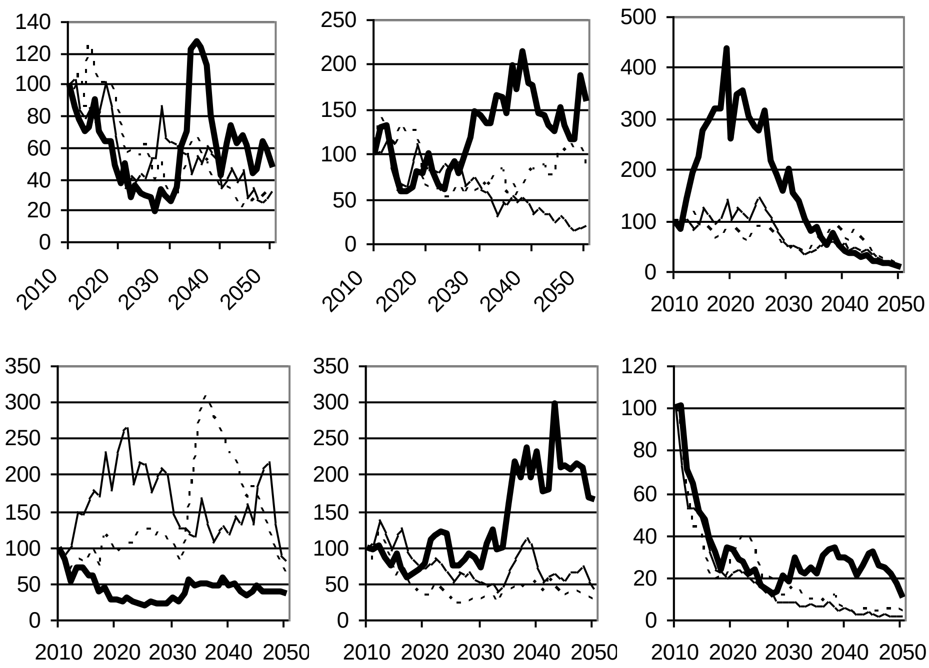


Figure 1: Examples of price scenarios used in the Monte Carlo simulation (OIL = thin line, GAS = dotted line, COAL = thick line), indexed to base year 2010

2.3.2. A numerical exercise

(1) The technology data

A small power sector investment model was built first in excel and then further extended in GAMS focussing on fuel price risk. The objective function can be either the mean-variance objective, the VAR objective or a linear model using the upper absolute deviation. As the interpretation of each objective function only differs in risk aversion weight, we choose the VaR approach for further calculations. The model also includes a 'salvage' component to take into account the investment cost of power plants which life duration extends over the time horizon. The constraints of the model are:

- activity/capacity constraint: the output of a power plant is constrained by its capacity and its availability factor
- demand/activity constraint: the sum of the power plants output must deliver the exogenous demand of electricity

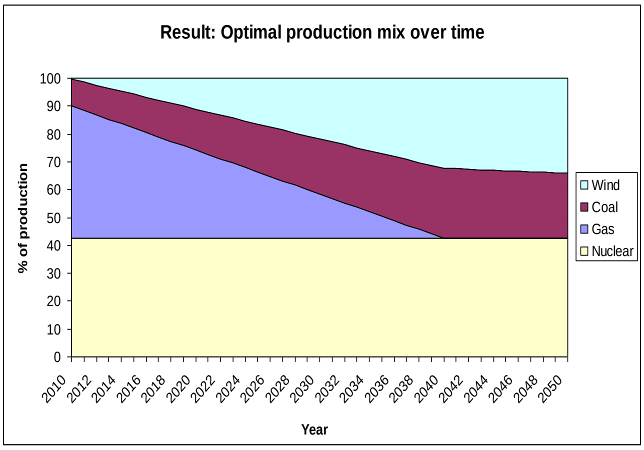
The technology data regarding power plants, are taken from the TIMES database. The technologies considered are: coal supercritical, gas combined cycle, nuclear, wind on and offshore, PV solar and oil turbine for peaking demand.

The data covers the investment cost, the fixed cost, the variable cost, the efficiency and the availability factor by time period, allowing some technical progress in the investment cost and the efficiency, mostly for wind and PV; At this stage the nuclear capacity is bounded to its current capacity in Belgium. The demand for electricity is derived from the TIMES reference scenario. A CO_2 constraint can also be imposed.

(2) The results

The results given here are for the VAR objective function for two values for α, 0 and 1.6 and a CO_2 constraint. The two graphs below show the evolution in the share of the power plants over time for the two values of α.

When $\alpha = 0$, the average share of wind is 21% and the CO_2 price is 18Euro/ton . The share of wind increases to 27% with $\alpha = 1.6$. In this case, the CO_2 emissions constraint is not binding anymore, because renewables are made attractive due to risk aversion.



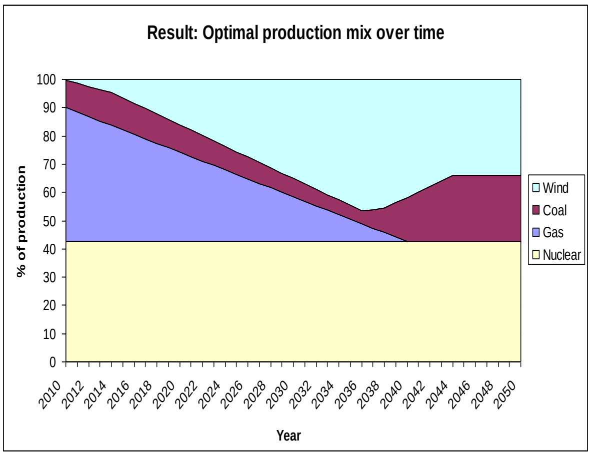


Figure 2: Optimal production mix over time using VAR approach with $\alpha = 0$ (left) and $\alpha = 1.6$

The average share of renewables in the production mix increases as a function of α, i.e. as risk aversion increases:

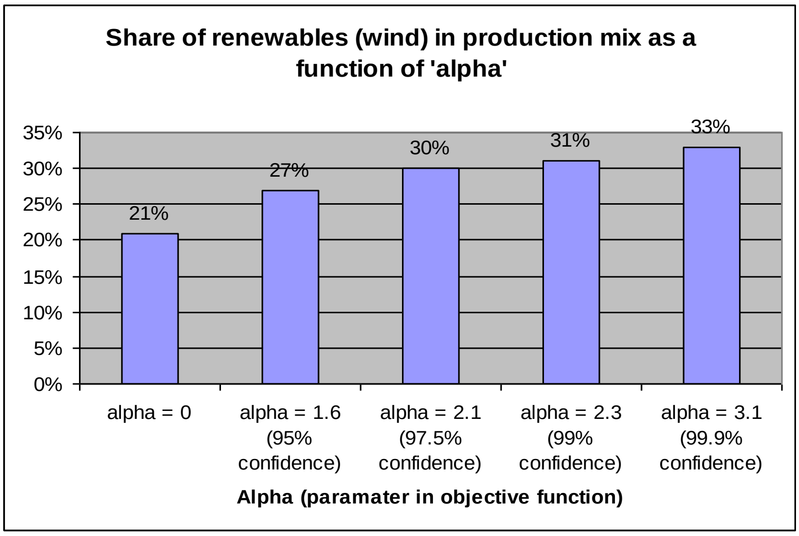


Figure 3: Share of renewables (wind) in production mix as a function of α

The results from the VAR approach can also be represented graphically with the expected cost per technology on the Y-axis and the standard deviation of cost (technology "volatility") on the X-axis. In Figure 4, the 4 technologies mentioned above are shown with the numbers used for the VAR approach.

From the graph, it is clear that Nuclear dominates all other technologies in terms of expected cost and/or standard deviation of cost, but the constraint on nuclear expansion is binding, so it will not dominate.

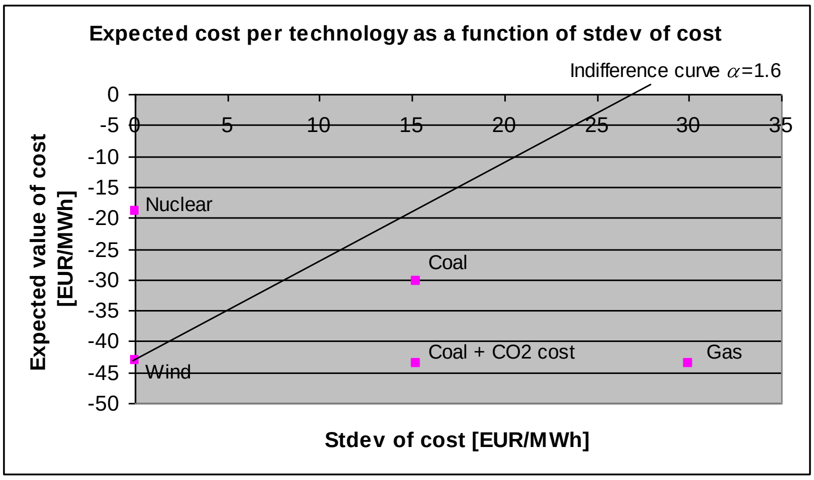


Figure 4: Diagram of technologies

On the other hand with the data used here, Gas is strictly dominated by Coal (even when the CO_2 cost of Coal is taken into account), which explains why no new Gas power plants are built; The old gas are not replaced when decommissioned.

Besides Nuclear, the optimal portfolio will be composed of Wind and Coal. The preference for either Wind or Coal will depend on the risk aversion, i.e. on the value of α.

- When $\alpha = 0$, the indifference curves are horizontal, and Coal is preferred over Wind. In this case, the constraint on CO_2 emissions will be binding. The shadow price of 18 EUR/ton CO_2 (as mentioned above) will be such that Wind and Coal are on the same horizontal indifference curve. This is consistent with Figure 2 (left).
- When $\alpha = 1.6$, the indifference curves are slanted as shown in the graph. In this case, Wind is preferred over Coal. The constraint on CO_2 emissions will therefore not be binding. This is consistent with Figure 2 (right) where the Coal capacity is decreasing until 2035. The construction of coal plants after 2035 is caused by the short planning horizon until 2050, which makes the investment in Coal look much less risky. No investments in Gas are made, since Gas is still strictly dominated by Coal.

This exercise will be pursued by considering a broader range of technologies to mimic better the power sector as it is modelled in TIMES. Further will be examined how the impact of energy price uncertainty could be integrated in the TIMES model for policy evaluation. One possibility would be to add a penalty to the investment cost or a risk premium through the hurdle rate for technologies the most prawn to fuel price risk, the value of which could be derived from scenarios with the power sector model. However this takes only very indirectly the covariance between fuel prices into account. An approach as proposed in Krey et al. (2007) by including a stochastic risk function linked to the fuel price uncertainty, is an interesting option. It is however then more difficult to combine the uncertainty on fuel price with other uncertainty within the energy system.

After Copenhagen, the EC has proposed to reach a 30% reduction compared to 1990 emissions in the EU GHG emissions by 2030. For 2050, a 80% reduction by 2050 is in line with the European commitment to limit global warming to 2°C max and is proposed in the EU roadmap. These targets will be used to explore a range of policies allowing to reach them with the EU and the Belgian TIMES models.

2.3.3. Fuel price uncertainty with TIMES

From the numerical example, we learn that price volatility leads to diversification to energy generation that is not affected by the price scenarios. In this section, we try to extend these findings to the Belgian TIMES model which includes a wider range of possible technologies and a more comprehensive approach of energy consumption in Belgium. We will test the optimal energy generation mix for 2010-2050, using the linear approach as presented in section 2.2.2(2). If we again define risk aversion as α, we analyze the effect the effect of uncertainty on fuel prices for a risk aversion parameter of $\alpha = 0,3,5$.

We compare six different scenarios. We run a reference scenario without any emission target for CO_2 or any risk aversion. Then, we run two scenarios with increasing risk aversion parameter α. Next, we compare these to three scenarios in which a CO_2 target is implemented of 70% reduction by 2050.

We analyze the difference in total cost and investment choices as a consequence of implementing the target, for each risk parameter separately. In all scenarios, the demand for energy services can change in function of the energy service price.

Table 2: Scenario overview

	No CO_2 reduction	-70% CO_2 reduction
risk neutral: $\alpha = 0$	Reference	CO_2_neutral
low risk aversion: $\alpha = 3$	$NoCO_2$_RA3	CO_2_RA3
high risk aversion: $\alpha = 5$	$NoCO_2$_RA5	CO_2_RA5

(1) Integration of price volatility in the TIMES framework

For the integration of fuel price uncertainty, we cannot rely on the existing stochastic framework that is implemented in TIMES, as this is restricted in a few parameters (Loulou and Lehtila, 2007). Therefore, we randomly select 150 fuel price scenarios, that were constructed in section 2.3.1. As these price paths are only constructed for oil, coal and gas, we do not take into account price uncertainty on biofuels, as data on biofuels are very unreliable to predict long term forecasts. We remind that these prices scenarios where constructed taking into account both the price variance as well as the covariance between price fluctuations of these fuels. As a consequence, the uncertainty under considerations consists of the total price variation of all fossil fuels simultaneously.

As mentioned in previous sections, the calculation of the uncertainty cost is in this exercise linearized to allow for solvability of larger models. For each of the 150 simulations, the possible extra fuel cost due to price variations is included in the objective function if and only if this cost is positive. Note that we consider the **total** extra fuel cost of the system: in some cases, it is possible that for a given scenario, low price for one fuel compensates for high prices of another fossil fuel. The total sum of all extra fuel costs needs to be positive:

$$\underset{time}{} \; P_{gas} - E\; P_{gas} \quad Q_{gas} + \; P_{coal} - E\; P_{coal} \quad Q_{coal} + \; P_{oil} - E\; P_{oil} \quad Q_{oil} \; > 0$$

The cost of uncertainty equals then the average of these extra fuel costs over the 150 simulations. This method has three disadvantages: First of all, any savings in costs due to price scenarios which predict a low fossil fuel price are not taken into account. Second, all operational costs are assumed fixed for the different possible fuel prices paths whereas in reality an investor can choose to operate its installations differently. These two simplifications might result in overestimating the cost of installing technologies with high variation of the operational costs. Third, by taking no negative variation, the total variation of fossil fuels is lower compared to the mean variance method or the Value ad Risk. This means, that for the same risk aversion α the cost of fossil technologies will be underestimated compared to the two other methods. As these 2 effects compensate each other, we do not take them into account in this analysis.

However, further research can correct for this inconsistencies. Moreover, as TIMES covers the whole energy system (and not only the power sector), it is the overall uncertainty due to price variation which is taken into account. It might be interesting in a further stage to separate these effects by sector.

In contrast with our numerical example, we limit the price volatility to 150 price simulations that are randomly chosen from the price generation in section 3.1. For a consistent estimation, we need that the average fuel prices scenario of this selection does not differ significantly from the general sample. Figure 5 compares the average fuel price scenarios for 150 and 1000 simulations for the price of crude oil. In addition, these averages are compared to the constant growth scenario. The same exercise can be done for coal and gas prices.

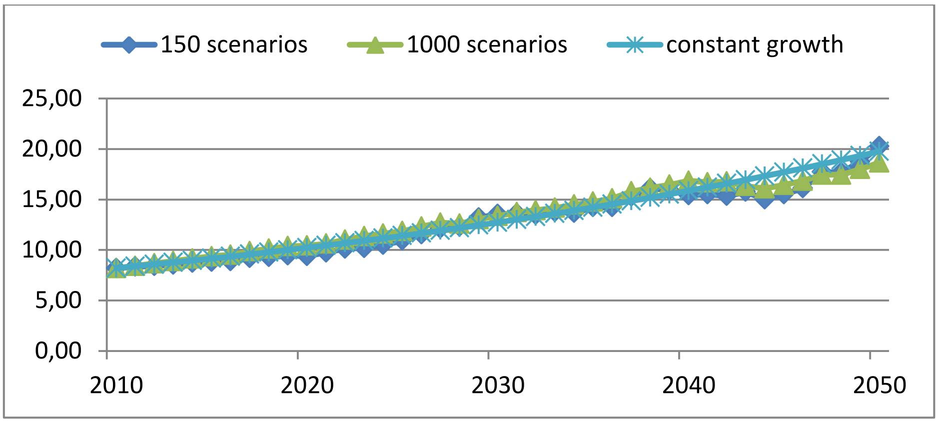


Figure 5: Comparison of the average oil price evolution in the deterministic case with the average prices for a selected number of scenarios (150 and 1000 respectively)

The average fuel price in both situations does not differ significantly with the constant growth scenario. However, we notice that there is a small but significant difference in standard deviation: For only 150 price simulation, standard deviation is lower. As a consequence, this could lead to underestimate the price uncertainty. This risk is nevertheless further reduced because the price variations are only considered for the global energy.

(2) Results

Cost of risk aversion and the cost of a CO_2 policy

The total discounted cost of the energy system is represented for each of the six scenarios in Table 3 for the different risk aversion parameter with and without a CO_2.

Table 3: Total discounted system cost and cost of a CO_2 policy

(Expressed in millions of euro's)

	No CO_2 reduction	-70% CO_2 reduction	Cost of target	Cost in %
risk neutral: $\alpha = 0$	2018647	2137478	118830	5.89%
low risk aversion: $\alpha = 3$	2367146	2480114	112967	4.77%
high risk aversion: $\alpha = 5$	2575054	2688082	113028	4.39%

For increasing risk aversion, the costs of the total system increase. This effect results from the increasing value given to any upward variation that results from the 150 fuel price scenarios. The system cost are increased directly through a higher α and indirectly because TIMES trades off new technology options for a lower variation in costs. These results are perfectly in line with the numerical example of section 2.3.2.

The cost of implementing a CO_2 policy is computed by taking the difference between the no-policy and policy scenario, for each of the risk aversion parameters. These differences are represented in the third column of Table 3. We notice that the cost of reducing CO_2 emissions is lower if we take into account fossil fuel price variations. However, this cost increases again if we further increase the risk aversion parameter. There are 2 explanations to these findings:

If we have no CO_2 policy, then the optimal solution for low risk aversion parameters chooses energy technologies that are not affected by price variations and these are more green technologies. As a consequence, the cost of implementing a CO_2 policy is lower because in the reference scenario already less CO_2 is emitted by the chosen energy mix.

Increasing the risk aversion lowers the cost of a CO_2 policy only as long as diversification can be obtained by choosing technologies that are not CO_2 intensive. For a very high level of risk aversion, the optimal energy mix without a CO_2 reduction consist of an increasing share of coal and oil, as it increases total diversification of the system. As a result, this again increases the cost of reducing CO_2.

We can conclude that the main findings coincide with the results of the numerical example. First, there is a diversification by investing in technologies that do not use fossil fuels. Then, if the risk aversion increases, there is a diversification within the fossil fuel mix. These results are briefly analysed hereafter by looking at the optimal energy mix.

Energy input and electricity mix

The results for all fossil fuels that are subject to variability in prices are given in Table 4. As the risk aversion increases, we see that the total consumption of fossil fuels decreases. The share of gas decreases while the share of coal increases. The numbers in Table 4 should be interpreted carefully. A decreasing gas share can be the result of decreasing demand or substitution of gas by non-fossil fuels. Similarly, coal shares can increase due to the decrease of gas investments.

Table 4: Total consumption of fossil fuels in 2050

-70 % CO_2 reduction	No risk aversion	low risk aversion	high risk aversion
Total Fossil Fuel consumption (PJ)	2822	2356	2122
Gas share (%)	33.6%	22.8%	13.8%
Oil Share (%)	58.4%	60.8%	64.5%
Coal Share (%)	8.0%	16.4%	19.5%

No CO_2 reduction	No risk aversion	low risk aversion	high risk aversion
Total Fossil Fuel consumption (PJ)	3881	2574	2392
Gas share (%)	29.3%	7.5%	5.8%
Oil share (%)	43.2%	55.8%	57.3%
Coal Share (%)	27.5%	36.7%	36.9%

Our main interest is the investments made in the electricity sector. We compare the electricity mix in four different scenarios. The scenarios with a low risk aversion are not represented.

- Starting from a reference scenario without risk aversion or CO_2 policy, we see that coal dominates all other technologies. Only wind energy is introduced from 2020 onwards. This scenario results from the least-cost approach, in which the cheapest technology is chosen.
- Price volatility increases the share of green technologies, such as wind power and PV. Even without any active CO_2 reduction, the total share of green technologies is higher than 20%. All fossil-free technologies are used to their full availability.
- If we then introduce a CO_2 reduction by 2050, we see the share of green technologies increases. This is mainly the consequence of a lower demand as we will show in the last graph of this section. In addition, coal again dominates gas in the electricity market.

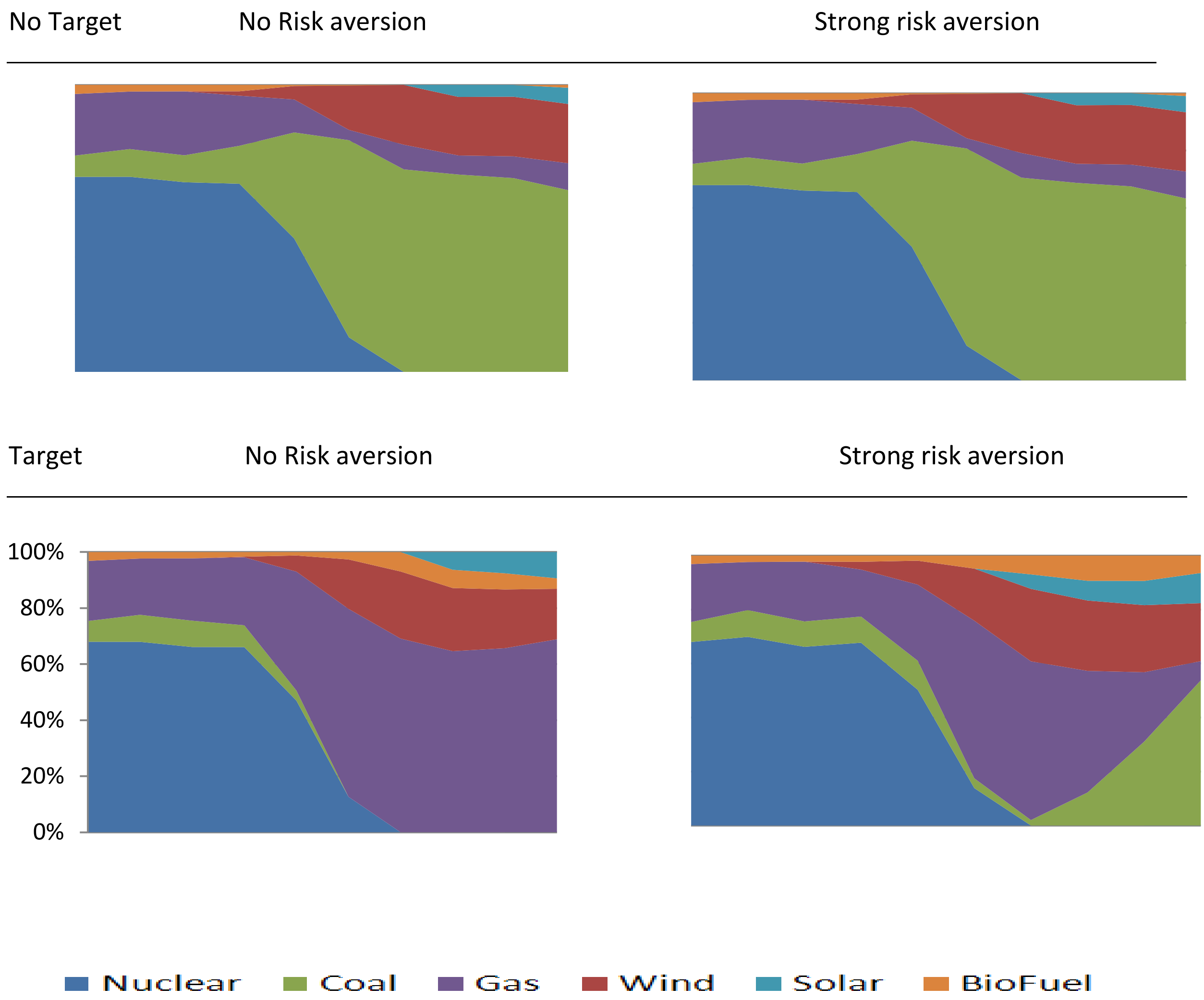


Figure 6: the relative share of fuels in the electricity sector over the planning horizon

These findings again demonstrate the two main effects of uncertainty: variable prices for fossil fuel increasingly support the introduction of green technologies. However, under stringent CO_2 reduction, variability in fossil prices might increase the cost of a CO_2 policy as coal investment increasingly gains profitability.

Demand

By introducing a cost of uncertainty, the total system cost increases and the price of the energy services increases. This implies a reduction in demand. We see that indeed demand reduces in every sector and very clearly for both increasing CO_2 reduction and an increasing risk aversion.

Table 5: Total energy service demand in 2050 for each scenario

	Reference	$NoCO_2$ RA3	$NoCO_2$ RA5	CO_2 RA0	CO_2 RA3	CO_2 RA5
Agriculture (PJ)	41.43	37.28	35.21	41.43	27.96	27.96
Commercial (PJ)	284.84	265.87	258.18	284.84	223.16	215.38
Residential (PJ)	309.65	282.65	270.13	309.65	230.41	223.40
Freight transport (tkm)	129.87	127.08	124.28	129.87	115.91	113.12
Passenger transport (pkm)	181.07	177.23	176.82	181.07	161.30	161.30
Industry (PJ)	290.28	254.11	244.15	290.28	176.38	169.00
Industry Ammonia demand in ton	1.16	0.95	0.90	1.16	0.84	0.78
Industry Cement and Lime demand in ton	19.83	19.18	19.06	19.83	13.94	13.76
Industry Copper demand in ton	0.40	0.39	0.38	0.40	0.34	0.33
Industry Glass demand in ton	5.52	5.09	4.83	5.52	4.02	3.88
Industry Iron and Steel demand in ton	9.86	9.86	9.86	9.86	9.86	9.86
Industry Paper demand in ton	2.17	2.09	2.03	2.17	1.85	1.80
Aviation transport (PJ)	128.13	105.70	99.30	128.13	102.14	96.45
Navigation transport (PJ)	523.52	407.78	381.09	523.52	403.16	378.01

2.4 Uncertainty with stochastic TIMES

Variable fuel costs are not the only source of uncertainty in an energy system. Section 2.2.4 discussed the stochastic module within TIMES that can provide an optimal strategy for variability in different model parameters. Examples are government policies, growth scenarios or availability of technologies. The stochastic module considers the possibility of learning about the uncertainty, i.e. new information becomes available as the actual value of the parameter is revealed. The optimization defines then a hedging strategy till the information disclosure. After this information disclosure, the solution will depend on the outcome which has occurred.

2.4.1. Model

In this section, we analyze the possible hedging strategies if both the final CO_2 target and the availability of carbon capture and storage are uncertain. By assuming two possible outcomes for each variable, we create four different 'states of the world' (SOW). Figure 7 represents the different SOW's that can occur.

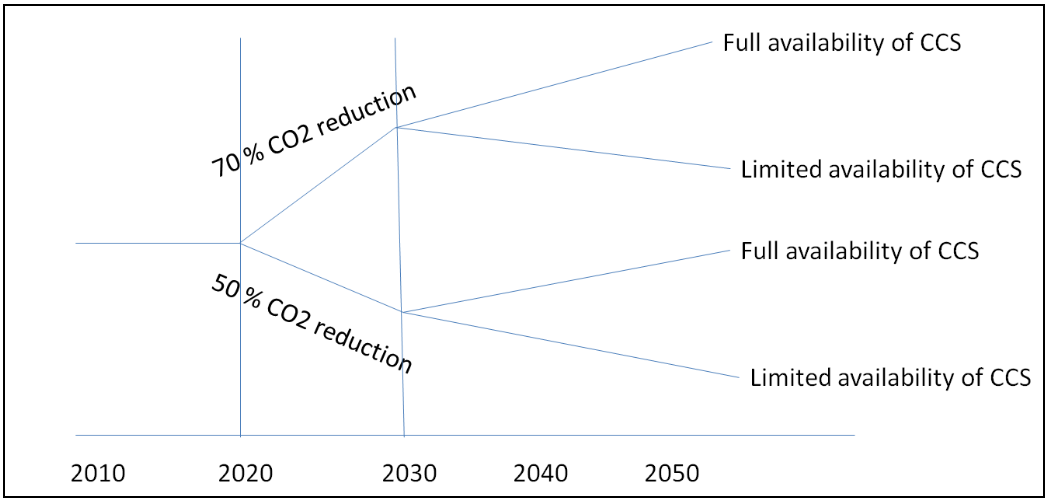


Figure 7: Event tree for uncertainty on CO_2 target, revealed in 2020 and uncertainty on carbon storage, revealed in 2030

According to the event tree, we have only limited insight on the CO_2-policy of the Belgian government. In 2020, the Belgian government will decide to reduce CO_2 emissions with 50 or 70 percent in 2050, compared to the 2005 level. Each scenario has equal probabilities of occurrence. Next, In 2030 information becomes available on the cumulative CCS potential for Belgium. We analyze two possible scenarios: in a first scenario, we have a full potential of carbon storage, equal to 1 071 664 tonnes of CO_2. A second scenario assumes half of this storage capacity. Note however that CCS technology can already be used from 2015 onwards. In total, we thus have four possible scenarios. We first analyze cost of hedging strategies for a risk neutral optimizer. Second, we can introduce risk aversion by introducing again a risk aversion parameter.

Before looking at the results, we remark that the options considered in this problem setup serve mainly as an example to demonstrate the effect of uncertain parameters: The magnitude of hedging costs, which equals the cost of information, always depends on the differences among the scenarios under consideration and the timing on which the information becomes available. The longer the hedging period, and for more extreme possible scenarios, we have an increasing information value.

2.4.2. Results

The value of information is given by the difference between total discounted cost of the energy system in the deterministic scenario and the system cost of the SOW that correspondents with this deterministic scenario. The two tables in Table 6 represent both the total discounted cost of the energy system and the information value for each of the scenarios. In the upper table, we have a risk neutral optimization, in the lower table we have set a risk aversion parameter of 3. Note that we do not consider fuel price variation of fossil fuels in this example.

Table 6: Total discounted cost of the energy system (in millions of euro) for optimal planning with uncertainty and in the deterministic case

risk neutral	Cost with uncertainty	Cost deterministic	Information Cost	Information Cost (%)
- 70% CO_2 /Full CCS	2221881	2137478	84404	3.80%
- 70% CO_2 /Lim CCS	2240547	2158287	82260	3.67%
- 50% CO_2 /Full CCS	2188803	2093574	95229	4.35%
- 50% CO_2 /Lim CCS	2195993	2106714	89278	4.07%

low risk aversion $\alpha = 3$	Cost with uncertainty	Cost deterministic	Information Cost	Information Cost (%)
- 70% CO_2 /Full CCS	2221164	2137478	83686	3.77%
- 70% CO_2 /Lim CCS	2239392	2158287	81105	3.62%
- 50% CO_2 /Full CCS	2210124	2093574	116550	5.27%
- 50% CO_2 /Lim CCS	2225514	2106714	118800	5.34%

We see that the information value is rather small compared to the total discounted costs (≤ 5%) . There is only a limited difference between all possible scenarios. Most investment decisions are thus not affected by these uncertainty variables. The most significant difference can be found in CO_2 production and carbon storage.

The information value is highest for the third and fourth scenario. This means that the hedging strategy mainly consists of postponing CO_2 production and storage. If turns out that the strict CO_2 policy is not implemented, than CCS increases already, to correct for delay on usage. Further revelation of full CCS capacity in scenario 4, corrects the CCS activity to the level of the deterministic scenario. In the third scenario, the CCS activity is again decreased until it attains the deterministic level. The same analysis can be done for the first two scenarios.

We find that CCS activity is significantly affected by the uncertainty within the model. The two optimal solutions, in a deterministic and stochastic set up, of course do not differ only in the CCS activity. However, taking into account the parameters on which the uncertainty is chosen, we see that the clearest differences lie within the level of carbon storage over time.

The value information can therefore also be intuitively interpreted using the graphs in Figure 8. These two graphs represent the CCS activity in both scenario 3 and 4. The area between the lines of the deterministic solution and the stochastic solution represents the effect of uncertainty.

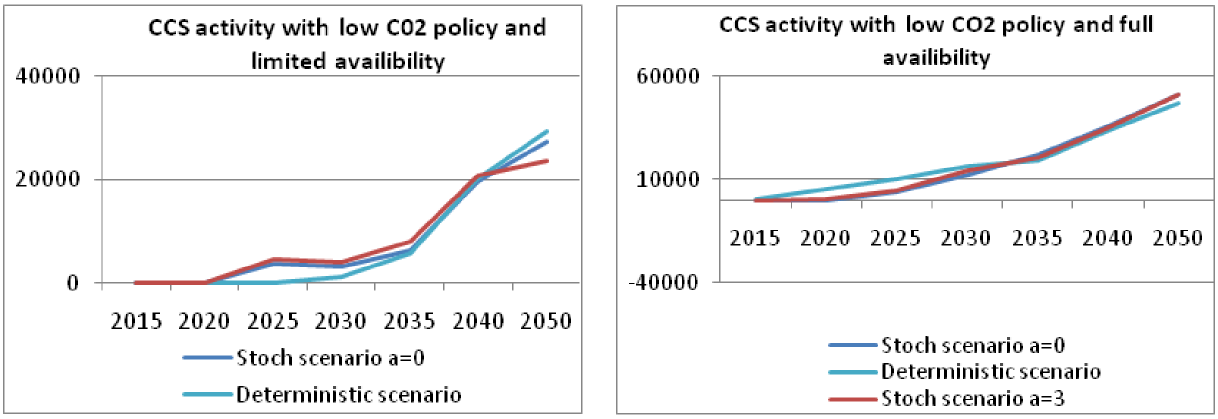


Figure 8: Carbon storage (in tonnes) over the planning horizon for both scenarios with a low C02 target

The model is also run including a risk aversion parameter equal to 3. Results are also represented in both graphs. We find that risk aversion increases the overall value of information. However, in those cases where the effect of risk aversion on the hedging strategy aligns the stochastic scenario with the deterministic scenario, we find a decline the value of information. In contrast, increasing risk aversion that leads the hedging strategy away from the deterministic case, increases the value of information.

We provide an example. In a deterministic scenario with a high CO_2 reduction, the optimal solution is to postpone CCS activity to the last periods, where the cost of reducing CO_2 is the highest. In a stochastic scenario, the hedging strategy consists of already using CCS as the probability of a high CO_2 reduction is only limited. If risk aversion supports the postponing of CCS, then this risk aversion aligns the hedging strategy towards the deterministic scenario. In such case, the information value will thus be lower. This immediately points out that in the opposite case, the information value has increased. The total value of information over the scenarios always increases.

2.5 Conclusions

Uncertainty can play a key role within an energy system. The effect of uncertainty depends highly on the possible scenarios and the variance between these different possibilities and on the adaptiveness of an energy system to take these scenarios into account.

In chapter 3, we showed that modelling variability in fossil fuel prices leads to a diversification of the energy mix, and more specifically, the electricity generation mix. We conclude that price fluctuations affect the optimal energy system in three different ways. First, technologies not affected by the price variation enter the optimal solution. Second, risk aversion increases the relative share of coal generated electricity under a stringent C02 policy. This results from diversification if all non-fossil technologies are used to their maximum availability. Finally, the total costs increase which reduces demand and causes higher energy prices.

Chapter 4 introduced the stochastic TIMES module and variability on policy measures and technology parameters. The proposed scenarios resulted in a small difference between the hedging strategy and each of the deterministic strategies. A lack of information on long term policy measures will lead to higher costs of the energy system. For increasing risk aversion, the overall costs of uncertainty increase. However, the information value for worst case scenarios becomes lower as they gain higher relative importance in the objective function.

In general, the effects of uncertainty for the Belgian energy system were limited. We can state three reasons for this low cost of uncertainty:

- The analysis was carried out with already very strict policy measures for CO_2 reduction. As a consequence, all available technologies that can provide such a strict CO_2 reduction were already used to their full capacity. This results in a strongly limited variations of the energy system caused by uncertainty
- The energy system for Belgium was analyzed in a 'closed-border' approach. Lack of coordination within Europe on CO_2 reduction targets again restricts the technology possibilities of the energy system.
- The domains in which we analyzed uncertainty effects were limited. More extreme scenarios or variability's will lead to a much higher cost of uncertainty. Examples are the introduction of variability in the prices of biofuel or long term wind availability.

The numerical examples in this chapter point out that uncertainties must be included in the long term optimization of an energy system. Future work should focus on combining multiple source of uncertainty and their relative dependencies. Also, more attention is needed to relax the assumption that both investment and operational decisions are fixed for the total time horizon. The question is not only which fuel to use but also which fuel to use in which situation (low or high fuel price). An approach that can cover this flexible operation of installations would give more realistic set of investments.

3. METHODOLOGY AND RESULTS: PRICE ELASTICITIES OF ENERGY SERVICE DEMAND

This chapter deals with the methodology and results of the estimation of price elasticities of energy service demand.

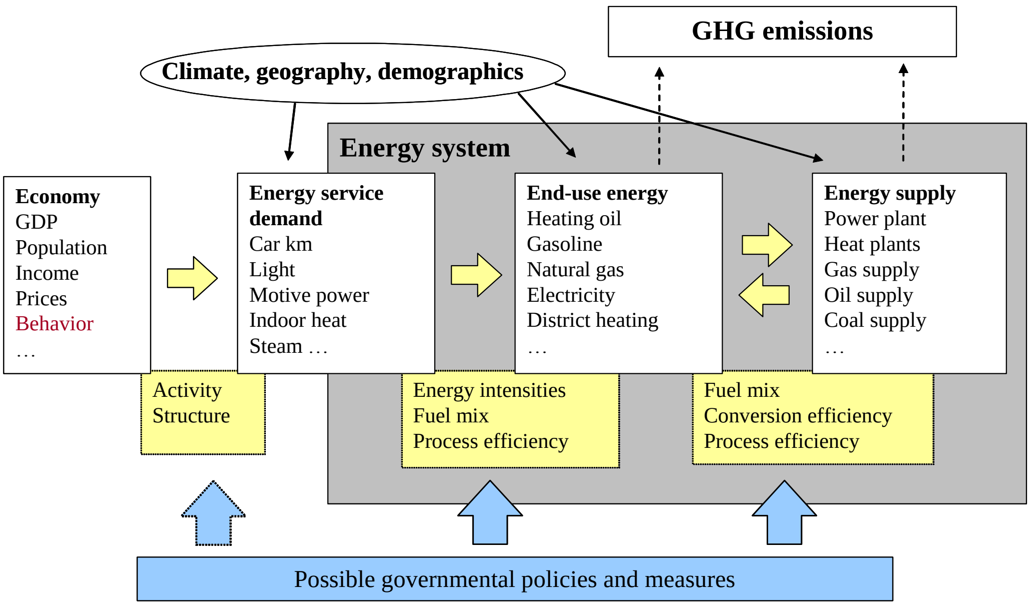
3.1 Introduction

The relevance of introducing price elasticities in the TIMES model has been demonstrated by Van Regemorter and Nijs (2007). The elastic version of TIMES allows incorporating e.g. reactions of reduced consumption because of increasing prices. Though a lot of information is available, the size and content of the elasticities vary largely: Different price elasticities are used in literature and for the calculation of price elasticities in partial equilibrium energy models, energy is often confused with energy service and energy price is often confused with energy service price.

This section will focus on the quantification of the elasticities. One particular problem is that prices for energy services and even energy services themselves are not direct observed. Indeed, the energy service obtained from fuel burning in residential houses is a pleasant inside temperature which, in passive houses can even be obtained without burning fuel (or very little).

3.2 Importance of price elasticities in defining sustainable energy policy

Energy service demand is not equal to energy demand. In figure 2, the difference with demand



of end-use or final energy is shown.

Figure 9: Energy system chart, Source: IEA "30 years of energy use in IEA countries".

Changing the energy service demand is changing the activity (for example passenger kilometres) or the structure (the mix of activities in a sector).

Price and income elasticities of energy services are a major source of uncertainty. They are crucial in defining a sustainable energy scenario. Different aspects of sustainable energy policy are influenced by the correct estimation of those elasticities:

- Different studies calculate the welfare cost of a sustainable energy future. In the case of a greenhouse gas policy, many policy discussions are based on those costs. The results are drastically influenced by the use of different price elasticities (as seen below).
- In all sectors, choices of energy technologies are influenced the supply as well as the demand side. The approach here is to have both in one model. Elasticities cannot be estimated without taking into account demand as well as supply. After all, energy prices are determined by the supply of all technologies.
- Integrating uncertainty covers all aspects of different technology options. To know whether a technology is sustainable it is not sufficient only to envisage that technology. One should also look at all "concurrent" technologies with all uncertainties on investment, fuel prices etc... One of those uncertainties is the price elasticity.
- The impact on the energy policy is different when defining energy scenarios with elastic demand. Indeed, a major contribution to reducing greenhouse gases is obtained from a reduction in the energy service demand. This reduction can cover a great number of changes outside the energy system: new production system, change in life style, in urban planning, ….

The relevance of energy service price elasticities is illustrated in Figure 10. The Belgian TIMES model has been used to develop GHG reduction scenario's assuming elastic and inelastic demand for energy services. Welfare aspects of these scenarios have been evaluated for those scenarios. Although the assumed elasticities in the elastic scenario are rather small (-.3), we have found very significant differences in welfare aspects.

In case of an elastic demand, an important impact of the CO_2 reductions is a decrease in the demand for energy services because of the price increase induced by the carbon constraint. This decrease leads to a loss of consumer surplus that is larger than the increase of producer surplus. There is an increase in investment costs and a decrease in operation and maintenance costs.

For the runs with inelastic (constant) demand (also figure 3), the costs are higher. Inelastic demand would occur if people are insensitive to higher prices and keep demand at similar levels as in the reference scenario.

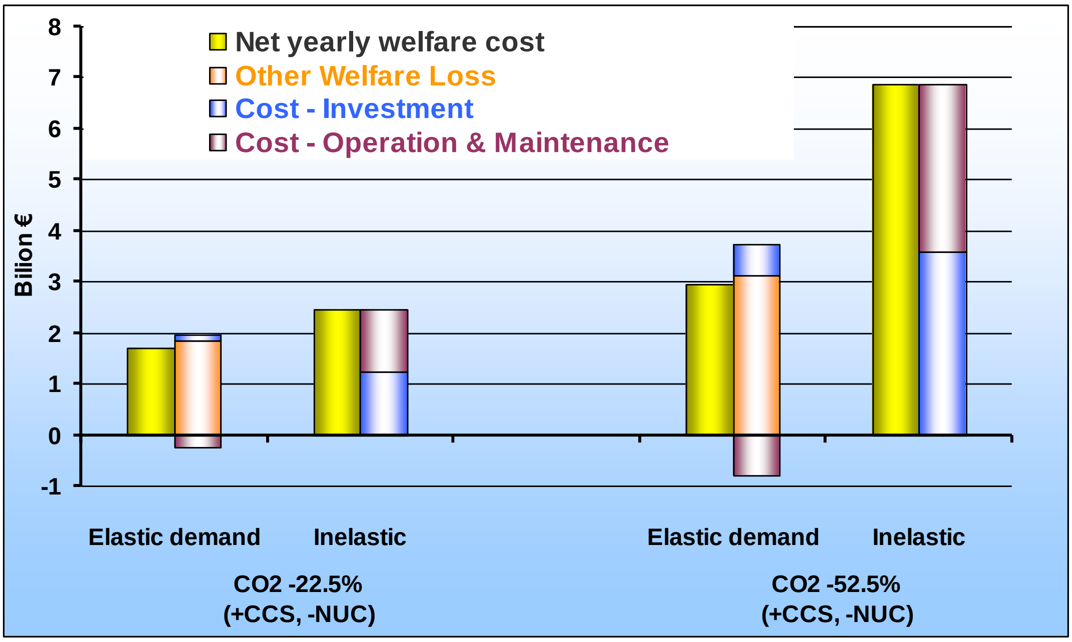


Figure 10: Yearly welfare cost and underlying cost increases/decreases of two CO_2 reduction scenarios in Belgium (demand decrease for elastic run, constant demand for inelastic run, model runs with old TIMES model).

In the previous BELSPO project, VITO and CES KULeuven have, among other things, calculated the welfare cost of stringent CO_2 reductions in Belgium by means of five scenarios (1 reference scenario + 4 policy scenarios). Four policy scenarios were developed for two CO_2 reduction targets in 2050: a reduction of 22.5% and 52.5% compared to the 1990 emissions. A nuclear phase-out is imposed in three scenarios. One scenario is based on extra nuclear power plants of a total capacity 1,7 GWe on top of the existing capacities. Three scenarios take advantage of carbon storage (CCS), with a maximum potential of 100 Mt at a distance less than 20km and 1000 Mt at a larger distance:

1. CO_2 -22.5% (+CCS, -NUC): a reduction of 22.5% in 2050
2. CO_2 -52.5% (+CCS, -NUC): a reduction of 52.5% in 2050
3. CO_2 -52.5% (+CCS,+NUC): same as 2, allowing extra nuclear power plants
4. CO_2 -52.5% (-CCS, -NUC): same as 2, not allowing carbon storage

The most expensive -52.5% scenario is the target without CCS option or nuclear option and costs 5.9 billion €/yr or more (2.7% of GDP2000). The inelastic run is impossible to run with the TIMES model under these conditions. Carbon storage limits the cost of the highest target considerably to a value between 2.9 and 6.9 billion €/yr (1.3 to 3.1% of GDP2000). If also the nuclear option is allowed, the yearly cost is between 2.2 and 3.9 billion €/year (1 to 1.8% of GDP2000). For a -22.5% target, the cost is between 1.7 and 2.4 billion €/yr (appr. 1% of GDP2000), without nuclear option. With neither nuclear nor carbon storage available, the welfare cost is at least 2.7% of GDP2000 on an annual base.

3.3 Importance of Belgian estimates

No good Belgian data are available for the price elasticity of energy-service demand. A recent study by ECOLAS "Verkennende studie naar prijs- en inkomens- elasticiteiten van milieugerelateerde goederen en diensten in Vlaanderen" analysed water, energy, transport and dust demand price elasticity and showed that there is a lack of good data at this moment.

Secondly, there are different concepts when it comes to defining elasticities (short versus long term, uncompensated versus compensated, used in partial equilibrium versus general equilibrium models).

Some studies have been realized abroad. Most of these studies consider the demand for energy in function of energy prices. Empirical results are derived by using econometric techniques on times series or cross-section data. These studies rarely consider energy efficiency improvements.

The objective here is to elaborate a methodology to provide TIMES users with reasonable and unbiased estimates for the demand of "useful" energy in various final demand categories. This knowledge is also relevant in the context of sustainable development.

3.4 Electricity and fuel consumption in Europe: a panel error correction model for residential demand elasticities.

Econometric estimation is highly empirical and requires extensive data sets. In principle two types of datasets can be used, either historical data or cross section data, the latter referring to observations from different agents at one point in time. One requirement to the dataset is that there should be sufficient variation between the observations. As energy prices are very homogenous at one point in time, time series should be used instead. The availability of data and the model specification interact with each other. Preferably, as many as possible, original observed data, or elementary transformations from original observed data should be used.

The paper "*Electricity and fuel consumption in Europe: a panel error correction model for residential demand elasticities.*" (Annex 1) focuses on the long term elasticities. Deriving long term price elasticities should be based on time series, as cross section data do not have the time dimension. But analysing time series also gives rise to particular problems, such as dealing with autocorrelation and choosing the appropriate historical period. Increasing the length of the time series might have a positive effect on the standard deviations. But it remains a study of historical data and still raises questions on the validity for the future, in particular for the very long horizon. We can consider two cases. First, elasticities being constant over time, implying that extending the period will only affect the standard errors and not the point estimates. Second, elasticities change over time in which case it becomes likely that we would be better off to rely on more recent data. So for energy scenario building, more recent data can be used.

A panel approach has the advantage that we have more variation in the prices and the quantities, a precondition for successful econometrics. In a way it also covers aspects of the time dimension, as different countries have different per capita income, different cultural and political situations, different tax regimes and many other aspects that may change in time. Another advantage is that we avoid the discussion of getting different results for different countries.

The econometric methodology used is based on the work of Granger (1974) on spurious regressions and by the work of Engle and Granger on cointegrating and error correction modelling (Engle and Granger 1987).

3.5 Residential fuel demand elasticities: what lesson's can be learned from bottom-up and top-down methodologies.

This section is a long abstract for the publication in annex 2. The objective is providing guidance in quantifying service demand elasticities in MARKAL-TIMES

JEL classification: C13, C23, C61, Q4

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Keywords : energy demand price elasticity, energy service price elasticity, MARKAL, bottom-up, top-down, econometric s, co-integration, panel-data

Motivation: In standard MARKAL, substitution between capital and energy is represented by a set of technology options and energy price shifts results in an opposite energy consumption movement, while keeping the energy service constant. Standard MARKAL does not count for non-technical solutions such as price driven behavioural changes. MARKAL-ED (Elastic Demand) includes a functionality to account for such behaviour. The energy service can be made price elastic by the means of a specific parameter. An increase in the price of an energy service, whatever the reason, results in a decline of the demand of this service and ceteris paribus for the demand of energy. We consider the case of residential fuel consumption and search for empirical evidence to quantify the parameter value of the energy service elasticity.

General methodology

We use a MARKAL model for the residential sector to derive energy price elasticities under different assumptions for the energy service elasticity and compare the results with modern econometric analysis based on panel data.

First we establish a theoretical relationship between the elasticity of the energy demand (pelasED) and the elasticity of the energy service demand (pelasES). This relationship involves two parameters: the budget share of energy in the energy service δ and the substitution elasticity σ

$$\boldsymbol{pelasED = pelasES * \delta - \sigma(1 - \delta)}$$

From this equation follows that for a high substitution elasticity σ and a small budget share of energy in the overall spending for the energy service that |pelasED| > |pelasES|.

Bottom-up methodology

We select a MARKAL model with a detailed and sound representation of the residential sector and analyse the price sensitivity of this model. The selection of the model is a delicate issue. Although the MARKAL model is widespread and a general accepted methodology for energy system analysis, there is no sound methodology or guidelines for determining the number of technologies and the characteristics of these methodologies to be feed in the model. We are aware that conclusions from one MARKAL model might not be relevant for other MARKAL models or other models of the same family like MESSAGE and TIMES, but we provide a methodology which is easily reconstructed by other bottom-up model users, allowing to drawn their own conclusions.

The price sensitivity analysis is done for variations in the fuel price increase (20 % and 100 %), variations in the energy service elasticity (0 and -.2) and for variations in the hurdle rate for investment in energy efficiency improvement technologies (0%, 15% and 30%). The use of hurdle rates changes the nature of the model solution and the interpretation of the results. A 0 % hurdle rate simulates pure rational behaviour under perfect competition. Hurdle rates turn the model into a "simulations mode" by considering more realistic consumer time preferences. We have found that this model simulates residential consumer behaviour "the best" with a hurdle of 15%.

Table 7: Residential fuel price elasticities obtained by the Flanders-Residential-MARKAL model

	Δ fuel price	20%		100%
	Pelaes	0	-0.2	0
Hurdle rate	0%	-0.4		
	15%	-0.63	-0.78	-0.23
	30%	-0.33		

The elasticities summarised in Table 7 are measured over a period of 15 years. An energy service elasticity of -0.2 results in 0.15 points increase in the energy demand elasticity. A doubling of fuel prices reduces the price elasticity significantly compared to result obtained for a 20 % increase. This finding is not coincidence but consistent with the methodology.

Note that formula (1) and the results in table 1 allow deriving the budget share parameter σ and the substitution elasticity σ. For instance from the two observations -0.63 and -0.78 we can derive a budget share of 0.75 and a substitution elasticity 2.52.

Top-down methodology

Contrary to bottom-up modelling, there is an extensive amount of scientific literature defining rules and standards for econometric analysis.

The theoretical background in long term econometric analysis has dramatically changed by the work of Granger and Newbold (1974) on spurious regressions and by Engle and Granger on cointegrating and error correction modelling (Engle and Granger 1987). New insights have invoked a shift from analysing correlation properties towards analysing cointegration properties. Econometric started to focus on developing new statistical methods and statistics for evaluating the cointegration properties of time series. In this section we derive long term price elasticities using panel data and cointegration analysis. The following steps have been undertaken:

We have compiled a new database form EUROSTAT data, covering the most recent available period (up to 2008) for all EU countries. The start data of the time series is 1991 or later. This means that we are dealing with relative short period which makes a panel approach attractive.

We analyse the stationary properties using the individual time series Dickey-Fuller test and the Levin et al. (2002) panel data tests. We conclude that fuel consumption, income and fuel prices are non-stationary whereas degree-days are stationary.

As critical values for cointegration test are derived for non-stationary values we propose a procedure for dealing with degree days in the analysis.

We derive heterogeneous country elasticities by OLS and DOLS as well as homogenous panel elasticities by using panel OLS and panel DOLS.

For all these sets of parameter values we compile the seven Pedroni (1999, 2004) panel co-integration tests. On this basis we conclude that co-integration should be rejected for homogeneous elasticities and accepted for heterogeneous elasticities. On this basis we conclude that, with respect to fuel price elasticities, Europe cannot be considered as a homogenous block. We obtain non-homogenous fuel price elasticities between -0.35 and 0 and one exceptional value of -0.58 obtained by DOLS for France.

Conclusions

The last section is dealing with the comparison of the results of the bottom-up and the econometric analysis. After having discussed the basic underlying assumptions of both methodologies we conclude to use a zero price elasticity for the energy service in this MARKAL model. However bottom-up models with an incomplete representation of the substitution possibilities might benefit from the introduction of energy service price elasticities. Moreover we recommend MARKAL users to measure the price elasticity of their models as a means of control and good modelling practise.

3.6 Price sensitivity of residential energy services (HUB Master dissertation)

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3.6.1. Abstract

A stated preferences method was used to examine the willingness to pay for energy services in Flemish residential dwellings. This involved examining the considerations made by property owners when they decide to renovate their properties, in relation to matters such as heating comfort, usable living space, running and investment costs for heating systems and the environment-friendliness of the heating system. A pilot choice experiment was conducted with 57 respondents and the data was analysed using the conditional logit model. The analysis showed that all attributes were significant, with the exception of the temperature attributes. The various models demonstrated that respondents want to pay €3500 for a new room. To reduce emissions of CO_2, respondents are prepared to pay €2.5 per kg CO_2 reduction or €176 to reduce emissions by 10%. Finally, a discount rate of 4.6% was used to evaluate investment costs against running costs.

3.6.2. Introduction

The aim of this thesis is to examine the willingness to pay for housing requirements that greatly influence the heat demand in a dwelling after a renovation. This involved examining the considerations made by property owners, in relation to matters such as heating comfort, usable living space, running and investment costs for heating and the environment-friendliness of the heating system, when they decide to renovate their properties. This involved the following questions: How much are property owners willing to pay to make their homes more energy-efficient and what do they demand in return? This will be examined using a choice experiment. This is a research method based on *stated preferences* and Lancaster's utility theory (cf. infra). The study does not address directly the willingness to pay for energy-saving measures or the various opportunities for renovating one's home. However, the intention is to examine which services directly or indirectly relate to energy consumption in residential dwellings and how they are appreciated by the respondent. The willingness to pay for these energy services is the main research topic. The term 'energy services in dwellings' refers to derived products and services that relate to heating and electricity. Thus, heating comfort is also seen as an energy service. Heating comfort is realised by using an energy carrier in the home, which results in a more pleasant climate.

Heating comfort consists of various elements, and these elements are appreciated differently by different people. Heating comfort is defined as a mood that expresses satisfaction with the heated environment (ASHRAE, 1992). To express this satisfaction with the heated environment, an index has been designed that incorporates the heat balance of the human body and the heat sensation scale. (Fanger 1970). According to the American society for heating and refrigeration and Air Conditioning Engineers (ASHRAE), the dry bulb temperature, relative humidity, air speed, the level of activity and clothes have an impact on heating comfort.

The final main objective is to compile a suitable research method that is able to examine past research topics. The aim of this study is to compile a choice experiment that accurately and reliably measures the demand for energy services in the homes of Flemish families. In concrete terms, this involves examining aspects or characteristics that influence demand for energy services and how much individuals want to pay for them. The results examined in this study have been derived from a pilot study; these results form the basis for further research.

The results of this study will help to better understand consumers. They will also offer a better insight into the rebound effect and allow policy makers to make their policy more compatible consumer behaviour.

This thesis starts with a literature study that briefly examines the rebound effect. This is followed by a comprehensive explanation of the research method used in this thesis. The various analysis methods and models are also explained. Finally, the results from this pilot study are analysed and discussed.

3.6.3. Literature overview and background

The demand for energy (E) is derived from the demand for energy services (ED) like heating comfort, cooling and ventilation. These services are provided by a combination of energy raw materials and related energy systems (Sorrell & Dimitropoulos 2007). Consumers benefit by consuming these services, rather than consuming energy raw materials and other market goods. An important feature of an energy service is the useful activity, which can be measured via thermodynamic or physical indicators (Patterson, 1996).

Because this is a completely new experiment, there is little scope to fall back on earlier research. There are few results specific to the field of energy services. In research carried out by Sadler(2003), 2 choice experiments were used to examine the preferences of consumers with regard to renovation and heating systems. The research showed that 59% of respondents chose energy-efficient renovations ahead of renovations without energy-efficiency improvements. Respondents use an average discount factor of 20.79% when evaluating investment costs against running costs, for a renovation that helps to reduce the running costs of the dwelling. A discount factor of 9% is used for heating systems.

On the other hand, the influence of changing energy prices on energy consumption, and the rebound effect that takes place if one heats in an energy efficient manner, has been analysed in depth. (Sadler, 2003) (Hens et al,. 2010).

Rebound studies

An increase in energy-efficiency is seen as a major strategy for tackling environmental problems associated with energy consumption. National energy plans have been established in many countries. If we retrospectively examine the results of these studies and plans, we see that only part of the theoretical energy reduction is realised in practice. This is because technical studies over-estimate the actual reduction and under-estimate the costs, because not enough attention is paid to the behaviour of consumers (Vine et al., 1994).

"The rebound effect" describes the discrepancy between the potential and actual energy saving that is realised via behavioural reactions in contrast to maintaining the status quo. (Khazzoom, 1987), (Cuijpers, 1995), (Wirl, 1994). It is normally measured as a percentage of the savings predicted by technical calculations, which are lost because of behavioural reactions (Madlener & Alcott. 2009).

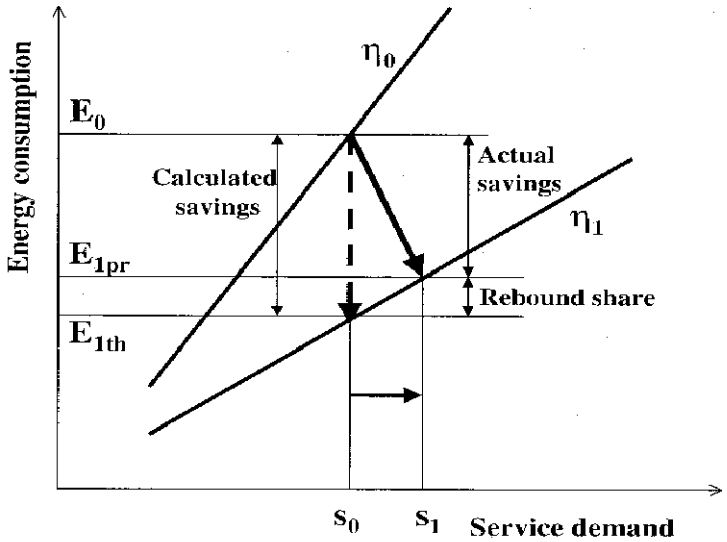

Figure 11: Relationship between price change, consumption, efficiency improvements and rebound effect (Haas & Biermayr, 2000)

Haas & Biermayr, (2000) have used figure 1 to explain rebound: "If the efficiency of n_0 is increased to n_1 consumption will drop from E_0 to E_{1th}. if one assumes that the level of demand for services remains the same. In real life, however, consumers will increase their demand for energy services from S_0 to S_1, which results in an energy consumption of E_{1pr}. We can conclude that the difference between E_{1th} and E_{1pr} is, in relation to ($E_0 - E_{1th}$) equal to the rebound effect" (Haas & Biermayr,. 2000).

Rebound studies examine whether increases in the technical efficiency of a delivered energy service (e.g. heating), are proportionate to the expected reduction in energy consumption (e.g. does a 10% improvement in energy efficiency of a heating installation results in a 10% reduction in a family's energy consumption?).

Economic theories suggest that this is not the case.

Two mechanisms ensure that the increase in energy efficiency is not equal to the reduction in energy consumption, namely:

- *Direct rebound effect*: Due to the increase in energy efficiency, the effective price of the supplied energy service will drop, which will result in an increase in demand for this energy service.
- *Indirect rebound effect*: A lower effective cost ensures that more money is available in the budget, which means other services can be purchased, such as holidays, leading to higher energy consumption (Greening et al., 2000).

The marginal utility of energy services is assumed to fall when consumption increases. The leads to a drop in the direct rebound effect of energy-efficient improvements. For example, the rebound effect that takes place when the energy-efficiency of heating systems is improved, will quickly fall when the indoor temperature approaches the maximum comfort temperature. Another effect that is observed in studies, is the impression that direct rebound effects are higher in families with low incomes. This is because they are further away from the saturation level for the consumption of individual energy services (Boardman & Milne, 2000)

Stated preference

This section takes a closer look at the various research methods. An important objective of this thesis is to define a suitable method for examining the research questions. The rebound effect can be measured using two different research techniques: *stated preferences* and *revealed preferences*. *Stated preferences* is the opposite to the commonly used *revealed preferences*. Both are research techniques that are used by researchers. *Revealed preferences* (hereafter referred to as RP) is based on real markets and is analysed using observation and questioning. *Stated preferences* (hereafter referred to as SP) in contrast, is based on a hypothetical market that can be manipulated by the researcher. There are a number of reasons why researchers opt for SP; a few of them have been summarised below:

- Organisation must be able to evaluate the demand for new products with new attributes or features. This cannot be done by examining the current market, because it does not yet exist. The use of SP can offer a solution for determining whether there is actually a demand and how much consumers want to pay for this new product.
- Observation studies take a long time and are very costly. While SP studies are often faster and cheaper.
- The product is not traded on the open market (natural products, public goods). SP is also commonly used in the medical sector for studies into willingness to pay.

Louviere (2000) provides, in the book "stated choice methods", a brief overview of the characteristics of both research methods.

RP data

- Takes the world as it is now (current market balance)
- Contains an inherent relationship between the attributes
- Only the existing alternatives can be observed
- High level of reliability and validity

Sp data

- Describes an hypothetical or virtual decision-making context
- Checks the relationship between attributes that allow utility functions to be compiled for products with various technologies
- Are reliable when the respondent is able to understand them, finds them appealing and can resolve them

Despite the fact that researchers still regularly opt for RP, this investigation will use SP. However, this research method also has disadvantages compared to RP, bearing in mind that consumers do not always do what they say.

The particular advantages offered by SP are the reason why this research method has been selected.

SP studies allow researchers to control variables that are of interest to their particular investigation. They are able to manipulate a variable because they control the context of the experiment. A disadvantage of RP studies is the high level of co-linearity between the attributes. This means researchers are unable to research an attribute's effect on the model with significance. This problem has been resolved in SP because the attributes vary independently from each other in all choice cards (Adamowicz, et al. 1998).

If one includes a wide range of attribute levels when compiling the experiment, this allows one to set up a robust model.

Choice experiment

A choice experiment is the best way of researching SP. The choice experiment is based on the theory that all products can be described in the form of attributes or characteristics and their various levels (Bateman et al 2002). For example, a bus service can be described by the attributes price, time and comfort. The theoretical basis of the choice experiment can be found in Lancaster's model of consumer choice (Lancaster, 1966), and its econometric basis in the *random utility theory* (RUT) (Luce, 1959; McFadden, 1974). Lancaster stated that consumers are not satisfied with the products themselves, but with the attributes they represent. The RUT states that consumers strive towards maximum utility and the *random term* is assumed to have a specific distribution: $Ui = Vi + e$.

Ui is the benefit of choosing scenario i, *Vi* is the deterministic component and e is the *random term*.

Benefit maximisation implies that consumers choose a quantity of the traded product, so that the price of the product is equal to their marginal willingness to pay (Proost & Rousseau, 2007). The welfare situation of a person determines his willingness to pay, which means willingness to pay is determined by the ability to pay (Field & Field, 2006).

The advantage of choice experiments is that they allow choices to be analysed in a multi-attribute setting. Respondents are presented with various alternatives that vary in the level of the various attributes. People are asked to choose the best (discrete choice), place them in a ranking (*contingent ranking*) or to assign a value (*contingent valuation).* This hypothetical choice task recreates the real-life situation, whereby the individual must consider various dimensions of the alternatives. Choice experiments have great potential. By selecting price as one of the attributes, they can be used to calculate the value of each attribute. Finally, the multidimensional structure of the alternatives allows a realistic image to be created of the complex reality or product (Green and Srinivasan, 1990).

3.6.4. Method

A decision has been made to conduct this research using *stated preferences*, which means that attributes are shown with accompanying levels. The target group is presented a number of choice cards based on X number of alternatives, consisting of Y number of attributes that vary over Z number of levels.

This means there are Z^{X*Y} choice cards, which represents *full factorial design*. It is practically impossible to use all these choice cards. Choice cards can be eliminated using *fractional factorial*. This must be done in order to examine the main effects (Louviere, Henser and Swait 2000).

During choice experiments, respondents are asked to choose between various options based on the variation in the characteristics of a product or service. These attributes represent the characteristics of the to-be-valued product.

In concrete terms, people are asked for their preferences concerning product alternatives, with the importance of each characteristic being derived from these choices. Various product alternatives can be designed by making attributes vary from each other.

In economic studies, one of the characteristics is always a price attribute, which indicates a monetary amount that the respondent is prepared to pay to obtain a particular option. Respondents are normally presented with multiple cards in a choice experiment. Each card contains a number of alternatives and a status quo. The status quo is described as a continuation of the current situation. Respondents are asked to choose their preferred alternative. If none of the alternatives is appropriate, they can select the status quo.

Steps

A choice experiment is developed by following various steps for creating a questionnaire:

Defining the product to be valued

Creating a hypothetical market

Determining the attributes and attribute levels

Formulating the other questions in the questionnaire

Determining the testing procedure

Defining the product to be valued

People are asked about their willingness to pay for residential energy services. In particular, their willingness to pay for changing the current situation into a situation that is more energy efficient and one which is accompanied by other benefits. The product to be valued or energy service in residential dwellings is described using the following attributes: temperature in main rooms, temperature in other rooms, creation of extra room, investment costs, reduction in running costs and reduction in CO_2 emissions. The status-quo maintains the current situation, although an investment cost of €5000 must be paid.

Creating a hypothetical market

By creating a hypothetical market, respondents are encouraged to display their true willingness to pay. This hypothetical market must be described carefully so that each respondent is able to get a feel for it. The scenario description must ensure that respondents base their choices on the same factors and must allow the researcher to derive appropriate conclusions. In this study, a decision was made to present the following scenario:

"You are the owner of a house built prior to 1995. Now imagine that you are about to renovate your home. Because you are going to renovate, you have the opportunity to invest in measures that will reduce your annual energy bill. The characteristics you are about to see only relate to making the home more energy efficient and energy-friendly, and not to the renovation itself.

It is important for you to realise that your house is about to be renovated: we would like to know the personal choices you would make in this fictional situation."

Further details will be provided later in the questionnaire, in order to give the respondent a clear idea about the purpose of the experiment. The questionnaire has been included in Appendix B.

Determining the attributes and attribute levels

In a choice experiment, the to-be-valued product is valued by allowing people to choose between the changeable attributes within the alternatives. The attributes are characteristics and properties that are directly and indirectly related to energy services in residential dwellings. Only a limited number of attributes can be used in a study. The main reason for this is mental overload. If respondents are required to consider too many attributes, this could result in them ignoring particular attributes. This means respondents do not provide any information about their actual preferences.

The second reason why the number of attributes must be limited is down to significant model estimation. The higher the number of attributes in the model, the higher the number of respondents that must be surveyed, which reduces the chance of significant model estimation. The choice cards presented to the respondents are created using experimental statistical design methods. The respondent is shown particular combinations of attribute levels. Proper design ensures that information about preferences can be measured in an efficient manner. This thesis uses an orthogonal design based on the theory by Street, Burgess and Louviere, (2005). The orthogonal design has been included in appendix 1.

Formulating the other questions and the entire questionnaire

The questionnaire consists of six parts:

Part one examines whether respondents have changed their behaviour over the years with regards to travel, the purchase of energy-efficient products, car usage and heating. The reasons for the changes are also addressed.

Part two examines the type of house owned by the respondent and how much usable living space there is.

Part three examines the heating method, the average temperature, consumption, etc.

Part four is the choice experiment.

Part five examines the respondent's socio-economic details.

And, finally, part six examines the respondent's stance on nature and climate change.

Determining the testing procedure

Due to practical reasons, a decision has been made to use an online questionnaire. This choice is accompanied by advantages and disadvantages. One of the advantages is that the questionnaire is better distributed throughout Flanders. One of the disadvantages of internet questionnaires is that respondents have a greater tendency to terminate the questionnaire when questions become too difficult. Further, face-to-face questionnaires give one a better opportunity to see whether the respondent understands the choice experiment and to ensure that options are not just selected randomly. For practical and time-related reasons, a decision was made to primarily distribute the questionnaire via the internet; had these issues not been a problem, a face-to-face questionnaire would probably have provided better results.

Choice of attributes and levels

The most important attributes are selected on the basis of discussions, literature and enquires. A decision was made to use six attributes, of which five vary over four levels and one over two levels. This approach was selected to make it understandable and familiar to respondents, but also because it was practical for the model.

Table 8: Attributes and levels

Temperature main rooms *Main rooms refers to living areas where a lot of time is spent and where heating is essential. (Living room, Bathroom, study/play room, Kitchen)*	1. +0°C 2. +1°C 3. +2°C 4. +3°C
Temperature other rooms *Other rooms refers to living areas where little time is spent and where heating is not essential. Bedrooms and other rooms (toilet, ironing room, cellar and loft if they are used)*	1. +0°C 2. +1°C 3. +2°C 4. +3°C
Investment costs *The investment costs are extra costs in addition to the renovation costs for your home. These are the extra costs that must be paid to make your home more energy efficient. Possible subsidies have already been deducted.* These costs are a one-off payment.	1. €5000 2. €10000 3. €15000 4. €20000
Running costs *The annual running costs is the amount that must be paid to heat your home. Considering that the energy efficiency is increased, energy costs will decline. The annual running costs include the distribution costs. The annual running costs are shown as a drop in percentage of the current running costs.*	1. -0% 2. -10% 3. -20% 4. -30%
CO_2 *emissions* CO_2 *emissions is a parameter that indicates the impact of your heating system on the environment.*	1. -0% 2. -10% 3. -20% 4. -30%
Extra room *Depending on the renovation of your house, an extension could be built or an empty and unfinished room could be transformed into a finished room. You can choose to insulate this empty renovated space, heat it and equip it with energy-saving features.*	1. Yes 2. No

Choice cards

In total, 16 choice cards were designed. Considering it was impossible to show all these cards to every respondent, a decision was made to compile two questionnaires. Each respondent was shown nine choice cards: One sample card and eight real cards. An example of a choice card can be found below.

Table 9: Example choice card

	Optie 1	Optie 2	No-choice
Temp hoofdkamers	+3°C	+0°C	
Temp andere kamers	+3°C	+0°C	
Investeringskosten	€ 5000	€ 10000	
Gebruikskosten	-20 %	-30 %	
Co_2-uitstoot	-10 %	-20 %	
Extra kamer	Nee	Ja	

3.6.5. Analysis

An Excel-based software programme was used to place the data in a dataset. This dataset was then imported into STATA, where all statistical calculations were carried out. The CLOGIT feature, which is an abbreviation of Conditional logit, was used to process data from the choice experiment. The dependent variable was choice and data was grouped per observation (choice set). The choice set for each respondent contains three alternatives: option1, option 2 and No-choice. The attributes are the dependent variable. The dataset was clustered per ID (respondent). This is necessary because respondents are shown eight choice cards.

The function is entered into STATA as follows: "Clogit choice a01 a02 a03 a04 a05 a06 asc1 asc2, group(obs) cluster(id)." The coefficients are deemed statistically significant if the p value is less than 0.05.

2 dummies must be created to allow the analysis to run correctly. These dummies must be assigned a value of 1 if option 1 or 2 is selected and a value of 0 if the No choice option is selected (Louviere et al., 2000). These dummies, which are referred to as alternative specific constants (asc), are specified to take into account share that want to make their homes more energy efficient. Positive and significant ASCs indicate that the respondent is prepared to pay for these energy services.

Finally, the coefficients of the attributes can be used to examine the willingness to pay. The attribute's willingness to pay is calculated by dividing the coefficient of the attribute by -1* the coefficient of the price attribute, (Karousakis, Birol, 2006)

Models

Seven models have been established for the analysis. Each model is different from the others based on the attributes included in the clogit function.

Model 1: Uses the attributes that appear on the choice cards. This is the basic model.

Model 2: This model uses the absolute reduction in energy costs. This attribute is obtained by linking the percentage reduction to current consumption. This makes it possible to calculate the actual drop in running costs. The 'percentage reduction in running costs' attribute included in model one is replaced by the 'absolute reduction in running costs' attribute. This makes it possible to calculate how much the respondent is prepared to pay for a €1 reduction in running costs.

Model 3: This model uses the average annual costs. The average annual cost can be calculated by taking the investment costs and the absolute reduction in running costs, and to trade them off against each other. The average annual cost is calculated by dividing the investment costs over a 10-year period, adding the absolute reduction in running costs and then implementing a 4.5% discount. Finally, this is added up and divided by ten. Table 10 contains an example for 1 average net current value.

Table 10: Calculation average annual costs

	Jaar 0	Jaar 1	Jaar 2	Jaar 3	Jaar 4	Jaar 5	Jaar 6	Jaar 7	Jaar 8	Jaar 9	Jaar 10	
Gebruikskost	0,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	
Investeringskost	-10000,0											
Cashflow	-10000,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	110,0	
Discontofactor	1,000	0,957	0,916	0,876	0,839	0,802	0,768	0,735	0,703	0,673	0,644	
NAW	-10000,0	105,3	100,7	96,4	92,2	88,3	84,5	80,8	77,4	74,0	70,8	
Jaarlijkse waarde	-913,0											

This average annual cost can be interpreted as the amount that respondents must invest for ten years in order to obtain the benefits shown on their choice cards (CO_2 reduction, temperature, extra room). A discount of 4.5% is implemented because this is a private consumer decision (Flemish government – Department for Environment, Nature and Energy, 2008). This annual average cost is included in the model as an attribute, instead of investment costs and running costs.

Model 4: The net current value is used to analyse model four. The net current value is calculated in the same way as the average annual cost, but without dividing it by ten at the end. The net current value is included in the model instead of investment costs and running costs. It can be interpreted as the amount that a person must possess in year zero in order to spread the investment over ten years.

The following three models have been compiled to examine how much the respondent is prepared to pay for a reduction of 1kg CO_2. The 3 models are estimates because the questionnaire does not ask how much CO_2 they currently emit. The questionnaire can tell us how they currently heat their homes (natural gas or fuel) and how much they paid in energy bills in the past year. These 2 factors are used to try and discover how many kg CO_2 they currently emit. For fuel, the running costs are used to determine the number of litres. Enquiries showed that the average price last year was 0.6€/l. By dividing the running costs by the average price, we are able to establish the number of litres that were consumed last year. The same is done for natural gas, with the number of KWh being calculated by dividing consumption by 0.062 €/KWh.

This figure was obtained by dividing the amount on the final bill by the number of consumed KWh. This ensures that distribution costs etc. are also included. All these figures include VAT.

This estimate is then used to calculate the number of Kg of CO_2. On the LNE website, a CO_2-meter is used to check how much CO_2 one litre of fuel and one KWh of natural gas can produce. One litre of fuel emits an average of 2.64 kg of CO_2, and one KWh of natural gas emits an average of 0.1834 kg of CO_2. By multiplying this figure by the consumption, one can estimate the number of kg CO_2.

Model 5: The calculation above is used to calculate the absolute reduction in CO_2. How much the respondent is prepared to pay for a 1kg reduction in CO_2.

Model 6: This model includes the absolute reduction in CO_2 and the average annual cost.

Model 7: Finally, this model includes the absolute reduction in CO_2 and the net current value.

3.6.6. Results

The questionnaires, distributed in both print and digital form, provided a total of 150 responses. Only 57 of these responses could be used for further analysis. Many questionnaires were not fully completed, and could thus not be used. The questionnaires where respondents had selected 8* No-choice, were removed from the dataset. There are various reasons why people may have selected 8*no choice:

The respondent did not understand the choice card and decided to choose No choice;

The respondent did not feel like completing the questionnaire, and thus selected 8* No-choice;

The respondent did not want to make his home more energy efficient.

If these choices were included, they would have a rather negative impact on the results. In total, 19 questionnaires were removed from the dataset for this reason. Further, people who live in an apartment were also removed from the dataset. The average age of respondents was 40 years, and the average number of family members was 3.68. 64% of the people who completed the questionnaire were men. The number of family members under 12 years of age was 0.75 and the number of family members old than 65 years was 0.19. There are two possible reasons why there was a low number of pensioners. Due to the complexity of the questionnaire, primarily older people ended the questionnaire prematurely. Finally, older people are less like to want to renovate their homes and are disadvantaged by the payback period of investments that improve energy efficiency.

Almost half of all respondents lived in Antwerpen(46%), followed by Oost-Vlaanderen(21%), West-Vlaanderen(16%), Limburg(12%) and finally Vlaams-Brabant(5%).

The pie chart in figure 3 shows that more than a third of all respondents has a university degree. Only 20% of respondents were educated up to primary and secondary school level. If we compare this data with the FGD for Economics, we can conclude that there is a distinct difference.

Official data shows that 75% were educated up to primary and secondary school level. The figures for professional, academic and university qualifications are: 12%, 4% and 9%. We can conclude that this sample is not representative in terms of level of education.

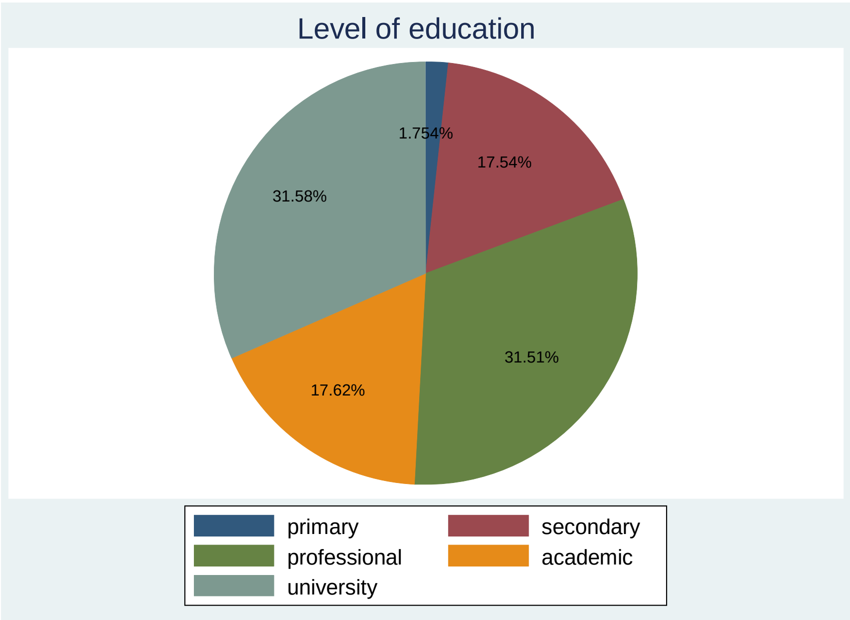

Figure 12: Pie chart level of education.

Analysis: dwelling

Within the framework of the study, it is important to know the respondent's current living situation. This includes the type of dwelling, usable living space, type of heating, annual running costs, temperature of living spaces and, finally, an analysis of the recent energy-saving measures.

Analysis shows that 62% of respondents lived in a detached house, 12% in a semi-detached house and 26% in a terraced house. The usable living space had a normal distribution around 200m², and an average of 200m².

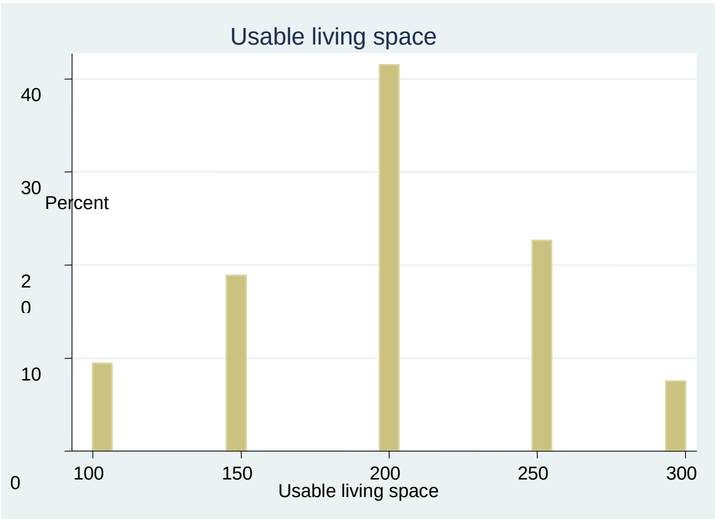

Figure 13: Histogram usable living space

The vast majority (41%) of respondents heated their homes using natural gas, followed by fuel (26%) and wood (17%). Nine percent of respondents stated that they (additionally) heated their homes with electricity.

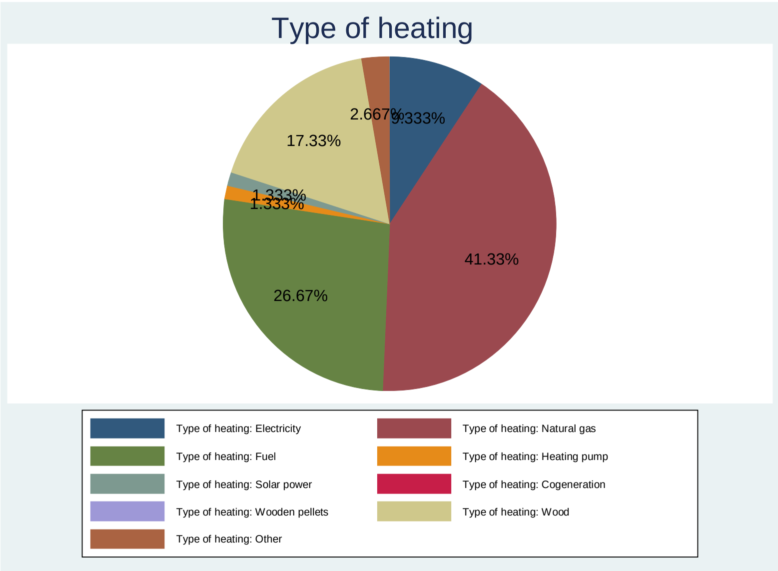

Figure 14: Pie chart type of heating

The annual running costs have a normal distribution around €1500 per year, with an average of €1416. The difference between the highest (€2300) and the lowest (€300) amounts was €2000, which is a very high amount.

Figure 15: Histogram annual running costs

The main rooms were heated to an average temperature of 20.5°C, while the other rooms were heated to an average temperature of 17.4°C. A large share of respondents (45%) decided not to heat their other rooms above 16°C. This was the lowest temperature they could select in the questionnaire. We can thus conclude that many families decide not to heat these extra rooms.

Finally, they were asked whether they had implemented energy-saving measures in the past five years. If so, they were asked about the implemented measures.

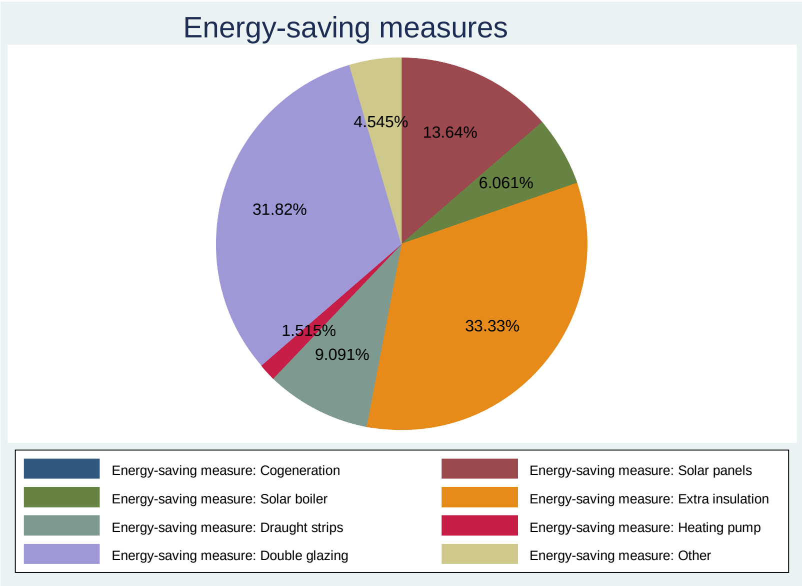

Figure 16: Pie chart energy-saving measures.

Primarily, insulating measures had been carried out in the past.

3.6.7. Research results

The main aim of this research was use a choice experiment to examine the willingness to pay for energy services in residential dwellings. The aim was to examine the considerations made by heads of families when presented with the hypothetical situation. Were they prepared to spend more during their renovation and which services/attributes did they want in return.

The results of a choice experiment are obtained via conditional logit analysis. This involves calculating the likelihood of someone selecting an alternative, and how this is influenced by the attributes.

Table 11: Coefficients for model 1, 2, 3 and 4

Attribute	*Model 1*	*Model 2*	*Model 3*	*Model 4*
Temperature main rooms	.0925782	.0735756	.0546937	.0546764
Temperature other rooms	-.0421935	-.0321469	-.0269798	-.0270013
Investment costs	-.0001086 ***	-.0001053***		
Running costs	.0402575 ***			
Reduction CO_2 emissions	.0193937 ***	.0185333 ***	.0206089 ***	0.0206088***
Creation extra room	.4412047 ***	.3686887 **	.3631588 ***	.3631067 ***
Average annual costs			-.0010879 ***	
Net current value				-.0001088 ***
Absolute reduction running costs		.0022782 ***		
ASC1	.5569977 **	.8815488 ***	1.177469 ***	1.177545 ***
ASC2	.6690926 **	.8934764 ***	1.216002 ***	1.216074 ***
p^2	0,202	0,202	0,19	0,19
Clusters	57	50	50	50
N.B. The asterisks indicate the significance: ***,**,* = Significance level 1, 5, 10%				

Table 12: Coefficients for model 5, 6 and 7

Attribute	*Model 5*	*Model 6*	*Model 7*
Temperature main rooms	.0641488	.0493322	.0493172
Temperature other rooms	-.0280246	-.035829	-.0358534
Investment costs	-.0001096 ***		
Running costs	.0389871 ***		
Absolute reduction CO_2 emissions	.0002643 **	.0002764 **	.0002763 **
Creation extra room	.357581 ***	.3317327 **	.3316797 **
Average annual costs		-.001105***	
Net current value			-.0001105***
ASC1	.833!946 ***	1.282135 ***	1.282214 ***
ASC2	.8708702 ***	1.343764 ***	1.343835 ***
p^2	0,20	0,18	0,18
Clusters	46	46	46
N.B. The asterisks indicate the significance: ***,**,* = Significance level 1, 5, 10%			

McFadden's P value in a *conditional logit* analysis is equal to the R^2 value in normal analyses, except that the level of significance is lower. According to Hensher et al. (2005) p^2-values between 0.2 and 0.4 can be seen as very high.

The coefficients above can be used to establish the willingness to pay for each of the attributes. The attribute's willingness to pay is calculated by dividing the coefficient of the attribute by -1* the coefficient of the price attribute. The results have been projected in the table below. This marginal willingness to pay must be interpreted in relation to the status quo, namely renovation without making the dwelling more energy efficient with a cost price of €5000.

Table 13: Willingness to pay for model 1, 2, 3 and 4

Attribute	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
Running costs	€ 371				€ 356		
Reduction CO_2 emissions	€ 179	€ 176	€ 19	€ 189			
Reduction 1kg CO_2					€ 2,4	€ 0,25	€ 2,5
Creation extra room	€ 4026	€ 3501	€ 334	€ 3337	€ 3262	€ 300	€ 3002
Reduction 1€ running costs		€ 22					

3.6.8. Discussion

Results

This pilot study, which was performed on a small sample, provided results significant enough to perform an analysis. With the exception of both temperature attributes, all attributes were significant. Because it is surprising that the "temperature of main rooms" attribute is not significant, a possible hypothesis was compiled. The sample analysis showed that primarily highly educated people with a high income participated in the questionnaire. For these people, we assume that the average temperature is consistent with their desired temperature. If these respondents can choose to increase the room temperature, this will not result in increased comfort, but rather a reduction in comfort. This is consistent with the research carried out by Boardman & Milne, (2000). This could mean that people with a lower temperature, who do not yet have the desired temperature, are prepared to pay extra for a higher room temperature. This hypothesis can be examined by performing the analysis again with only people with an income lower than €50,000. If the 'temperature main rooms' attribute is significant and positive, it can be assumed that people with a lower income are prepared to pay extra for a higher room temperature.

Table 14: Coefficients for people with an income lower than €50,000

Attribute	*Model 8*
Temperature main rooms	.2221185 ***
Temperature other rooms	-.2374201 **
Investment costs	-.0001514 ***
Absolute reduction running costs	.0022924 **
Reduction CO_2 emissions	.0121659
Creation extra room	-.0693782
ASC1	1,456902 ***
ASC2	1,283277***
p^2	0,23
Clusters	23

The hypothesis is correct; people with a lower income are prepared to pay €1467 for an extra 1°C in their main rooms. This confirms the hypothesis that people with a lower income do not currently possess the desired room temperature. This is a study on a limited sample, which is a possible reason why the other attributes were not significant.

For each significant model, the willingness to pay was then calculated for each attribute. Model one, which uses the attributes that appear on the choice cards, provides the willingness to pay for 3 attributes. We can interpret these results as, how much is the respondent currently prepared to pay to have one of the attributes carried out during the renovation. Respondents are thus prepared to pay €371 to reduce their running costs by 10% in the future. This is twice as much as they are prepared to pay for an equal reduction in CO_2 emissions. The largest willingness to pay was seen for an extra room. Respondents are prepared to pay €4026 to extend their usable living space. This is a strong contender for the rebound effect. Considering respondents have a high level of willingness to expand their usable living space, this will result in part of the energy efficiency benefits being lost in the new room.

Model two shows one eye-catching result, namely that respondents are prepared to pay €22 for a €1 reduction in running costs. This represents a minimum payback period of 22 years. We can assume that this has been influenced by the composition of the sample. If the same calculation is made using the coefficients in table 6, we arrive at a figure of €15.

Models three and four calculate the average annual investment cost and the net current value. Respondents are prepared to spend €19 each year, for a period of 10 years, to realise a ten percent reduction inCO_2 emissions.

The benefits have already been deducted from this €19, namely the 10% reduction in running costs. This means the person in question is prepared to pay €189 for a 10% reduction in CO_2 emissions. The same can be said for an extra room. Respondents are prepared to pay €3337 for an extra room when the benefits (reduction in running costs) have already been accounted and deducted.

If we calculate the discount factor for model 2 by dividing the coefficient of investments costs by the coefficient of the absolute running costs, we arrive at a discount factor of 4.6%. This discount factor is a lot less than the discount factor in the choice experiment conducted by Sadler(2003).

Models 5, 6 and 7 calculate the extent to which the respondent is prepared to pay for a 1kg reduction in CO_2 emissions. Respondents are prepared to pay an average of €2.5 to reduce their CO_2 emissions. These models have been formed using assumptions and estimates, and the results provided by these models only serve to provide an indication of the willingness to pay for a 1kg reduction in CO_2.

Research method

This study is the first Flemish study to focus on this specific topic. In order to improve and further define this model and accompanying results in the future, one must consider a number of findings. Thus, the size of the sample, in particular, will have to be increased. The sample is currently too small to examine whether people, who are members of a nature society, are prepared to pay more for a reduction in CO_2 emissions. This hypothesis was examined, but was not significant. If the sample size increases, and the sample becomes more realistic in terms of age, incomes and levels of education, it will be possible to better evaluate the results.

One of the disadvantages of this questionnaire was the inability to check why people opted for the No choice option. This could have led to some people being unfairly removed from the dataset. This problem can be resolved by introducing an extra question after each choice question, which examines why the respondent selected No choice.

Furthermore, one must ask respondents how many litres of fuel or KWh or natural gas respondents used in the past year. These figures will make it possible to more accurately examine the willingness to pay per kg reduction of CO_2 emissions.

In terms of attributes, the 'temperature of other rooms' attribute can be removed from the model. This attribute is of no value because respondents don't really heat other rooms and also do not intend to do so in the future. The *levels* of the 'creation extra room' also need to be modified. The attribute should consist of four *levels* that express the expansion of usable living space as a percentage: "0%, +5%, +10%, +15%." This data can be used to examine how much respondents want to pay for a 5% expansion of living space. If this data is linked to the existing usable living space, one can examine how much people want to pay per extra M^2.

Finally, primarily older people had difficulty understanding the choice experiment. It would thus be advised to implement a face-to-face research method for these people in order to obtain useful results for this target group.

3.6.9. Conclusion

A pilot study was used to examine the willingness to pay for energy services in residential dwellings. This involved examining the considerations made by property owners, in relation to matters such as heating comfort, useable living space, running and investment costs for heating and the environment-friendliness of the heating system, when they decide to renovate their properties. Respondents were able to express their preference via a choice experiment.

Despite the small and not fully representative sample, we were able to reach a conclusion for each attribute. Analysis showed that respondents were not prepared to pay extra for a higher room temperature because they had already achieved their desired room temperature. On the other hand, it appeared that people with a lower income were prepared to pay €1500 for a higher room temperature. In concrete terms, this means that when respondents renovate their homes and implement energy-efficient measures, they are prepared to pay €1500 to make their homes 1°C warmer. This means they lose out on the energy saving from increased efficiency, by making their living spaces warmer. The same result is obtained for the 'creation extra room' attribute. Respondents are prepared to pay an average of €3500 to extend their living spaces. This means more space must be heated, which means the energy saving from investments is lost. Both examples can be categorised under the rebound effect. Furthermore, it appeared that respondents were prepared to pay €376 to reduce their energy bills by 10%.

3.7 The price sensitivity of travelling by car (HUB Master Dissertation)

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3.7.1. Abstract

This thesis examines the influence of travel costs with respect to the travel behaviour of Flemish households. The price elasticity of travelling measures the sensitivity for the willingness to pay for car travels. Parameters such as income, fuel prices, family characteristics and car properties will be researched in this study. By establishing price elasticities of energy services, it enables an estimation of the future energy demand for a region or country. This makes price elasticities of energy services essential for a successful energy policy. The price elasticity of the consumptions per kilometre per Flemish household has been estimated at -0.2 in this study.

This means that a 10% price increase of the consumptions costs will cause a 2% decrease of the household kilometres of Flemish families. At a constant fuel price, this elasticity is -0.08%. Household kilometres increase when the net household income increases, when the quantity of family members increases or when the quantity of cars per household increases.

3.7.2. Introduction

This thesis defines the climate issues. An increasing quantity of greenhouse gases in the atmosphere leads to an enhanced greenhouse effect. This effect is defined by changing weather conditions with far-reaching impacts on ecosystems, water resources, industries, agriculture, welfare and society (IPCC, 2007). In 2004, 56.6% of anthropogenic greenhouse gas emissions contained carbon dioxide (CO_2) that resulted from burning fossil fuels (IPCC, 2007). Besides CO_2, methane (CH_4), nitrous oxide or laughing gas (N_2O) and fluorocarbon (F-gases) are also important long-lived greenhouse gases. The transport sector (road transport) was responsible for 16% of the global CO_2 emissions in 2007 (International Energy Agency, 2009). Road traffic does not only emit CO_2, but also particulate matter, nitrogen oxides (NO_x), carbon monoxide (CO) and hydrocarbons (VOC). All these substances can cause severe breathing problems (TMLeuven, 2006). Passenger cars travelled about 60 billion km on the Belgian roads in 1990, while in 2004 this grew to 80 billion, and the estimation is an increase to 100 billion in 2030 (TMLeuven, 2006). Despite this traffic growth, the emissions of harmful gases, except for the total CO_2 emissions, have decreased. This is due to an improved engine technology; an initiative of various European standards (Annex I). These emission standards do not only apply for passenger cars, but also for trucks that already caused a large emission decrease of noxious substances, despite the increasing quantity of truck kilometres (TMLeuven, 2006). The emission of the greenhouse gas CO_2 has risen in recent years due to an increase in traffic, but this trend is turning hesitantly. This is due to efficient cars and new technologies, such as an efficient generator or a shift point indicator. Annex II gives a brief overview of various new technologies and its efficiency improvement. Also note that the fuel production (refining and transport) causes atmospheric pollution. This rises along with the volume of traffic and will grow even larger than the exhaust fumes around the year 2030 (TMLeuven, 2006). The transport sector could therefore make a major contribution when it comes to reducing CO_2 emissions.

On a global scale, but also in Europe and Belgium, several agreements have already been made to reduce the emissions from greenhouse gases. The Kyoto Protocol can be considered here (global reduction of 5.2% around 2008-2012 in comparison to the levels of 1990) or Europe's objectives in order to reduce greenhouse gas emissions with 20% below the levels of 1990 against 2020, or even with 30% if other developed countries should provide similar efforts.

However, transportation is not only associated with environmental damage, but also with other adverse secondary effects such as noise, traffic accidents and congestion. It is important to make a trade-off between the economic and social benefits of transport, as well as the private and external costs.

The government tries to solve problems associated with the increasing mobility, by taking a series of policy measures. This is because the traffic causes social expenses that are insufficiently brought into charge against the user, or not at all. These adverse effects are called negative externalities (Immers and Stada, 2010). The energy and climate policy is often confronted with uncertainties, for example the volatile energy prices and the development of new technologies. VITO Researchers have developed a methodology to quantify the impact of uncertainties. One specific uncertainty charged by researchers, is the price elasticity of energy services. Elasticities measure the sensitivity of a dependent variable for changes in an independent variable. The price elasticity of an item demonstrates how much percentage is needed to change the demand of that item, if its price should change. The price elasticity of the demand is thus a ratio that reflects to what extent the quantity changes as a result of a price change (De Cnuydt & De Velder, 2008). A price elasticity of -1.5 means that a 10% price increase (if other determining variables remain unchanged) will lead to a -15% reduction of the demanded amount (-1.5 x 10%). Elasticities are quantities without dimensions. This enables easy comparison of demand responses between the different items. Elasticities can have a positive or negative indication. The indications show whether the cause and effect are evolving in the same (positive) or opposite (negative) direction. Value 1 is an important reference value for elasticities. When the price elasticity is equal to 1, the price change leads to a proportionate change in the demanded quantity. Elasticity in an absolute value greater than 1 is a price elastic demand. This means that the change in price leads to a more than proportionate change in the demanded quantity. Elasticities smaller than 1 in absolute value are price inelastic. A price change leads to a less than proportionate change in the demanded quantity (Bogaert et al., 2006). A complete price inelastic demand signifies that the price elasticity is equal to 0. This means that the price change did not cause any change in the demanded quantity. However, the value of the price elasticity is ceteris paribus. This means with a level income, level prices of other items and level preferences. If one of these factors changes, it shall also change the value of price elasticity. A recent study (Anandarajah & Kesicki, 2010) showed that reducing the energy demand could contribute to 3 to 7% decrease of CO_2 emissions in the 21st century; the transport sector even reached 16%. The results from this thesis can be implemented and further elaborated in this model.

In order to examine how different objectives can be reached, the MARKAL/TIMES energy model can be a great resource. The MARKAL/TIMES model calculates the fact that the demand for energy services is price sensitive. This model, coordinated by the International Energy Agency (IEA) is a generic, dynamic model which includes data on energy demand and various supply activities and technologies of one country with a horizon of 50/60 years. It calculates the cheapest combination of energy services in order to comply with the energy demand of a country. This model also takes environmental boundary conditions into account. (VITO, 2005). In Belgium, this is elaborated by KULeuven and VITO (Flemish Institute for Technological Research).

The purpose of this thesis is examining the price elasticity of energy service travelling by car. By calculating the price elasticities of energy, it allows for a better estimation of the energy demand in the future. This is important in order to draft an energy policy that could limit CO_2 emissions, for example. Many researchers are studying the price elasticity of energy, such as litres of gasoline, and not the price elasticity of energy service such as the car kilometres. Energy services describe the physical benefit, the physical utility or physical welfare that is achieved by a combination of energy and technology and/or actions (European Parliament, 2006). Energy services consist of derivative products of energy. Energy includes all forms of commercially available energy such as electricity, gas, charcoal... (European Parliament, 2006).

The central research question of this thesis can be described as follows: what are the Flemings willing to pay in order to travel from place A to B? How does the demand for travelling by car changes in Flanders, if the price of travelling changes? The price elasticity of travelling measures the sensitivity of willingness to pay for travelling by car. Parameters such as income, fuel rates, family features and properties of the car are examined in this research.

It is important to note that the purchase prices of the cars are not included in this study. Another limitation of this research is that the kilometres per household are investigated and not per individual.

3.7.3. Summary of literature

As described in the previous chapter, there is a difference between the price elasticity of energy services and the price elasticity of energy. Comparing the price elasticity of energy and a price elasticity of energy service would be similar to comparing apples with oranges. Therefore, this literary review only discusses the price elasticities of car kilometres (energy service), because other elasticities are less relevant in this context. Goodwin, Dargay & Hanly (2004) have calculated the price elasticity of car kilometres based on the fuel prices. Figure 1 provides an overview of these elasticities. It demonstrates that the 10% fuel price increase causes a mileage decrease of 1 to 1.6% in the short term and a decrease of 2.6 to 3.3% in the long term for the passenger transport. These elasticities are based on a dozen studies from over 25 countries worldwide.

Table 15 : Price elasticity vehicle kilometres: fuel price ST and LT

		Elasticity car kilometres (fuel rates)			
		Short Term (ST)		Long Term (LT)	
		Min	Max	Min	Max
Mileage	Total	**-0,10**	**-0,16**	**-0,26**	**-0,33**
	Commuter traffic	-0,12	-0,15	-0,23	-0,25
	Work	-0,02	-0,02	-0,20	-0,26
	School	-0,06	-0,09	-0,38	-0,41
	Other	-0,20	-0,22	-0,47	-0,29

Similar results are found with Litman (2008). He considers a fuel price elasticity of -0.29 in the long term in Europe.

Table 16 : Price elasticity vehicle kilometres: fuel price LT (Litman, 2008)

			Elasticity car kilometres (fuel rates – long term)
Both	Mileage	Total	**-0,29**
		Commuter traffic	-0,20
		Work	-0,22
		School	-0,32
		Other	-0,44

studies reveal that commuter traffic (home-work) and business travels (work) expose a lower elasticity than transportation for other purposes. This means that an increase in fuel prices has little impact on the commuter and business traffic. An increase in price does however have a significant impact on recreational travels.

The study conducted by Ecolas, TMLeuven and Ehsal (2006) does not only examine the fuel prices, but also other price changes, volume changes, tax revenues and emissions in Belgium. The TREMOVE model has been used in order to calculate those elasticities. TREMOVE is a model that calculates the effects of transport and environment policy within the transport sector, such as traffic volumes, car fleet, fuel consumption and emissions. The study uses three different scenarios that focus on the reform of the price of road traffic in 2010. The first scenario proposes a 25% increase in mobility tax (fixed and variable), which leads to 1% fewer traffic and 1.5% fewer emissions. The following provides a 3% decrease in emissions due to higher fuel prices and scenario 3 leads to a differentiation of the car tax (depending on engine capacity and environmental performance of the car) due to rejuvenation of the car fleet and a reduction in particulate matter. The table below displays the price elasticities of kilometres per car for the three scenarios.

Table 17: Price elasticities of kilometres per car

Car	Price elasticity car kilometres Scenario 1	Price elasticity car kilometres Scenario 2	Price elasticity car kilometres Scenario 3
Small car	**-0,80**	**-0,53**	**-1,54**
Large car	-0,67	-0,74	-1,31

The elasticities clearly vary across scenarios. This demonstrates that the results are strongly influenced by the definition of scenarios. The first column shows an elasticity of -0.80 (in bold). This means than a 10% increase in car kilometres for small cars will create an 8% decrease in volume in Scenario 1, to 5.3% in Scenario 2 and 15.4% in Scenario 3. The largest elasticities in absolute value can be found in the third scenario. This can be explained as this scenario includes a combination of measures: fixed taxes were replaced by other environmentally-based fixed taxes. This causes a changing cost structure that leads to larger volume changes than seen in Scenarios 1 and 2.

Litman (2008) included an additional variable in his model, namely time consume. The elasticities displayed in Figure 4 apply to the generalized price. A generalized price includes the car costs plus consume of time converted in money. Litman establishes a fixed elasticity of -0.76 in Europe. This means that a 10% increase of costs with car transport (this is including time consume), will lead to 7.6% decrease in travels.

Table 18: price elasticity car kilometres generalised price Europe (Litman, 2008)

		Price elasticity car kilometres (generalised price - long term)
Travel purpose	Total	**-0,76**
	Commuter traffic	-0,96
	Work	-0,12
	School	-0,78
	Other	-0,83

Keppens (2006) used data where this thesis has also been based upon, by using a nested model. This means that he has drafted some simulations consisting of various phases. The first phase contains for example, the determination of the quantity of cars owned by one household. Subsequently, the kilometres for households with two cars are divided by the travelled kilometres of the first car and the travelled kilometres of the second car. With this method, the obtained elasticities are only valid through the assumptions made by Keppens. Figure 5 outlines his findings.

Table 19: price elasticity car kilometres: nested model (Keppens, 2006)

	Ln (annual kilometres travelled by only car	Ln (annual kilometres travelled by car 1 of 2)	Ln (annual kilometres travelled by car 2 of 2)
Ln (variable cost km)[2]	**-0,08**	**-0,05**	**-0,05**
Ln (fixed household costs with high income)	0,55	0,47	**0,77**
Ln (fixed household costs with low income)	0,56	0,49	**0,76**
Ln (household income)	0,24	0,50	
Ln (total travelled kilometres)	0,26	0,08	0,31
Dummy recent car	0,40	0,15	0,31
Dummy old car	-0,17		-0,29
Dummy diesel car	0,12	0,15	
n=	1073,00	433,00	433,00

Explanation of variables:

- Variable km costs = fuel costs, repair costs, tire costs, small and major maintenance
- Fixed costs = depreciation, insurance, taxes, car inspection and annual maintenance
- Households with high income = annual income > 15617.45 euro
- Households with low income = annual income < 15617.45 euro
- Dummy recent car = zero with cars older than 1 year and 1 with cars between 0 and 1 years
- Dummy old car = zero with cars younger than 7 years and 1 with cars older than 7 years

From Figure x we can draw the following conclusions: A 10% increase of the variable kilometre costs will result to a 0.8% decrease of the annual household kilometres with people who own 1 car. With households owning multiple cars, this price increase has a smaller impact on annual mileage (0.5%). An increase in fixed costs has a greater influence on the use of the second car, then when using the first. The household income has no significant parameter for the use of the second car as the elasticity for low and high incomes do not differ much from each other (0.77 and 0.75). Families with a new car are travelling more kilometres annually than families with an old car.

Almost all price elasticities are smaller than 1. This suggests that transport is a price inelastic item.

[2] Log-transformations (Ln) are adjusted for the 'straighten out' of data that have a skewed distribution.

Price inelasticity means that the price increase has a relatively small impact on the demanded quantity (Immers and Stada, 2010). Another conclusion can be drawn from the impact of the time period over which the elasticity is measured. In the short term the demand for transport is relatively inelastic. In the long term, a change in transport prices can have a much larger impact on the demand for transport. It is also conspicuous that the demand for commuter traffic and travelling during work hours is much less sensitive to price changes than travelling for recreational purposes.

3.7.4. Method

A first phase in the study was defining the target population. These are all Flemish households, whether or not in possession of one or more cars. This thesis uses data from the study of travel behaviour by Flemings (OVG), retrieved from the Department of Transport and Traffic Policy (Department of Transport and Public Works) of the Flemish government. The data is based on the samples from the entire population of the Flemish Region across three periods: OVG 1 (April 1994-April 1995), OVG 2 (January 2000-January 2001) and OVG 3 (September 2007-September 2008) with n = 19925. The following variables were taken from the OVG-research:

Table 20: List of OVG variables

Name variable	Definition variable	Unit
CarQ	Quantity of cars	
Brand	Car brand	
Type	Car Van Other	
Ownership	Private newly bought car Private second-hand bought car Company car Other	
Year	Year of purchase	
YearM	Year of manufacture	
Fuel	LPG gasoline diesel Other	
Mileage	Mileage	km
Last	Mileage over the last year	km

MemberQ	Quantity of family members	
Inc:	Total net income household: 0-1000 1001-2000 2001-3000 3001-4000 >4000	€/month

Subsequently, additional information was sought regarding the consumption of cars (VITO, 2010), fuel costs (brandstofprijzen.be, 2010), time (TMLeuven, 2004) as well as fixed and variable costs (Keppens, 2006) connected to the car.

Table 21: List of variables

Name variable	Definition variable	Unit
Consumption	Car consumption	l/100km
PriceF	Fuel price	€/l

These expenses are converted to monetary values of the year 2007, so that the costs of different periods can be compared with each other (FPS Economy, SMEs, Middle Classes and Energy, 2010). A third phase was the data analysis through the statistical program STATA. This consisted of regression analysis and calculating elasticities in order to detect systematic relationships between various variables. The model evaluation was based on the T value, P value, adjusted R^2 value and F value. This phase will be elaborated in the next chapter. The last phase included drawing conclusions.

3.7.5. Results and Discussion

A preliminary analysis of the dataset provides the following results: 12.94% of households do not own a car and 87.06% of the households own at least one car. Households without cars are not further included in the study, which decreases the quantity of observations from 19918 to 17341. 7% of the households own at least one company car, 52.5% own at least one new car and 40.4% hold at least 1 second-hand car.

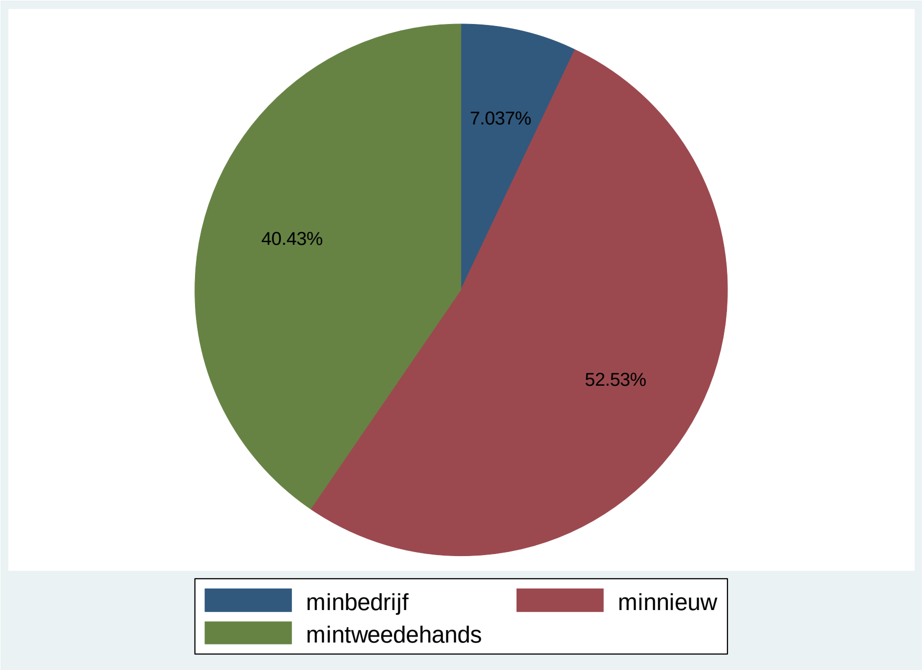

Figure 17 : Chart –Car Model

Most households (63.96%) have 1 car. 32% own 2 cars and 4% of the households own three cars.

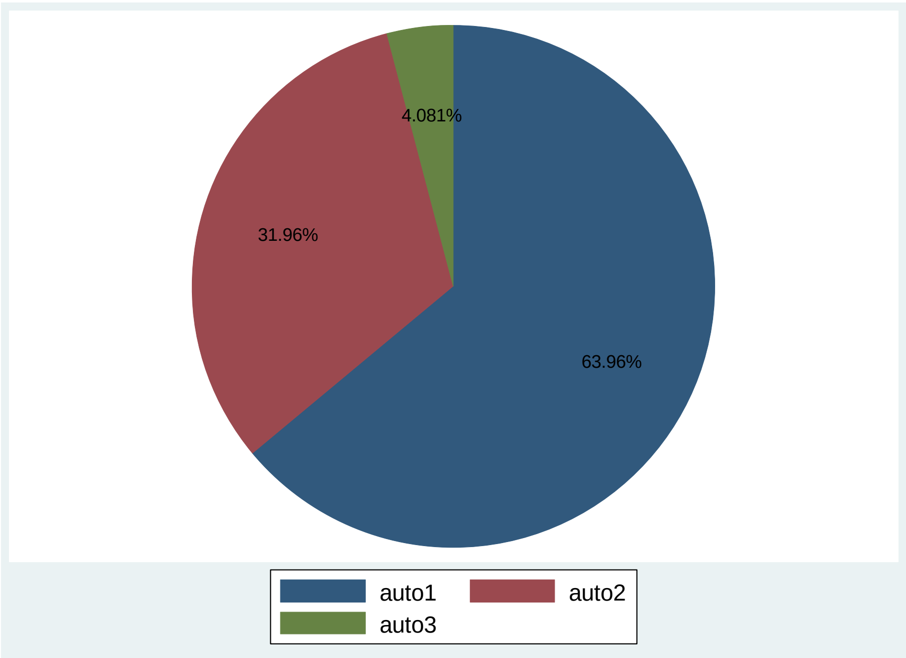

Figure 18: Chart - quantity of cars

The elasticities calculated in this thesis are short term elasticities. This is because the interviewed households in the three various surveys are not the same households, and weren't followed in the long term.

Type of car

By comparing the mileage of company cars and non-commercial cars, we expect that a company car will make more mileage. This is because we suspect that people with a company car will have to conduct more business travels than those who own a private car. The difference is investigated, based on regression equation with dummies. The independent variable is the type of car (households with at least one private car, one company car or both) and the dependent variable is the household kilometres. These include the mileage over the past year[3] of all household cars (with a maximum of three cars per household). The regression analysis only includes households where the household kilometres have a value greater than zero. The dummies are explained as: a household with at least one private car and without company car has a zero value with dummy 1 and dummy 2. If a household has at least one company car, but no private car, then dummy 1 is equal to 1 and dummy 2 is equal to zero. A household with at least one private car and at least one company car has a value of zero with dummy 1 and a value of 1 with dummy 2. The results are shown in Figure 10.

Table 22: Regression results car type

Independent variable	Coefficients	Standard deviation	T value	P value
Constant	20443	147	139,19	0,000
Dummy 1: at least 1 company car - without private car	12799	908	14,09	0,000
Dummy 2: at least 1 company car – at least 1 private car	17854	580	30,77	0,000
Dependent variable = Household kilometres N = 15826 Adjusted R^2 = 0,0655 F value = 555,85				

The regression analysis results are significant (P values < 0.05) and could reveal that households with at least one company car and without a private car (20442.87 + 12799.34 km) conduct more mileage then households with just one or several private cars (20,442.87 kilometres). Households owning both a company car and a private car have the highest mileage (20,442.87 + 17,853.72 kilometres).

Upon testing the residues, it revealed that they were normally distributed and are independent from one another. Residual analyses consist of analysing the differences in model values and observed values.

[3] The past year signifies the year prior to this survey.

Household features

With the following analysis, some of the Flemish households' features are compared to the mileage by means of a regression analysis. The independent variables are the total net income of a household (per month), the quantity of family members, the quantity of cars owned by the household and the model year. The dependent variable is the same as in the above regression the household kilometres. Household kilometres that are equal to zero are not included in the model. The variables income, quantity of cars and model year are included as dummies. These are interpreted as follows: Incomes in Category 1 (€ 0 - 1000) receive the value zero for all income dummies.

Incomes in Category 2 (€ 1001 to 2000) receive a 1 for income dummy 1 and a zero for the other income dummies. Incomes in Category 3 (€ 2001 to 3000) receive a value of 1 for income dummy 2 and a zero for the other income dummies. Household incomes in Category 4 (€ 3001 to 4000) receive a value of 1 for income dummy 3 and a zero for the other income dummies. Households in the last category (> € 4000) receive a value of 1 for dummy value 4 and zero for the other income dummies. With the variable quantity of cars we see a similar principle: households with one car receive a value of zero for all car dummies, households with two cars receive a value of one for car dummy 1 and zero for the other car dummies, households with three cars receive a value of 1 for car 2 dummy and a zero for the other car dummies, etc. The year dummies are interpreted as follows: households that were surveyed in 1995 receive a value of zero for the two year dummies. Interviewees of 2000 receive a value of 1 for year dummy 1 and zero for the other year dummy. With the interviewed households in 2007, the year dummy 1 equals to zero and year dummy 2 equals 1. We expect that the kilometres increase according to the increase of household incomes. This effect is also expected in the variables: quantity of cars and quantity of family members. Furthermore, we suspect that the mileage shall increase with the years, this in response to the findings of TMLeuven (2006) which indicate that the mileage of passenger transport increases each year (60 billion km in 1990 and 80 billion in 2004). The results of the regression analysis are displayed in Figure 1.

Table 23: Regression results household features

Independent variable	Coefficients	Standard deviation	T value	P value
Constant	10850	624	17,39	0,000
Income dummy 1: € 1001 – 2000	2089	599	3,49	0,000
Income dummy 2: € 2001 – 3000	5875	632	9,29	0,000
Income dummy 3: € 3001 – 4000	9426	680	13,85	0,000

Income dummy 4: > € 4000	11683	790	14,78	0,000
Quantity of family members	908	115	7,92	0,000
Car dummy 1: Households with 2 cars	11674	321	36,42	0,000
Car dummy 2: Households with 3 cars	22792	722	31,57	0,000
Car dummy 3: Households with 4 cars	24813	1784	13,91	0,000
Car dummy 4: Households with 5 cars	32082	4255	7,54	0,000
Car dummy 5: Households with 6 cars	39449	5788	6,82	0,000
Car dummy 6: Households with 7 cars	-10659	15264	-0,70	0,485
Year dummy 1: OVG2	-1892	407	-4,64	0,000
Year dummy 2: OVG3	-3250	379	-8,58	0,000
Dependent variable = Household kilometres N = 13482 Adjusted R^2 = 0,27 F value = 398,26				

All variables are significant at level $P < 0.05$, except variable car dummy 6. This dummy represents the households that own 7 cars. Upon closer examination, it becomes evident that these are merely 4 households of the 13,482 households that own a car. The small quantity of households included in this group can explain why no significant result can be found for this.

As expected, the household kilometres increase as the income increases. The household kilometres increase relatively the most for dummy 2 (income category 3). These are the households with a monthly net income between € 2001 and 3000. The household kilometres also increase when the family members within the household increase. With the variable quantity of cars, we also see an increase in the household kilometres along with an increasing quantity of cars per household. The largest relative increases are seen with dummy 1 and dummy 2. These dummies represent households with 2 and 3 cars.

Starting with 4 cars per household, the household kilometres increase less rapidly. In contrary to the expectations, the household kilometres decrease with time. A possible explanation could be the increase in fuel prices (see Annex III).

The residuals here are also normally distributed and independent of one another.

Consumption costs

The last and most important phase is this one, where the costs are included in the model. The following regression analysis is based on the previous one, but here, the consumptions costs have been added per kilometre. The consumption costs are a multiplication of the consumption (l / km), the fuel price (€ / l) and mileage (km). The consumption expenses are added per household and subsequently divided by the household kilometres, obtaining a consumption cost per kilometre (€ / km). Another change is absorption of the logarithmic transformations for some variables. One advantage is that the results become much more accurate. The transformations result to an increase of R^2 (from 0.29 to 0.33) in the regression. With these transformations, the results can be interpreted as elasticities. Furthermore, all household kilometres which are smaller or equal to 1000 km were omitted from this model, because they give a distorted picture. Because the consumption costs are divided by the quantity of household kilometres, the consumption cost per kilometre for households that travel fewer kilometres, run very high. These high values have a significant impact on the model. A final adjustment is excluding company cars in this regression, because households with company cars do not have consumption costs.

We expect a negative elasticity of consumption cost per kilometre, because we suspect that an increase in price will result in a decrease in household kilometres. For other variables, we expect the same effect as in the previous paragraphs. The independent variables are income (dummy), family members (ln) of the household, quantity of cars (ln) within the household, year (dummy) use and consumption costs per kilometre (ln). The dummy variables are explained in the same way as the model above. The dependent variable is the household kilometres (ln). Figure 12 displays the research results.

Table 24: Regression results consumption cost per km with ln (elasticities)

Independent variable	Coefficients	Standard deviation	T value	P value
Constant	8,55	0,19	45,96	0,000
Income dummy 1: € 1001 – 2000	0,20	,05	3,82	0,000
Income dummy 2: € 2001 – 3000	0,41	0,05	7,68	0,000

Income dummy 3: € 3001 – 4000	0,51	0,06	9,17	0,000
Income dummy 4: > € 4000	0,62	0,06	10,35	0,000
Ln (quantity of family members)	0,19	0,02	8,47	0,000
Ln (quantity of cars)	0,71	0,03	26,02	0,000
Year OVG 2 dummy 1	-0,15	0,18	-0,83	0,405
Year OVG 3 Dummy 2:	-0,19	0,18	-1,09	0,277
Ln (consumption costs per km)	**-0,20**	**0,02**	**-11,14**	**0,000**
Dependent variable = Ln (household kilometres) N = 5424 Adjusted R^2 = 0,33 F value = 302,98				

Significant of these results is the fact that the year dummies are not significant anymore (P-value > 0.05). They were always very significant in the previous analysis.

One possible explanation is that this model shows the increase in fuel prices over time and therefore the decrease of household kilometres are already included in the consumption costs.

The most important quantity in Figure 12 is -0.20: the elasticity of consumption cost per kilometre. In other words, this means that a 10%, increase in consumption cost per kilometre results in a 2% decrease in household kilometres. Starting from a specific situation, this result can also be expressed in absolute quantities. We take one household as an example, with an income between 2000 and 3000 Euros containing 3 family members and 1 car. The car consumes 0.05 Euros per kilometre. Without taking the year into account, the expected ln (householdkm) shall be calculated as follows:

$$\text{Ln(householdkm)} = 8{,}55 + 0{,}41 + 0{,}19\ln(3) + 0{,}71\ln(1) - 0{,}20\ln(0{,}05) = 9{,}77$$

$$\text{Householdkm} = e(9{,}77 + 0{,}43) = e(10{,}2) = 27000 \text{ km}$$

[0.43 is the variation of the model residual]

When the consumption cost per kilometre of this household increases with 20% to € 0.06, the household kilometres decrease around 4%. The absolute increase in the consumption cost of € 0.01, will decrease household kilometres of this household with 1000 km (slightly less than 4% of 27,000).

The next phase includes adding the weighted average fuel costs per kilometre to the model. The weighted average fuel price is created by multiplying the fuel price (€/l), consumption (l/km) and kilometres (km) and then divided by the total consumption (l/km). In order to draw the weighted average fuel price per kilometre, another division is made by the household kilometres. We expect that this weighted average fuel price per kilometre also has a negative elasticity.

The dependent variable is the household kilometre (ln), and the independent variables are the income (ln), consumption costs per kilometre (ln), average fuel price per kilometre (ln), quantity of cars per household (ln), family members (ln) and the year. Also, the household kilometres smaller or equal to 1000 kilometres are not included in the model, just as the households with company cars, because they do not have consumption costs or fuel costs. The results are displayed in Figure 13.

Table 25: Regression results consumption cost and weighted average fuel costs per km (elasticities)

Independent variable	Coefficients	Standard deviation	T value	P value
Constant	8,83	0,18	48,81	0,000
Income dummy 1: € 1001 – 2000	0,19	0,05	3,75	0,000
Income dummy 2: € 2001 – 3000	0,38	0,05	7,36	0,000
Income dummy 3: € 3001 – 4000	0,48	0,05	8,86	0,000
Income dummy 4: > € 4000	0,57	0,06	9,80	0,000
Ln (quantity of family members)	0,14	0,02	6,41	0,000
Ln (quantity of cars)	0,76	0,03	28,59	0,000
Year OVG 2 dummy 1	0,15	0,17	0,88	0,382
Year OVG 3 Dummy 2	0,20	0,17	1,18	0,238
Ln (consumption costs per km)	-0,08	0,02	-4,00	0,000
Ln (weighted average fuel costs per km)	-1,58	0,08	-18,77	0,000
Dependent variable = Ln (household kilometres) N = 5424 Adjusted R^2 = 0,37 F value = 325,6				

From the figure above we can conclude the impact of the consumption cost (elasticity of -0.08) in regards to level fuel costs.

The elasticity of consumption costs seen in this model has a lower value (-0.08) than in the previous model (-0.20), where fuel costs were not included separately. Both costs are significant and have a great influence on household kilometres.

A variation on the regressions above is the division of household kilometres. In the first phase, only the household kilometres between 1000 and 15,000 km are included. In the next phase, only the household kilometres exceeding 15,000 km. We expect that households with a high mileage are more sensitive to price changes than households with lower mileage, because the first 15,000 kilometres are considered more necessary in daily life. These are used for commuter traffic, going to the supermarket, or collecting the children from school. The kilometres exceeding these 15,000 km, are suspected to fulfil recreational purposes. The independent variables are identical as revealed in previous regressions. The dependent variable is the household kilometres between 1,000 and 15,000 km and for the second regression, the household kilometres exceeding 15,000 km.

Table 26: Regression results consumption cost per km between 1,000 and 15,000 km (elasticities)

Independent variable	Coefficients	Standard deviation	T value	P value
Constant	8,56	0,28	30,38	0,000
Income dummy 1: € 1001 – 2000	0,12	0,05	2,32	0,021
Income dummy 2: € 2001 – 3000	0,22	0,06	4,03	0,000
Income dummy 3: € 3001 – 4000	0,22	0,06	3,50	0,000
Income dummy 4: > € 4000	0,24	0,08	2,89	0,004
Ln (quantity of family members)	0,11	0,03	3,58	0,000
Ln (quantity of cars)	0,18	0,05	3,58	0,000
Year OVG 2 dummy 1	-0,12	0,27	-0,42	0,674
Year OVG 3 Dummy 2:	-0,15	0,27	-0,57	0,570
Ln (consumption costs per km)	**-0,08**	**0,03**	**-2,81**	**0,005**
Dependent variable = Ln (household kilometres between 1,000 and 15,000 km) N = 2016 Adjusted R² = 0,05 F value = 13,71				

Table 27: Regression results consumption costs per km > 15,000 km (elasticities)

Independent variable	Coefficients	Standard deviation	T value	P value
Constant	9,96	0,14	69,16	0,000
Income dummy 1: € 1001 – 2000	-0,02	0,07	-0,33	0,738
Income dummy 2: € 2001 – 3000	0,01	0,07	0,08	0,936
Income dummy 3: € 3001 – 4000	0,09	0,07	1,29	0,197
Income dummy 4: > € 4000	0,16	0,07	2,22	0,027
Ln (quantity of family members)	0,03	0,02	1,61	0,107
Ln (quantity of cars)	0,29	0,02	14,60	0,000
Year OVG 2 dummy 1	-0,05	0,13	-0,42	0,676
Year OVG 3 Dummy 2:	-0,06	0,13	-0,47	0,639
Ln (consumption costs per km)	**-0,05**	**0,01**	**-3,99**	**0,000**
Dependent variable = Ln (household kilometres exceeding 15,000 km) N = 3062 Adjusted R² = 0,14 F value = 55,41				

The two previous regression analyses reveal that the price elasticity of consumption costs decreases according to the increase of household kilometres. This is contrary to the expectation. In other words, the households become less sensitive to price when they have more travelled more mileage.

As the last four regression analyses revealed that the years are not significant, they are no longer included in the regression.

Table 28: Regression results consumption costs per km without dates (elasticities)

Independent variable	Coefficients	Standard deviation	T value	P value
Constant	8,36	0,07	122,38	0,000
Income dummy 1: € 1001 – 2000	0,21	0,05	3,87	0,000
Income dummy 2: € 2001 – 3000	0,42	0,05	7,73	0,000

Income dummy 3: € 3001 – 4000	0,51	0,06	9,16	0,000
Income dummy 4: > € 4000	0,62	0,06	10,30	0,000
Ln (quantity of family members)	0,19	0,02	8,35	0,000
Ln (quantity of cars)	0,71	0,03	26,12	0,000
Ln (consumption costs per km)	**-0,20**	**0,02**	**-11,38**	**0,000**
Dependent variable = Ln (household kilometres) N = 5424 Adjusted R^2 = 0,33 F value = 388,88				

By not including the date dummies, this doesn't have a significant impact on the coefficients.

Apart from this regression analysis, also various other alternative models were examined. Thus, a variable "total cost per kilometre" was prepared. This consisted of fixed costs, variable costs, consumption costs and time consume. The annual fixed costs included: depreciation, insurance, taxes, car inspection and annual maintenance (Keppens, 2006). For company cars, these are the employees' costs for using the company car (Ministry of Finance, 2004). Variable costs are the maintenance costs. This was documented when the tires were replaced after 50,000 km and the timing belt was replaced after 100,000 km. When the costs for households that own a private car, are compared with the costs for households that have a company car, it can be established that these costs are not the same. Households with a company car only have fixed costs and time consume. Households with a private car have the fixed costs, variable costs, consumption cost and time consume. The costs are shown in Annex II. After performing the regression analysis it revealed that the total cost per kilometre is not a good parameter, since it had no large variation of values before they were divided by the household kilometres to reach the costs per kilometre. This resulted in a value that was far too high for some total costs per kilometre. In contrary to the consumption costs per kilometre, this could not be used in an explanatory model. The consumption costs have enough variation in values before the division was conducted. This makes this cost a good parameter.

One of the original purposes of this thesis was making the distinction between elasticities of households with company cars and households without company cars. But as company cars do not have any consumption costs per kilometre, no comparison could be made between the two groups.

Finally, an analysis was conducted using the Heckman selection model. This model consists of two parts. One part is the regression model and another part is the selection model that affects the regression model. In our case, the household kilometres are determined by income and family members (selection model).

The result of this analysis is a price elasticity of consumption cost per kilometre of -0.21 with a standard deviation of 0.04, a T value of -5.32 and P value of 0.000. This elasticity does not deviate extremely from the previously found results in this thesis (-0.20), but the Heckman model needs a more complete data input, such as distance to school/work, the purchase price or the features of the cars, such as cylinder maintenance... for optimal results.

An exact comparison of the obtained results with the values from the literature is difficult because its values vary considerably and because each study works with other variables, and with other assumptions.

3.7.6. Conclusion

The data is based on the sampling of the entire population of the Flemish Region spread over three periods between 1994 and 2008. Additional information was examined regarding car consumption and fuel costs.

The study results revealed that over half of Flemish households owned at least one new car and 40% owned at least one used car. Only 7% have at least one company car. 2/3 of Flemish households own one car and 1/3 owns two. Most mileage is conducted by the first car. The mileage of a household increases according to increase in income or family members. Flemish households travelled longer distances in 1995 than in 2000 or 2007.

The elasticity of the family kilometers is estimated at -0.05 with a cross section regression that includes a dummy for the data year, income, the number of family members, the number of cars and the fuel cost per kilometer as independent variables. Only families are considered that own and use at least one car. The regression can be corrected for sample selection bias originating from this by using two-stage or nested models.

When only families are considered that drive more than 15000 kilometers, the kilometers driven get more inelastic. The main reason is that the relative reduction in kilometers is lower for families with higher kilometers, although the absolute reduction in family kilometers is rather uniform among families. By narrowing the sample (for example into a group with <15000 and >15000 km), the sample selection bias increases and the elasticity decreases.

When including the average price of the fuel as an independent variable in the regression, a very high elasticity of -2 is found for this fuel price. This high elasticity is unrealistic and could be explained by the method being not dynamic or it could be a prove that gasoline cars do less kilometers.

Another remark is that the number of families, the number of cars in one family and the number of family members might increase.

3.7.7. Data tables

Table 29: Costs and effects of more efficient automobile technology (OECD/IEA, 2005)

Technology	Surplus Value (€)	Average Efficiency Improvement (%)					
		Gasoline			Diesel		
	Tyre Width	Low	High	**Average**	Low	High	**Average**
Electric Water Pump	100-150	1.0	4.0	2.3	0.5	2.0	1.1
Efficient Generator	40-60	0.5	2.0	1.1	0.5	2.0	1.1
Efficient AirCo	80-120	0.0	3.0	1.0	0.0	3.0	1.1
Heated Pump AirCo	200-300	0.0	5.0	1.8	0.0	5.0	1.9
Heated Battery	80-100	0.0	3.0	1.0	0.0	1.5	0.5
Twin Cooling System	30-50	1.0	2.0	1.5	0.5	1.0	0.8
Stop/Start System	300-400	0.0	8.0	3.0	0.0	4.0	1.5
Low Rolling Resistance Tyres	50-80	1.0	2.0	1.5	1.0	2.0	1.5
Low Viscose Motor Oil	40-60	0.5	2.0	1.0	0.5	1.0	0.6
Tyre Pressure Monitor	30-40	1.0	1.0	1.0	1.0	1.0	1.0
Shift Point Indicator	25-35	1.0	2.0	1.5	1.5	2.5	2.0
Driving Training	150-250	5.0	10.0	7.5	5.0	15.0	10.0
Adaptive Cruise Control	1000-1500	3.0	10.0	6.5	3.0	15.0	9.0

Table 30: Cost of fuels (petrolfed)

Costs	1995	2000	2007
LPG (€/l)	0,3088	0,4558	0,5146
Gasoline (€/l)	0,9555	1,2381	1,3847
Diesel (€/l)	0,7564	0,9398	1,0941
Time consume (€/person/hour)	5,63	6,05	7,02
Fixed private costs (€/year)	2605,34	2605,34	2605,34
Fixed costs company (€/year)	2610,52	2610,52	2610,52
Private costs (€/50,000km)	338,37	338,37	338,37
Private costs (€/100,000km)	469,96	469,96	469,96

3.8 Alternative methodology: the use of neural networks

Classic econometrics uses parametric regression for estimating elasticities. Literature shows that also non-parametric methodologies can be used for this estimation. Non-parametric models differ from parametric models in that the model structure is not specified a priori but is instead determined from data. The term nonparametric is not meant to imply that such models completely lack parameters but that the number and nature of the parameters are flexible and not fixed in advance.

A model based on neural networks can cope with the problem that the forms of functional dependencies between energy-service demand and independent variables are often unknown. The problem of lack of good data can maybe solved by this modelling approach. In a publication of Elsevier Energy, the university of Karlsruhe developed such a model to estimate energy price elasticities of energy-service demand for passenger traffic in the Federal Republic of Germany (Energy price elasticities of energy-service demand for passenger traffic in the Federal Republic of Germany, M. Dreher, M. Wietschel, M. Go¨belt, O. Rentz, Institute for Industrial Production, University of Karlsruhe (TH), Hertzstr. 16, D-76187 Karlsruhe, Germany, 13 March 1998).

The researchers derived statistical significant energy price elasticities with respect to price level and direction of price change. An MLP (multi-layer perceptron) with three input nodes and two nodes in the hidden layer is chosen. The dependent variable is the passenger kilometres. The model consists of three independent variables: number of households, GDP and fuel price index (representing motorised traffic) No distinction between means of transportation or traffic purposes is made. From the neural network elasticity values have been derived by varying the energy price index while the other input variables are fixed to average values. The conclusion is that the reactions of energy-service demand on changes of energy price are very small and that this is a sign for the independence of passenger traffic volume and energy price.

In TIMES, the formulation of the problem is more consistent because there, the reaction of energy-service demand on changes of energy-service price is needed. However, the modelling approach seems to be adequate in estimating price elasticities when sufficient time series data are available.

This methodology is considered to be unuseful for the Belgian situation because of lack of long term time series data.

4. UPDATE AND EXTENSIONS OF THE MODEL

Model updates and extensions are a necessary input before policy evaluations. The European and Belgian TIMES model used in this project are based on the model developed in the FP6 EU project NEEDS, in which the KULeuven participated. The EU model covers 30 countries, the EU27 countries plus Norway, Switzerland and Iceland. For each country the full energy system is represented with four demand sectors (industry, residential, commercial and transport) and the supply sectors (electricity, fuel production, biomass and biofuel supply). Besides electricity and fuel trade the countries are also linked through trade in environmental certificates, allowing e.g. to define EU markets for CO_2 or for green certificates. The development of the Belgian TIMES model is also complementary to the development of the Flemish environmental cost model, supported by the Flemish environmental authorities.

The **development** within this project with the collaboration of some ETSAP partners covers three topics:

- A better representation of the peaking equation for electricity demand
- The endogenisation of the supply price of world energy resources in function of the EU demand in non reference scenarios.
- Development of an excel file for the ex-post analysis of the cost/benefit ratios of technologies based on the IER add-on. The duality theory is used to capture the rationale of the model choices. Basically, we focus on the ACTIVITY and FLO variable to be able to express the cost in terms of energy output. The sumproduct of the matrix coefficients and the prices of all equations where the variable is active gives this cost overview.

The update covers the technology database, an essential component of the model. The update technologies for the different sectors was based on data available at VITO and on the technology 'briefs' elaborated within ETSAP (www.etsap.org) to which VITO also collaborated. Other sources are the EPA data and the EU SET-plan data. New templates for the introduction of the technology data were constructed. They are more transparent and include an ex-ante computation of the levelised cost of the technologies with a detailed decomposition according to the cost type (investment, fixed and variable costs). The model was calibrated to 2005, as initial year.

The potentials for renewables and carbon capture, an important element in the evaluation of the EU targets, were also updated mainly based on EU projects such as RES2020 and REALISEGRID and on data at VITO.

For biomass, it is assumed that only set aside land can be used for the production of biocrops, such as wheat, rapeseed or grasswood. Ethanol and biodiesel are also available from imports, with a maximum respectively of 30 and 15PJ.

For wind energy a distinction is made between on and off shore. The cost of the grid expansion needed for the implementation of the full potential of offshore is included in the cost of the power plants[4].

The table hereafter summarizes the potentials assumed for the different sources.

Table 31: Domestic potential for energy sources

Biomass (PJ/y)	Biocrops	28
	Biowaste	33
Wind (GW)	Onshore cat1	0.9
	Onshore cat2	0.7
	Onshore cat3	0.7
	Offshore cat1	1.0
	Offshore cat2	1.1
	Offshore cat3	1.6
Solar(GW, PJ/y)	PV type 1	27
	PV type 2	∞
	Hot water	25
Geothermie(PJ/y)		44

Carbon capture and storage could be an important option when a high reduction target is imposed. Geological disposal in deep aquifers is modelled for the storage of the removed CO_2. A maximum cumulative potential of 100 Mt at a distance less than 20km and of 1000 Mt at higher cost is considered. This potential is present in Belgium (Laenen B. et al., 2004). The 100 Mt can be performed with high certainty in Belgium; 1000 Mt is uncertain (although, if not in Belgium, this could represent foreign sinks).

Besides the extension and update of the model, it must be mentioned that the project has allowed to train young researchers, both at KULeuven and at VITO, in the understanding and the use of the model. This guarantees a continuity in the expertise in Belgium regarding the TIMES model.

[4] As TIMES is not running in mixed integer mode, binary investment options are not possible. The cost is therefore included as a cost per kwe installed; therefore the cost computation is only correct if the full potential is installed in one time when this option is used. (rem. this is usually the case).

5. POLICY SUPPORT

5.1 Introduction

Different case studies covering issues related to sustainable energy (climate change, energy security) were examined with the model. The case studies will contribute to the definition of sustainable energy policies by addressing the role of technologies, by identifying the optimal allocation of the efforts and by evaluating their overall cost (direct and indirect). They can also orient R&D policies towards the more promising technologies. The precise choice and definition of the case studies were made in close collaboration with the Steering Committee. The policy analysis was done with the Belgian TIMES model with the European dimension given by the Pan European TIMES model. GEM-E3 (www.gem-e3.net), a computable general equilibrium model for the EU (25 countries) is used to derive the macroeconomic and sectoral evolution in Europe and in Belgium for the period 2010-2050 for the generation of the TIMES reference scenario.

The scenarios cover the two following topics:

- Evaluation of the EU renewable target for Belgium (done in 2008, cf; Annex 1)
- The EU Climate policy perspectives and their implications for Belgium

The starting point is the construction of the reference scenario. It is important to stress the role of this scenario for policy analysis with the TIMES model. The reference scenario has not as objective to give a forecast of the energy system. It gives a consistent path for the energy system, given the cost optimisation approach and the simplified representation of the energy users and suppliers behaviour in TIMES. It is the comparison basis for the policy scenarios to evaluate the cost of policies and their impact on the technological choices in the energy system. The reference scenario can therefore deviate from the evolution of the energy system in recent years which reflects the behaviour of the economic agents in real life, their expectations and the dynamic adjustment of the energy system. It allows however a consistent treatment of the technologies in the policy evaluation.

5.2 General assumptions and Reference Scenario

5.2.1. Background Assumptions

The construction of the reference scenario is based on assumptions regarding the macroeconomic evolution for Belgium and the World energy prices evolution till 2050 complemented with energy policy assumptions.

Macroeconomic assumptions

The macroeconomic background for Belgium was derived with GEM-E3, a general equilibrium model for the EU countries. It gives the general growth assumption used for deriving the energy service demands (tons of steel, km driven, etc..) of the different consumption sectors in the reference scenario. The international energy prices are those derived with the POLES World energy model by IPTS, a research centre of the European Commission, for the EU roadmap in 2011.

Table 32: Macroeconomic Assumptions for Belgium and international energy prices

	Unit	2010	2015	2020	2025	2030	2035	2040	2045	2050
Population	%/y		0.70 %	0.60 %	0.50 %	0.50 %	0.40 %	0.40 %	0.30 %	0.30 %
GDP	%/y		1.90 %	2.30 %	2.30 %	2.20 %	2.10 %	2.00 %	1.90 %	1.90 %
Import price crude oil	EUR2005/ GJ	8.84	9.67	12.85	15.06	16.01	16.75	17.53	18.34	19.20
import price natural gas	EUR2005/ GJ	4.20	5.09	6.97	8.54	8.94	9.50	10.11	10.75	11.43
import price coal	EUR2005/ GJ	2.43	3.31	4.30	4.96	5.08	5.11	5.14	5.17	5.19

The sectoral activity levels and the growth in housing stock and private income are the main determinants for the evolution in the demand for energy services. The heat demand of the baseyear is corrected for temperature to compute the demand projections. They correspond therefore to an average temperature. The drivers' evolutions are combined with assumptions on the elasticities relating the energy service demand or the product demand to the activity of the sector or the disposable income. The trend obtained determines the shift of the demand curves for these services in TIMES over the horizon considered. The demands are exogenous in the reference scenario but can change in the policy scenarios in function of price changes.

Table 33: Energy service demand (annual growth rate)

	2020/2010	2030/2020	2040/2030	2050/2040
Agriculture (PJ)	-0.4%	0.7%	0.1%	0.7%
Commercial (PJ)	0.2%	0.5%	0.8%	0.7%
Residential (PJ)	-0.4%	-0.1%	0.1%	0.1%
Freight transport (tkm)	2.0%	2.1%	2.1%	2.0%
Passenger transport (pkm)	0.9%	0.7%	0.8%	0.8%
Industry (PJ)	0.1%	1.1%	0.9%	0.6%
Industry Ammonia demand in ton	-0.1%	1.2%	0.8%	0.4%
Industry Cement and Lime demand in ton	1.0%	2.0%	1.6%	1.5%
Industry Copper demand in ton	-0.7%	0.6%	0.4%	0.0%
Industry Glass demand in ton	1.4%	1.9%	2.0%	1.7%
Industry Iron and Steel demand in ton	-1.0%	0.1%	0.2%	-0.1%
Industry Paper demand in ton	1.5%	0.3%	1.4%	1.0%
Aviation transport (PJ)	1.9%	2.6%	2.5%	2.3%
Navigation transport (PJ)	1.6%	2.3%	2.3%	2.1%

General policy assumptions

In the reference scenario, after the 2008 crisis, the economy is slowly recuperating but no profound changes regarding the Belgian economic, energy and environmental policies are assumed. The nuclear phase-out is kept in the reference scenario. The EU emission trading system (ETS) is assumed to remain in place and to impose a price of 20 €/ton CO_2. It has been assumed for this modelling exercise that the sectors covered by the ETS would include all the industrial sectors and the electricity sector as this seems to reflect the actual tendency of enlarging the sectoral participation[5]. This leaves for the non ETS sectors the residential, service and transport sectors. The Belgian renewable target of 14% in 2020 is imposed and kept constant after 2020.

In all scenarios, the discount rate is fixed to 4%, reflecting the public sector approach in the policy evaluation with TIMES. Policy measures like subsidies for energy efficient investment or similar measures implemented in the different regions are not explicitly accounted for. This is necessary to allow for a consistent comparison of the technologies. It must be mentioned that in the reference scenario, the perfect foresight/optimisation approach in TIMES can already induce the use of some of the policy-promoted options without any carbon constraint, if they are cost-efficient (the 'no-regret' options). Moreover, the assumption regarding the carbon value for the ETS in the reference induces a shift towards less carbon intensive technologies.

5.2.2. The Reference Scenario

Given the demand for energy services derived from the macroeconomic assumptions, TIMES optimizes the choice of energy processes, the energy efficiency, the choice of fuel by the energy users as well as the choice of energy production processes by the energy sector. The choice is based on the information on the present and future availability of energy technologies, their costs and performance at the level of the energy user and at the level of the energy producer. It is clear therefore that the energy path as derived from this optimisation process, takes into account all the no-regret options and may therefore slightly underestimate the growth of the energy demand. Other criteria besides cost minimisation driving consumer behaviour are not reflected in this reference. Expectations on the implementation of a more severe carbon policy that may induce further investment in less CO_2 intensive technologies are also not taken into account.

The final energy demand increases around 0.8% over the time horizon. The growth is highest in the industry and the transport sector. A gradual improvement in the insulation of buildings contributes to a decrease in the demand of energy for heating, which is also shifting towards gas. The electricity demand increases more than the fuel demand except for oil products which demand are driven by the increase in transport. The coal consumption remains rather high in the absence of any carbon constraint and because of the importance of the iron and steel sector in Belgium.

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[5] The model does not allow to make a distinction between small and large installations in the non energy intensive sectors.

Table 34: Final energy consumption (PJ)

	2010	2020	2030	2040	2050
by fuel					
Bioenergy	20	120	111	131	135
Solid fuels	233	226	270	304	345
Electricity	250	248	263	284	301
Gas	314	292	294	313	305
Heat	131	131	138	149	159
Oil & other transport fuels	544	445	500	558	637
Renewables	0	11	11	0	8
Synthetic fuels	0	0	0	0	0
Total	1491	1474	1588	1739	1890
by sector					
Agriculture	37	35	38	38	41
Commercial	184	177	179	187	196
Industry	589	592	661	726	785
Residential	293	246	231	232	228
Transport	389	423	480	556	641
Total	1491	1474	1588	1739	1890

After the nuclear phase-out, coal becomes the dominant fuel for electricity generation, in the absence of any carbon constraint. Because the increase in energy prices, there is a gradual penetration of wind energy but not covering its full potential.

Table 35: Net electricity generation (PJ)

	2010	2020	2030	2040	2050
Solids	28	28	99	99	110
Gas	42	37	55	61	59
Oil	5	1	0	0	0
Nuclear	171	119	0	0	0
Bioenergy	1	1	1	2	2
Waste	2	5	7	8	8
Hydro, wind, geo, photovoltaic	1	43	73	86	93
Total	251	234	235	256	273

In terms of primary energy consumption, the average growth follows the final demand growth. There is a shift to solids when coal power plants replace the nuclear power plants. Oil products keep a relatively high share but the increase in oil price induces a shift towards transport fuel derived from coal and natural gas. Renewable energy with a share of 6.7% in 2020, does not really penetrate much more after 2020.

Table 36: Primary Energy Consumption in the reference scenario

(abs. in PJ and % share)

	2010	2020	2030	2040	2050
Solid fuels	329	309	488	521	580
Gas	437	396	980	1068	1156
Oil products	1076	1026	746	856	984
Nuclear	513	356	0	0	0
ELC from trade	15	34	50	50	50
Bioenergy	21	99	90	105	107
Waste	11	33	33	34	35
Hydro, wind, geo, photovoltaic	1	55	84	86	101
Total	2403	2308	2472	2720	3014
Solid fuels	13.7%	13.4%	19.8%	19.1%	19.3%
Gas	18.2%	17.2%	39.6%	39.3%	38.4%
Oil products	44.8%	44.4%	30.2%	31.5%	32.7%
Nuclear	21.3%	15.4%	0.0%	0.0%	0.0%
ELC from trade	0.6%	1.5%	2.0%	1.8%	1.7%
Bioenergy	0.9%	4.3%	3.6%	3.9%	3.5%
Waste	0.5%	1.4%	1.3%	1.2%	1.2%
Hydro, wind, geo, photovoltaic	0.0%	2.4%	3.4%	3.2%	3.4%

The evolution in the primary energy consumption induces an increase in the CO_2 emissions linked to energy, especially after 2025 when coal power plants should replace the nuclear power plants. Industry and transport remain the biggest emitters in the first period but the electricity sector becomes an important polluter when new coal power plants are installed.

Table 37: CO_2 emissions in the reference scenario (Mio.ton and %)

	2010	2020	2030	2040	2050
Industry	32	31	35	40	45
Hous, Com & Agr	26	19	18	18	18
Transport	27	25	30	35	41
Electricity	14	15	31	31	33
Other supply	1	2	8	9	9
Total emissions	100	92	122	133	146
Industry	32%	33%	29%	30%	31%
Hous, Com & Agr	26%	20%	15%	14%	12%
Transport	27%	28%	24%	26%	28%
Electricity	14%	16%	25%	23%	23%
Other supply	1%	3%	7%	6%	6%

5.3 Evaluation of the EU renewable target of Belgium

In the first year of TUMATIM, eight scenarios have been performed, concentrating on the renewable target for Belgium. The results were presented at a workshop of the International Energy Agency (http://www.etsap.org/Workshop/Paris_07_2008/3Wouter-IEW2008.pdf) and a book chapter was written on the basis of these results (W. Nijs and D. Van Regemorter, 2010), see annex 1. The renewable policy scenarios were performed with the Belgian TIMES model version 2008.

The main conclusion from this scenario is that for the total period (2010-2050), the addition of a renewable and biofuel target on top of the climate target increases only slightly the total cost of a climate only policy. This increase is however mostly concentrated around 2020 and can then be substantial compared to the no renewable case. The addition of the renewable target represents an increase of the annual cost of the energy system of some 4% compared to the reference in 2020. After 2020, the policy for renewable energy only increases slightly the cost of achieving the Belgian climate target as a limited introduction of renewables is part of a cost effective climate policy. As renewable technologies are still in their development phase, the renewable targets could contribute to more innovation in renewable energy and contribute as such to future more stringent climate targets. It could also induce other external benefits (air pollution etc).

Another conclusion was that a policy targeted on renewable energy alone is insufficient to reach the climate target. Climate and renewable policies interact, they both contribute to the reduction of the CO_2 emissions, but the technological choice they induce can be different, e.g. carbon capture versus electricity production from renewables.

5.4 The EU climate policy perspectives and their implications for Belgium

After Copenhagen, the EC has proposed to reach a 30% reduction compared to 1990 emissions in the EU GHG emissions by 2030. For 2050 an 80% reduction by 2050 is in line with the European commitment to limit global warming to 2°C max and it is proposed in the EU roadmap. These targets will be used to explore a range of policies allowing to reach them with the EU and the Belgian TIMES models.

The EU target (-30% in 2030 and -80% in 2050) was modelled with the Pan European model. This gives the cost optimal way to reach the target at EU level, inclusive the cost efficient allocation of the reduction between the EU countries. From this run, the implications for Belgium in terms of CO_2 reduction are derived. With the Belgian model, then we explore in more detail what is the impact on the Belgian energy system, on the choice of technologies and on the energy system cost. We explore also what is the impact of the availability of nuclear and of carbon storage.

The scenarios considered in this report for the general evaluation of the EU targets for Belgium are:

- **NoNuc_GoCCS_58%**: CO_2 target of 58% compared to 2005 in 2050, with nuclear phase-out and possibility of carbon storage up to its potential
- **NoNuc_NoCCS_58%**: same as previous but without carbon storage
- **GoNuc_GoCCS_58%**: with nuclear and with carbon storage
- **GoNuc_NoCCS_58%**: with nuclear but no carbon storage

The CO_2 target for Belgium is derived from the EU TIMES model where a CO_2 target was imposed, -19% in 2020 increasingly gradually to -78% in 2050, compared to the 2005 emissions. The cost efficient allocation of the reduction between the EU countries implies a reduction target of 58% for Belgium in 2050. We do not include the cost of buying CO_2 permits abroad as this will depend on the burden sharing agreement within the EU. Only CO_2 emissions are considered as the other GHG are not modelled in TIMES and the energy system is only responsible for a small part of the other GHG.

5.4.1. A stringent climate target, NoNuc_GoCCS_58%

General

The impact of the CO_2 reduction is threefold:

- a decrease in the demand for energy services because of the price increase induced by the carbon constraint
- a shift towards less carbon intensive fuels, initially from coal to gas and afterwards towards more renewables and hydrogen
- a shift towards more energy efficient technologies.

The overall welfare cost increases with 3.4%. In annualized terms it represents 0.8% of GDP2005. This cost is the cost on the market of energy services. It does not take into account possible side benefits through the reduction of other external cost linked to energy use. Neither does it include the derived effects on other markets, depending on the policy instrument used[6].

Table 38: Total discounted welfare cost (consumer/producer surplus loss)

	%DIF	%GDP2005	Annualized %GDP2005
NoNuc_GoCCS_58%	3.4%	17.0%	0.8%

This cost increase is also reflected in the marginal abatement cost of CO_2, i.e. the shadow price of the CO_2 constraint. The marginal cost gives the level of CO_2 tax that would have to be imposed to arrive at this result, i.e. the adoption of the technological options which can satisfy the energy needs in the most cost efficient way given the carbon constraint.

[6] Cf. double dividend literature.

It increases from 103€ in 2030 to 472€/ton in 2050. The average cost per ton CO_2 reduced increase from 33€/ton to 88€/ton.

The possibility of having a EU CO_2 permit market is important for Belgium. If the same reduction of -78% would be imposed on all EU countries without possibility of trade, the total discounted welfare cost for Belgium would be 1.1 % and the CO_2 marginal cost would reach 532€/ton in 2050.

Energy service demand

The demand function for energy services, linking the demand to the price is a short cut to represent all substitution and behavioural reactions outside the energy use and production sector. Every policy scenario that affects the energy sector will alter the marginal cost of energy services and this will affect the level of demand for energy services.

Reduction in demand represents an important contribution to CO_2 reductions. It can cover various options such as the substitution of energy by another good, a better overall organisation in the industry and the service sector or a loss in comfort, a change in life style, construction norms or urban planning. The high increase in the energy cost can make the tracking of energy savings a high priority.

Table 39: Energy service demand

(% difference compared to reference)

	2010	2020	2030	2040	2050
Agriculture (PJ)	-6.0%	3.2%	-9.0%	-15.5%	-24.0%
Commercial (PJ)	-2.5%	0.6%	-6.9%	-8.3%	-9.8%
Residential (PJ)	-4.8%	-0.2%	-5.1%	-11.1%	-15.5%
Freight transport (tkm)	-1.1%	0.0%	-2.6%	-5.2%	-7.8%
Passenger transport (pkm)	-2.5%	0.1%	0.0%	-5.3%	-3.1%
Industry (PJ)	0.0%	0.0%	-10.6%	-16.8%	-22.9%
Industry Ammonia demand in ton	0.1%	0.0%	-3.1%	-6.2%	-9.3%
Industry Cement and Lime demand in ton	0.8%	0.0%	-15.0%	-22.7%	-29.3%
Industry Copper demand in ton	0.0%	0.0%	-3.0%	-6.0%	-9.0%
Industry Glass demand in ton	0.0%	0.0%	-6.6%	-9.7%	-12.8%
Industry Iron and Steel demand in ton	0.0%	0.0%	0.0%	-3.1%	-6.2%
Navigation transport (PJ)	-0.4%	0.1%	-0.4%	-0.7%	-0.9%
Aviation transport (PJ)	-1.3%	0.7%	-1.3%	-3.3%	-4.7%

Final energy consumption

There is a shift away from coal, which is replaced by gas and in a lesser proportion by electricity and renewables. The change in the cost of electricity is driving some of the technological options chosen.

At the beginning of the period the main reductions are in the industry and commercial but at the end of the horizon higher reduction are observed in the residential sector and also in the transport sector, where there is a gradual shift towards biofuels and at the end also towards electricity.

Table 40: Final energy consumption

(abs difference compared to reference in PJ)

by fuel	2010	2020	2030	2040	2050
Bioenergy	7	1	-3	-32	-22
Solid fuels	-2	-3	-57	-231	-283
Electricity	-1	1	-14	-2	13
Gas	-5	-7	-51	22	5
Heat	0	0	-13	-23	-33
Oil	-43	3	-57	-157	-284
Renewables	0	0	5	20	20
Synthetic fuels	0	0	0	0	0
Total	-44	-6	-189	-403	-584
by sector					
Agriculture	-2	1	-3	-6	-13
Commercial	-8	-12	-69	-109	-119
Industry	-1	4	-57	-108	-170
Residential	-24	0	-28	-64	-83
Transport	-9	1	-32	-116	-200
Total	-44	-6	-189	-403	-584

Primary energy

The different options chosen in the energy system are reflected in the impact on the primary energy consumption. The carbon constraint reduces the primary energy consumption of coal and gas. Oil is increasing because of the shift in the production of transport fuels. Renewables are penetrating up to their limit.

Table 41: Primary energy

(abs. differences compared to reference in PJ)

	2010	2020	2030	2040	2050
Solid fuels	-2	-16	-133	-263	-237
Gas	-2	9	-590	-592	-737
Oil products	-43	3	366	318	260
Nuclear	0	0	0	0	0
ELC from trade	0	0	0	0	0
Bioenergy	7	0	19	4	2
Waste	-6	0	0	-22	-23
Hydro, wind, geo, photovoltaic	0	0	15	36	39
Total	-45	-4	-322	-519	-696

CO_2 emissions

The main contributors to the CO_2 emission reduction are first the power sector and the industry and then the other sectors when the constraint is becoming more stringent. The contribution of transport remains limited till 2040. Storage of carbon penetrates after 2020 and uses its full potential at the end of the horizon. All emissions coming from fuel combustion in the power sector are stored. This raises the question about the very long term potential of this option.

Table 42: CO_2 **emissions**

(abs. in Mio.t and % differences compared to reference)

absdif	2010	2020	2030	2040	2050
Electricity	0	-2	-26	-31	-33
Other supply	0	0	-5	-5	-8
Agr & Commercial	-1	0	-3	-4	-6
Industry	0	0	-10	-27	-30
Residential	-2	0	-2	-4	-5
Transport	-1	0	-2	-9	-18
Total	-4	-2	-49	-81	-100
Storage	0	1	26	37	44
%dif					
Electricity	-2%	-13%	-85%	-100%	-100%
Other supply	0%	1%	-60%	-63%	-84%
Agr & Commercial	-11%	-3%	-40%	-60%	-76%
Industry	0%	0%	-30%	-66%	-68%
Residential	-11%	0%	-17%	-39%	-53%
Transport	-2%	0%	-8%	-27%	-44%
Total	-4%	-2%	-40%	-61%	-69%

5.4.2. Impact of nuclear and carbon storage availability

The three other scenarios, with different options for nuclear and carbon storage, are aiming at evaluating the importance of these technologies for the potential and cost of CO_2 emissions reductions. They are:

- **NoNuc_NoCCS_58%**: without nuclear and without carbon storage
- **GoNuc_GoCCS_58%**: with nuclear and with carbon storage
- **GoNuc_NoCCS_58%**: with nuclear and without carbon storage

The availability of these two technological options is very important in terms of total welfare cost. When both are available the total welfare cost can be reduced by nearly 50% (scenario 23) and vice versa when not available (scenario 22).

Table 43: Total discounted welfare cost (incl. consumer/producer surplus loss)

	%DIF	%GDP2005	Annualized %GDP2005
NoNuc_GoCCS_58%	3.37%	17.0%	0.8%
NoNuc_NoCCS_58%	5.33%	26.8%	1.2%
GoNuc_GoCCS_58%	1.95%	9.8%	0.5%
GoNuc_NoCCS_58%	2.70%	13.6%	0.6%

This is also reflected in the CO_2 marginal abatement cost.

Table 44: Marginal abatement cost of CO_2 (€/ton)

	2020	2030	2040	2050
NoNuc_GoCCS_58%	19	103	262	472
NoNuc_NoCCS_58%	19	175	464	680
GoNuc_GoCCS_58%	19	71	187	422
GoNuc_NoCCS_58%	19	124	380	544

The changes in the CO_2 marginal abatement cost induces a change in the price of the energy service demand and thus also in the demand itself. The changes are the most pronounced in the industry.

Table 45: Energy service demand
(% difference compared to reference)

	NoNuc_GoCCS_58%		NoNuc_NoCCS_58%		GoNuc_GoCCS_58%		GoNuc_NoCCS_58%	
	2030	2050	2030	2050	2030	2050	2030	2050
Agriculture (PJ)	-9%	-24%	-15%	-30%	-6%	-21%	-9%	-24%
Commercial (PJ)	-7%	-10%	-11%	-16%	-2%	-6%	-4%	-10%
Residential (PJ)	-5%	-16%	-8%	-21%	-3%	-14%	-5%	-17%
Freight transport (tkm)	-3%	-8%	-3%	-10%	-3%	-8%	-3%	-8%
Passenger transport (pkm)	0%	-3%	-3%	-6%	0%	-3%	-3%	-3%
Industry (PJ)	-11%	-23%	-17%	-29%	-6%	-20%	-11%	-25%
Industry Ammonia demand in ton	-3%	-9%	-12%	-28%	0%	-6%	-9%	-25%
Industry Cement and Lime demand in ton	-15%	-29%	-21%	-41%	-14%	-27%	-15%	-37%
Industry Copper demand in ton	-3%	-9%	-6%	-12%	-3%	-6%	-3%	-9%
Industry Glass demand in ton	-7%	-13%	-10%	-22%	0%	-10%	-4%	-13%
Industry Iron and Steel demand in ton	0%	-6%	-6%	-15%	0%	-6%	-3%	-9%
Navigation transport (PJ)	0%	-1%	-1%	-1%	0%	-1%	0%	-1%
Aviation transport (PJ)	-1%	-5%	-3%	-5%	-1%	-5%	-2%	-5%

The same is observed for the final energy demand with however some differences.

The switch to electricity which occurs in the scenario 21 (no nuclear but with CCS) is not observed when nuclear and carbon storage are both not available, because the increase in the electricity price is too high. Hydrogen for transport is even appearing at the end of the horizon.

Table 46: Final energy consumption
(abs difference compared to reference in PJ)

	NoNuc_GoCCS_58%		NoNuc_NoCCS_58%		GoNuc_GoCCS_58%		GoNuc_NoCCS_58%	
by fuel	2030	2050	2030	2050	2030	2050	2030	2050
Bioenergy	-3	-22	36	-24	4	10	33	7
Solid fuels	-57	-283	-207	-333	-38	-283	-105	-332
Electricity	-14	13	-25	-8	-1	31	-4	21
Gas	-51	5	-1	-36	-53	-18	-58	-55
Heat	-13	-33	-21	-43	-7	-28	-14	-36
Oil	-57	-284	-82	-331	-56	-287	-80	-281
Renewables	5	20	5	16	10	24	10	22
Synthetic fuels	0	0	0	28	0	0	0	0
Total	-189	-584	-295	-730	-140	-553	-217	-653
by sector								
Agriculture	-3	-13	-6	-15	-2	-12	-3	-13
Commercial	-69	-119	-91	-126	-52	-114	-67	-121
Industry	-57	-170	-108	-260	-35	-152	-77	-226
Residential	-28	-83	-44	-97	-22	-77	-30	-89
Transport	-32	-200	-45	-232	-30	-197	-40	-204
Total	-189	-584	-295	-730	-140	-553	-217	-653

Besides the decrease in electricity demand, there is a shift away from solid fuels when nuclear is available or when no carbon storage is possible. The carbon sequestration is then linked to gas power plants or to power plants on biomass. When nuclear is allowed, the full allowed capacity is implemented. There is a further penetration of solar energy and geothermal in the extreme case with no nuclear and no carbon storage.

Table 47: Net Electricity generation
(abs. differences compared to reference in PJ)

	NoNuc_GoCCS_58%		NoNuc_NoCCS_58%		GoNuc_GoCCS_58%		GoNuc_NoCCS_58%	
	2030	2050	2030	2050	2030	2050	2030	2050
Solids	-41	13	-99	-110	-99	-110	-99	-110
Gas	12	-12	58	-6	-26	-8	-27	-52
Oil	0	0	0	0	0	0	0	0
Nuclear	0	0	0	0	171	171	171	171
Bioenergy	13	7	-4	9	2	-7	-3	-3
Hydro, wind, geo, photovoltaic	10	20	21	56	-26	-3	-37	12
Total	-5	27	-24	-50	21	43	5	19

The Belgian TIMES model is based on marginal pricing and so it can cope with variations of the prices of electricity within the time slices and it can produce more coherent prices than methods based on average prices. **Figure 19** indicates that the price of electricity increases even in the reference scenario. Depending on the technology choices, the prices in the longer run can vary, although the difference is getting really important in the situation without having nuclear and CCS.

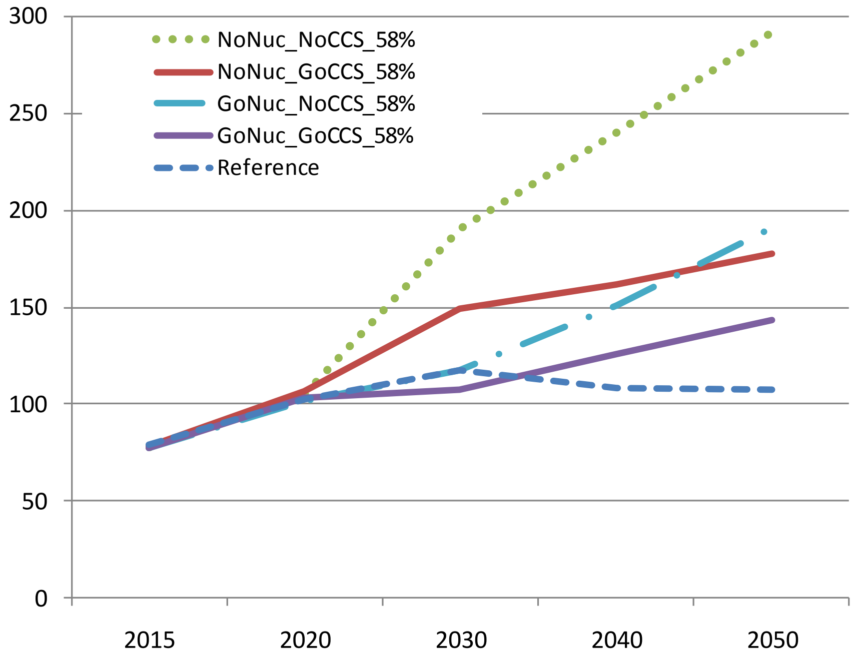

Figure 19: Residential electricity price (€/MWh)

The different options chosen in the energy system are reflected in the impact on the primary energy consumption. It is the most significant in solid fuels where the consumption is nearly halved in all scenarios compared to the scenario without nuclear and with carbon capture.

Table 48: Primary energy

(abs. differences compared to reference in PJ)

	NoNuc_GoCCS_ 58%		NoNuc_NoCCS_ 58%		GoNuc_GoCCS_ 58%		GoNuc_NoCCS_ 58%	
	2030	2050	2030	2050	2030	2050	2030	2050
Solid fuels	-133	-237	-417	-566	-246	-511	-315	-565
Gas	-590	-737	-469	-710	-657	-751	-667	-868
Oil products	366	260	342	164	368	258	344	256
Nuclear	0	0	0	0	475	475	475	475
Bioenergy	19	2	19	2	7	2	19	2
Waste	0	-23	-11	-23	-4	-23	-7	-23

The availability of nuclear or carbon storage does not change fundamentally the contribution of the different sectors to the CO_2 emission reduction.

Table 49: CO_2 emissions
(abs. in Mio.t and % differences compared to reference)

	NoNuc_GoCCS _58%		NoNuc_NoCCS _58%		GoNuc_GoCCS _58%		GoNuc_NoCCS _58%	
absdif	2030	2050	2030	2050	2030	2050	2030	2050
Electricity	-26	-33	-17	-33	-29	-33	-25	-33
Other supply	-5	-8	-5	-6	-5	-6	-5	-9
Agr & Commercial	-3	-6	-3	-6	-3	-6	-4	-6
Industry	-10	-30	-17	-30	-9	-33	-11	-30
Residential	-2	-5	-3	-6	-2	-6	-2	-6
Transport	-2	-18	-3	-21	-3	-18	-3	-18
Total	-49	-100	-48	-102	-49	-102	-49	-102
Storage	26	44	2	2	11	18	2	2
%dif								
Electricity	-85%	-100%	-54%	-100%	-92%	-100%	-79%	-100%
Other supply	-60%	-84%	-60%	-62%	-60%	-68%	-60%	-100%
Agr & Commercial	-40%	-76%	-45%	-81%	-38%	-77%	-48%	-77%
Industry	-30%	-68%	-49%	-67%	-25%	-74%	-32%	-67%
Residential	-17%	-53%	-25%	-55%	-16%	-57%	-20%	-58%
Transport	-8%	-44%	-11%	-52%	-9%	-44%	-11%	-44%

The total absolute CO_2 emissions in **Figure 20** and **Figure 21** give an overview of the importance of the reduction in each sector as well as the importance of CCS when the option can be used.

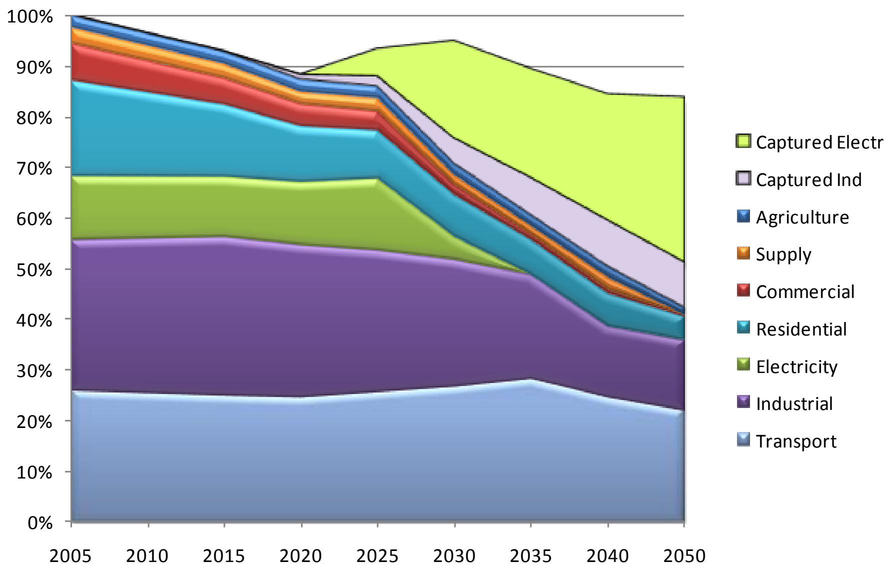

Figure 20: CO_2 emissions (emitted and captured) in the scenario NoNuc_GoCCS

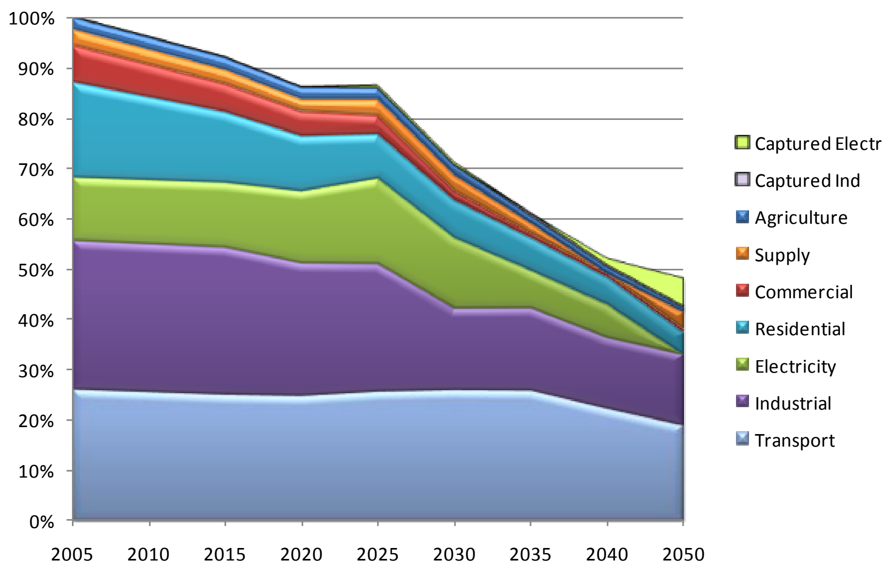

Figure 21: CO_2 emissions (emitted and captured) in the scenario NoNuc_NoCCS (except for a smaller negative amount of Electricity CO_2 emissions from biomass with CCS)

5.4.3. Technological options

The chosen technological options in the different sectors are the following.

RESIDENTIAL SECTOR

Gas and oil remain the dominant fuel for heating till the middle of the horizon, after that heat pump on electricity and gas and delivering heat and hot water, are penetrating. For hot water, gas is the dominant fuel but solar water heating (with gas backup) is penetrating after 2040. Bio energy is not penetrating as there is better use for it and the potential is limited.

The contribution of insulation is very limited as nearly the whole potential was cost efficient in the reference. Savings lamps were also cost-efficient in the reference scenario.

COMMERCIAL SECTOR

Heat pumps are penetrating fast for heating. For the rest the evolution is rather similar as the one in the residential sector.

INDUSTRY

There is a gradual shift to the more energy efficient technologies and towards less CO_2 intensive fuels when the substitution is possible as for steam and heat production. The use of solid fuels remains important because of the iron and steel sector.

TRANSPORT

There is no great shift in the transport before 2030 when the carbon constraint becomes more stringent. However there is a shift back to oilproducts from transport fuels produced from coal and gas observed in the reference. Ethanol and biodiesel are penetrating from 2030 onwards as alternative fuels till the full potential of import and domestic production of bio-crops is used. At the end of the horizon (2040-2050), plugin hybrid cars (on electricity and ethanol) are also penetrating.

The battery electric cars are more efficient but this fuel efficiency comes at a much higher cost, almost independently of the scenario.

Following tables report the cost efficiency gap or equivalently, the subsidy that is needed for the penetration of some of the new car technologies. This cost gap is expressed in euro per 100 km for both cars and trucks. A technology that is chosen in a certain year has a zero cost efficiency gap. All other technologies are near optimal. The cost gaps in Table 50, Table 51 and Table 52 are calculated over the 4 climate scenarios. The number shown is the highest number of cost gap out of the 4 scenarios. The transport technologies with the lowest cost efficiency gap are on top (sorted for 2050). Most transport technologies are very close in terms of cost. In 2030, all cost gaps for long distance cars are lower than 4.1 €/100 km, for small distance cars it is lower than 6.8 €/100 km.

Table 50: Cost efficiency gap for cars, long distance (€/100 km, 0 is chosen)

	2020	2030	2050
Ethanol Plugin Hybrid	2.7	1.2	0.0
Ethanol ICE	0.0	0.1	1.7
Ethanol Hybrid	0.5	0.9	1.8
Gas ICE	0.0	0.0	2.0
Biodiesel ICE	0.0	0.0	2.3
Gasoil ICE	0.0	0[illegible]	2.4
Gasoline ICE	0.1	0.7	2.8
LPG ICE	0.2	0.	2.9
Gasol[illegible]e hybrid	1.2	1.3	2.9
Biodiesel hybrid	1.3	1.6	3.1
Gasoil hybrid	1.3	1.6	3.1
Hydrogen fuel cell	3.6	3.9	3.6
Hydrogen ICE	2.6	3.3	3.7
Gasoline Plugin Hybrid	4.0	3.2	4.2
Hydrogen ICE (liquid)	3.7	4.1	4.7

Table 51: Cost efficiency gap for cars, short distance (€/100 km, 0 is chosen)

	2020	2030	2050
Ethanol Plugin Hybrid	4.0	1.8	0.0
Ethanol Hybrid	0.8	0.9	2.0
Ethanol ICE	0.0	0.0	2.1
Gas ICE	0.2	0.4	2.7
Electric car with battery	11.3	6.8	3.0
Gasoline hybrid	1.6	1.5	3.2
LPG ICE	0.0	0.0	3.2
Gasoline ICE	0.2	0.6	3.4
Biodiesel ICE	0.3	0.5	3.8
Gasoil ICE	0.3	0.5	3.9
Biodiesel hybrid	1.9	2.1	4.1
Gasoil hybrid	1.9	2.1	4.1
Gasoline Plugin Hybrid	3.9	4.1	4.5
Hydrogen ICE	3.7	4.2	4.8
Hydrogen fuel cell	5.6	5.8	5.6
Hydrogen ICE (liquid)	4.9	5.1	6.2

The plug-in hybrid electric car is an efficient technology if it can use ethanol as a fuel. Electric cars on batteries are never chosen by the model, assuming a cost decrease for a car battery from 1000 €/KWh today (2011) to 300 €/KWh in 2040. The table shows high cost gaps that are almost entirely caused by the battery cost.

Table 52: Cost efficiency gap for a battery electric car (€/100 km)

	2020	2030	2050
Reference	17.5	12.7	4.4
NoNuc_GoCCS_58%	18.0	10.1	4.5
NoNuc_NoCCS_58%	17.5	11.5	5.1
GoNuc_GoCCS_58%	19.2	11.0	4.4
GoNuc_NoCCS_58%	19.0	9.6	4.6

The main conclusion for trucks is that they will be fuelled with alternative fuels.

Table 53: Cost efficiency gap for trucks (€/100 km, 0 is a chosen technology)

	2020	2030	2050
Biodiesel hybrid	0.2	0.0	0.0
Ethanol ICE	0.0	0.0	0.0
Gasoline hybrid	0.5	0.4	0.0
Gasoil hybrid	0.2	0.0	0.3
Hydrogen fuel cell	9.1	8.4	1.0
Gas ICE	0.9	1.2	1.1
Biodiesel ICE	0.0	0.0	1.5
Gasoil ICE	0.0	0.0	1.8
Gasoline ICE	1.3	1.9	4.3

ELECTRICITY GENERATION

The impact of the carbon constraint is a switch to gas and an increase in electricity demand. The carbon sequestration is linked to coal power plants and at a later stage to gas power plant. Though the cost of sequestration per ton of CO_2 is lower when linked to a coal power plant, the final cost per kWh (including the penalization of CO_2 and sequestration cost) can be lower with gas power plant when the relative cost of gas decreases and this is the relevant variable for the choice of sequestration option.

Table 54: Net Electricity generation
(abs. differences compared to reference in PJ)

	2010	2020	2030	2040	2050
Solids	0	-8	-41	-20	13
Gas	0	7	12	6	-12
Oil	0	2	0	0	0
Nuclear	0	0	0	0	0
Bioenergy	-1	0	13	11	7
Hydro, wind, geo, photovoltaic	0	0	10	16	20
Total	-1	1	-5	12	27

When analysing the different electricity producing technologies, it is clear that different options exist and that the mix depends on the scenario.

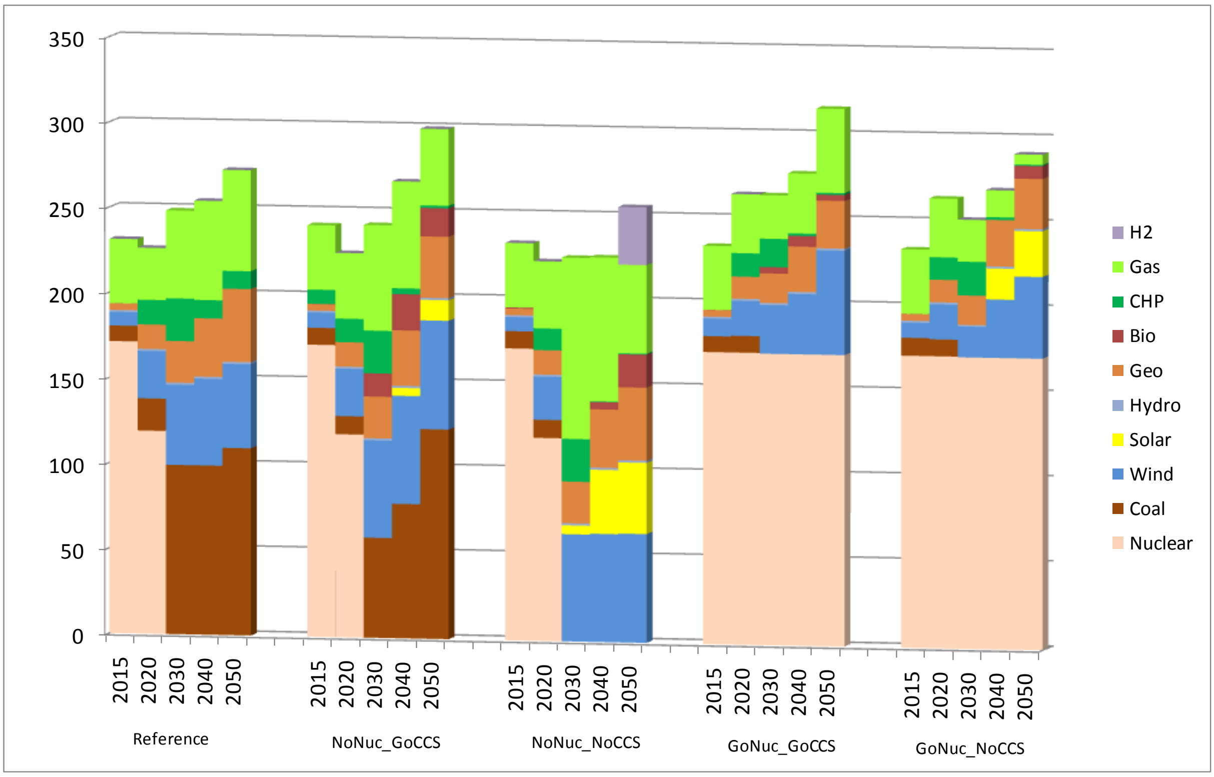

Figure 22: Future electricity production in the 5 basic scenarios up to 2050 (PJ, without imports)

Some observations for the electricity mix are:

- Although overall emissions decrease with 58%, the amount of electricity produced is rather stable over the scenarios.
- The net CO_2 emissions from the electricity sector in 2050 are 38 Mton in the reference scenario, mainly by the combustion of coal and gas.
- All climate scenarios have zero emissions in the electricity sector in the year 2050.
- Geothermal, wind and gas electricity production are present in all scenarios
- Geothermal electricity is favourable in all scenarios for three reasons:
  1. Low discount rate
  2. High availability factor
  3. Flexible operation conditions
- Fossil electricity production is part of all scenarios
- In the NoNuc_NoCCS scenario, following technology choices are chosen to end up with a CO_2 neutral electricity production:
  - Renewable electricity including biomass
  - Domestic power plants consuming H_2 that is produced with gas and solar energy inputs (emissions shift to supply sector).
  - CO_2 converting processes. The captured CO_2 emissions from fossil electricity production are consumed in a process that creates fuel that is used in the transport sector. This backstop technology is only chosen in the NoNuc_NoCCS scenario and is preferred above the use of the other backstop technologies[7].

[7] The other two backstop technologies are 1) 100% renewable and carbon free electricity production and 2) CDR. CO_2 removal from the atmosphere (CDR), also called "negative emissions," may or may not become a serious component of climate change policy some decades ahead. In the Belgian TIMES model, the CDR emissions can be "taken" from the commercial, the industrial, the electricity and supply sectors.

- The use of BECS (Biomass Energy with Carbon capture and Storage). The remaining CO_2 emissions from the fossil electricity production (both with capturing and some smaller without capturing) are compensated by a biomass electricity production plant with CCS, resulting in negative emissions.

For the electricity sector, similar cost efficiency gaps are calculated. These numbers represent the subsidy that would be necessary to let a certain technology be competitive, if this money was received on a MWh basis, for a period of 20 years with a discount rate of 10%.

Table 55: Cost efficiency gap for Photovoltaic Electricity (€/MWh)

Type I	2020	2030	2050
Reference	163	73	62
NoNuc_GoCCS_58%	143	18	0
NoNuc_NoCCS_58%	130	0	0
GoNuc_GoCCS_58%	126	30	18
GoNuc_NoCCS_58%	126	9	0
	2020	2030	2050
Type II	230	140	129
NoNuc_GoCCS_58%	210	86	67
NoNuc_NoCCS_58%	197	67	64
GoNuc_GoCCS_58%	194	97	85
GoNuc_NoCCS_58%	193	76	67

The cost efficiency gap for photovoltaic electricity is zero in 2050 in 3 climate scenarios. Depending on the learning rates, it takes however still a long time for the cost gap to be low. For type II photovoltaic panels, it is assumed that an extra cost is necessary for the panels to be connected to the grid.

A total overview is given in the table below to compare all electricity producing technologies, both chosen (zero cost gap) and near optimal, for the two extreme climate scenarios. The left part is for the NoNuc_NoCCS_58% and the right part for the NoNuc_NoCCS_58% scenario. The technologies are ranked according to the cost gaps in 2050 of the NoNuc_NoCCS scenario. Three categories can be made for the very long time horizon (2040-2050). A first group of technologies is efficient in any of the scenarios: all renewables except PV and wind onshore with bad wind conditions, nuclear, standard gas power plants and gas and biomass power plants with capturing. The second group is not efficient in any of the scenarios: coal and biomass plants without capturing. The third group can be efficient depending on the choices of nuclear or CCS: smaller fuel cell production plants on gas and hydrogen, PV, wind onshore with bad wind conditions and coal with CCS.

The results are only valid in the context of the Belgian isolated scenario runs. In this exercise, it was assumed that biomass is a limited resource. This has important consequences for the choices made. It can be seen that biomass is only used in the electricity when in combination with capturing technology. It is more efficient to use biomass in other sectors to replace fuels where less alternatives are available (for example some industrial processes).

Table 56: Cost efficiency gaps for electricity production in the two extreme climate scenarios (Euro/MWh, 0 is a chosen technology, the arrows show how much more efficient technologies get when going from NoNuc_NoCCS to GoNuc_GoCCS)

		NoNuc_NoCCS_58%				GoNuc_GoCCS_58%		
Process	**Fuel**	2020	2030	2050		2020	2030	2050
Geothermal		0	0	0		0	0	0
Wind Offshore close		0	0	0		0	0	0
Wind Onshore high		0	0	0		0	0	0
Geothermal HDR		0	0	0		0	0	0
Wind Offshore very far		0	0	0		9	29	0
Wind Onshore low		0	0	0	↓	19	42	6
Comb Cycle	Gas	4	0	0		7	0	0
Turbine Peak	Gas	8	0	0		8	0	0
Fuel Cell SOFC	Gas	33	0	0	↓↓	36	3	12
PV Roof panel1		130	0	0	↓↓	126	30	18
Fuel Cell SOFC	Biogas	33	1	0	↓↓	41	7	16
Comb Cycle CO_2 Capt	Gas	29	19	0	↑	18	0	0
Fuel Cell Hydrogen	H2	69	25	0	↓↓↓	72	22	26
IGCC CO_2Capt	Wood	45	31	0	↑	15	0	0
Turbine Peak	Light oil	16	7	7	↓	16	7	7
Steam Turbine	Coal	27	28	27		27	28	26
IGCC	Coal	22	30	29		29	30	28
Sup Critical	Coal	29	32	31		34	33	30
IGCC	Wood	33	39	40		36	40	40
IGCC CO_2Seq	Coal	41	43	44	↑↑↑	31	24	9
Sup Crit. CO_2 Capt	Coal	47	46	45	↑↑↑	39	31	18
Steam Turbine	Wood	81	77	70		79	78	70

Similar to the calculation of the cost efficiency gap of 'near optimal' technologies, one can calculate the cost of having only limited technology potential. Results for nuclear and wind electricity show that these costs can be very high in the scenarios without nuclear energy. The number is the benefit of enlarging a certain technology potential with one extra capacity. These costs are in some scenarios so high (>200 €/kW) that if the scenario would become reality, it will be likely that technological improvements relax these boundaries.

Table 57: Price of limited availability (€/kWe)

	NoNuc_GoCCS_58%		NoNuc_NoCCS_58%		GoNuc_GoCCS_58%		GoNuc_NoCCS_58%	
	2030	2050	2030	2050	2030	2050	2030	2050
Nuclear	-648	-1015	-987	-2169	0	0	0	0
Offshore Close	-32	-230	-145	-679	0	-77	0	-56
Offshore Far	0	-178	0	-627	0	-20	0	0
Onshore high	-146	-258	-267	-638	-34	-124	-62	-107
Onshore low	10	20	0	-188	0	0	0	0

5.5 Exploring modelling uncertainties through a comparison with one of the scenarios developed in the SEPIA project

1.1.1. The SEPIA project

In the SEPIA project (http://www.ua.ac.be/main.aspx?c=.SEPIA), three representative long-term energy scenarios for a sustainable development of the Belgian energy system were defined using a hybrid backcasting approach by a group of experts (the scenario builders group or SBG). Scenario building took place starting from a systematic exploration of futures, by studying all the combinations resulting from the breakdown of the system according to the DPSIR categories. Scenario building involved a series of in-depth deliberative discussions (workshops) using a range of qualitative research techniques (expert panel, scenario workshop, focus group). The scenario storylines were then modelled using an energy accounting model (LEAP). The three scenario storylines are called 'Global Consensus', 'Oil shock(s)' and 'Confidence in RD&D'.

Global consensus starts from the assumption that climate change policy is the main driver behind energy system development, in the sense that early action is taken with the support of civil society. Over the next decade, bottom-up initiatives first take root as cities, regions or coalitions of business take the lead. These become progressively linked as national governments are forced to harmonise resulting patchworks of measures and take advantage of the opportunities afforded by these emerging political initiatives. Faced with the prospect of a patchwork of different policies, businesses start to lobby for regulatory clarity. As a result, effective demand-side efficiency measures emerge quickly, and CO_2 management practices spread. The rate of growth of atmospheric CO_2 is constrained at an early stages leading to a more sustainable environmental pathway. Both supply-side (e.g. electric vehicles) as well as demand-side innovations (behavioural change, energy efficiency improvements) are implemented. Energy RD&D spending on the EU level is increased substantially and is geared towards realising a common European vision – a low-carbon energy system with maximum penetration of renewable and distributed energy sources. A combination of low public acceptance and unresolved waste, safety and proliferation issues leads to a rejection of the nuclear option in many countries (including Belgium). Public support for carbon capture & storage (CCS) is also reluctant, though CCS is needed to reach the -80% target in Belgium by 2050. By 2050, energy supply is largely based on renewable energy sources.

In the "Oil shock(s)" storyline, the oil (and possibly also the gas) market goes through a series of crises in the period 2020-2030, caused by physical (peak production or refinery capacities are surpassed) or political factors (e.g. crisis in the Middle East), resulting in sudden and unpredictable price increments. Governments of the oil-consuming industrial countries typically react following a three-step pattern: first, nations deal with the signs of tightening supply by a flight mainly into coal (later on equipped with carbon capture & storage technology), renewables (mainly wind energy and biofuels) and extending the lifetime of existing nuclear power plants (where applicable); next, when the growth in fossil fuels can no longer be maintained, an overall supply crisis occurs (between 2020-2030); and finally, governments react with rather draconian measures.

Over the period between 2010-2030, leading powers try to control the remaining resources by engaging in strategic alliances, as energy policy is to a large extent dictated by foreign policy and security considerations. Demand-side policy is not pursued to its maximum potential until supply limitation become acute. Eventually however, energy security concerns are alleviated over the period 2030-2050, allowing the climate change agenda to take over as a priority issue.

The "Confidence in RD&D" storyline stands for a scenario where the speed of technological innovation is the key factor enabling the transition towards a sustainable energy system. A combination of high oil (and gas) prices, climate policy and competitive energy markets decisively influence the pace of transition to a low-carbon energy future in the OECD countries. In the EU the Lisbon agenda (and possible successors) carries high priority. The EU protects and expands its previous economic achievements, including the internal energy markets. However, governments are still heavily involved in securing their external energy supplies (this goes for 'government' as well on the EU as on the national level in Europe), albeit in a more subtle and indirect way than in the "Oil shock(s)" scenario. In general, market forces determine the investments choices made by energy industry between renewables, 'clean fossil' or nuclear power, but public and/or political perceptions sometimes lead to targeted interventions. The use of the nuclear option is especially closely associated to national preferences. Independently from the developments in the fields of nuclear, Europe is on its way to a smooth and accelerated transition towards renewable energy. Large off-shore wind farms are the most important renewable source for electricity production and biomass playing a major role in heating or cogeneration. On the demand side, the increase in energy efficiency is also determined by market forces as new energy end-use technologies emerge in electricity use, space heating, 'smart' decentralised energy systems and transportation.

5.5.1. Assimilated scenario

Essentially, the three SEPIA scenarios are built up by combining sets of scenario assumptions taken from three 'building blocks': energy consumer behaviour, technological development, and the international dimension (climate policy, developments on international energy markets). Even though the modelling principles underlying the energy accounting approach adopted in SEPIA with the LEAP model are fundamentally different from those applied in TIMES, it is still interesting to see how the TIMES model 'reacts' to the scenario assumptions modelled in SEPIA. The comparison of the 'assimilated' scenario modelled with TIMES with the 'original' scenario modelled with LEAP adds significantly to the policy maker's capacity of taking robust decisions for reducing GHG emissions in the face of huge uncertainties on long term energy system development. The uncertainty analysed in this part of the scenario modelling is the uncertainty introduced by the use of specific scenario and modelling approaches.

In order to do create an 'assimilated' scenario, the scenario assumptions on modelling parameters used in LEAP are 'translated' to assumptions on modelling parameters in TIMES. We choose to translate the assumptions on energy consumer behaviour of SEPIA into TIMES by forcing the model to attain a similar lever of energy end-use demand.

The results of this assimilated climate policy scenario need to be consistent with the results previously described. To ensure this, not too many model parameters can be changed. For this report, we chose not to change any of the parameters that characterise the behaviour of the energy system and thus did not change the price elasticities of the energy end-use demand, used within TIMES (mainly -0.3).

1.1.2. Method and results

The assimilated scenario LowDemand_58% is an exact copy of the NoNuc_GoCCS_58% scenario, except for one thing. The model was forced to attain levels of energy end-use demand in all sectors that are about 30% below the demand of the reference scenario in 2050, with a gradual shift. This change resulted in prices of energy end-use that are higher than in the standard climate scenario. Compared to the reference scenario, prices can be three times higher[8]. Another difference is that in this LowDemand_58% scenario, the reduction of energy end-use is similar for all sectors. As was discussed in the previous chapter, this is not the case in the cost efficient climate scenario. Differences in the demand reduction exist mainly depending on the share of the energy cost in the total cost of end use.

The results for the LowDemand_58% scenario show that the sum of all fixed, investment and variable annual costs decrease on average with 15 B€$_{2005}$. This decrease is much stronger than in the standard climate scenario.

Table 58: Annual increase of costs and expenditures, compared to the reference scenario (B€2005)

	Total welfare cost	Energy production cost	Energy expenditure
NoNuc_GoCCS_58%	2.6	-0.2	6.5
NoNuc_NoCCS_58%	4.1	-0.5	10.5
LowDemand_58%	10.8	-15.3	60.1

On the other hand, the total welfare cost has increased by a factor 4, mainly because the reduced demand generates losses for the energy user. The energy expenditures of this consumer will go to a smaller quantity of energy services and this shift is important in terms of welfare loss. Another conclusion is that, although the expenditures go to fewer energy services, the level of expenditures increase with about 60% when averaged over the total time horizon. This number can be compared to a maximum increase of the energy expenditures of 10% in the cost efficient climate scenario without the option for nuclear and carbon storage. This scenario is in a certain way an extreme scenario since a very high price increase is assumed to cause the demand drop. However, it demonstrates that an extra policy of demand reduction being imposed on top of a climate policy can lower the increase of the CO_2 price (Table 59).

[8] One can calculate that increasing the price level from 100 to 300 decreases the demand level with about 30 %, according to the formula $Q_1/Q_0 = \exp[-0.3.\mathrm{Ln}(3)] = 72\%$

As the technology choices are driven by costs including this CO_2 price, one can expect that some low-carbon technologies are not cost efficient.

Table 59: CO_2 **price in the LowDemand_58% scenario, in comparison to the standard climate scenario**

	2020	2030	2040	2050
NoNuc_GoCCS_58%	19	103	262	472
LowDemand_58%	19	30	143	206

Another way of explaining is that regarding technology choices, the average emission intensity is higher in the scenario LowDemand_58% because both scenarios have the same CO_2 emissions level. This is reflected in higher levels of oil consumption and lower levels of the use of renewable energy.

Given the assumption regarding low and fixed price elasticities, these results indicate that there are reasons to believe that a policy primarily oriented towards deep or uniform demand reduction is questionable for efficient tackling CO_2 emissions. Instead, a climate policy directly oriented to the reduction of CO_2 emissions induces only modest relative reductions of energy services, but it will be more cost efficient and it will induce more technology development.

An alternative approach to decrease the demands would be to lower the demand price elasticities. This has an opposite effect in a certain way because the total welfare cost will go down. This approach will be shown in the cluster project FORUM.

5.6 Policy recommendations

The scenarios analysed above show that it is possible to attain very stringent CO_2 reductions in Belgium. The welfare cost in annualised terms varies from 0.5% of the 2005 GDP when nuclear and carbon capture are available to 1.2% of GDP2005 when none of these options are available. The participation in a global EU CO_2 market is essential for Belgium. Without the possibility of trade and the same EU target of -78% imposed on all EU countries, the cost increase to 0.8% of GDP2005. These costs are the cost within the energy system without considering any potential side benefits and assuming a EU permit system as policy instrument for achieving the CO_2 reduction target.

The renewable target scenario, done in the beginning of the project, already showed that a renewable target only is not sufficient to reach the climate target.

The CO_2 constraints do not impose major shifts in the energy system in the middle term. The use of more energy efficient technologies and a switch to gas are predominant. It should be mentioned that building insulation and saving lamps are already cost efficient in the reference scenario and because of the many barriers to their use in real life, it is important to address this issue by specific policies. Renewables such as wood and wind on shore are also penetrating rapidly.

In the long term, alternative fuels such as ethanol and biodiesel and electricity are penetrating in the transport sector, offering further reduction possibilities. Their relative cost seems to be rather close and therefore the choice between these different options is very sensitive to the potential of biomass production, the cost of biocrops and of electricity.

Also, in other sectors, the choice of technological options is dependent on the options in the electricity sector and the relative price of electricity when high reduction target are imposed. The availability or not of nuclear and carbon storage are important determinant of the price of electricity and thus of the choice of technological options.

A major contribution is also obtained from a reduction in the energy service demand. This reduction can cover a great number of changes outside the energy system: new production system, change in life style, in urban planning, ….

Focussing on a specific renewables target can contribute to the CO_2 target but the technological choices might not be optimal regarding this last target and not induce R&D in the most appropriate direction. The results from those scenarios show the importance of using a model covering the whole energy system with sector specific technologies to correctly evaluate the trade-off between the options given the overall CO_2 target.

These different conclusions are clearly dependent on the cost and assumptions implemented in the model database and in the scenarios. Therefore this analysis should be complemented by sensitivity studies around the main parameters. Also, though the cost of implementing a complete infrastructure for the penetration of some option is integrated in annualised term in the cost of these options, large resources will have to be mobilised over a rather short period to invest in these infrastructure.

One should also keep in mind the characteristics and limitations inherent to a model as TIMES. The strongest point of the model is its consistency in treating technology related problems in the energy-environment domain. It gives good and consistent first insights for energy policy formulation and guidelines for technology policy but should be supplemented by complementary studies in both fields. A major difficulty in the direct use of the TIMES model results for specific policy formulation comes from the naive representation of energy users and suppliers in the model. It is assumed that all market participants use the same objective function (cost minimisation with imputed shadow costs for the active environmental constraints), that they have the same information and the same subjective beliefs (perfect foresight solution) and finally that the market prices equal the discounted marginal costs corrected for imputed shadow prices. The model has also limitations due to its structure: no explicit uncertainty, convex cost functions (no increasing returns to scale) and linear technologies, limited geographical scope (internal energy market), and aggregation of activities

6. DISSEMINATION AND VALORISATION

The valorisation of the activities went through four main channels:

- Presentation on (ETSAP) seminars of the empirical results obtained:
    - Nijs W., 2008, "Post Kyoto scenarios for Belgium 2012-2050" , Belgian Environmental Economics Day, Ehsal
    - Nijs W., Van Regemorter D., 2008, "Post Kyoto scenarios for Belgium 2012-2050" , Energy & Climate course, UA, Antwerp
    - Nijs W., Van Regemorter D., 2008, "EU Objectives on Climate Change and Renewable Energy for 2020 in Belgium", Annual ETSAP Workshop, 30 June – 2 July, International Energy Agency, Paris
    - Nijs W., 2009, "Technological Choices for Achieving the EU-Objectives on Climate Change and Renewable Energy in Belgium, a Sensitivity Analysis", International Energy Workshop, Venice, June 17th-19th
    - Renders N., 2009, "ECM Households: How to deal with no-regret measures?", presentatie op ETSAP bijeenkomst, Venice, 15/06 -17/06
    - Nijs W., 2010, "CCS possibilities for Iron and Steel, simulations with TIMES", ETSAP workshop, Delhi

      The Iron and Steel sector is the second-largest industrial consumer of energy - after the chemical sector. It accounts for about 20 percent of the world's industrial energy consumption. In Belgium, 10.5 Mton CO_2 is emitted for the production of steel. This is about 30% of industrial CO_2 emissions. One criticism of much of the past scenario work is the consistency of technological data. New energy scenarios up to 2050 have been preformed with the Belgian TIMES model with a focus on the iron and steel sector. To assess the sector, the updated technology data of the ETSAP Technology Database was used. The presentation seeks to address the question of technology choice under different scenario assumptions.
    - Nijs W., "TIAM, The Initial experiences And More", ETSAP workshop, Stockholm, 2010 (unofficial presentation)
    - Nijs W., Van Regemorter D., Benoot W., Morbee J., "Energy diversification through fuel price variation within TIMES", Stanford, 2011
    - Started in 2010: FORUM, Establishment of an ad hoc forum for the comparison of the TIMES-MARKAL and LEAP model as a support for Belgian long-term energy policy.

- Preparation and publication of a scientific article on the subject and presentation at international conference: see next chapter.
- Presentation of the results to policy makers through the organisation of meetings
    - Simulation exercise: How does a model like MARKAL/TIMES work ? - Wouter Nijs/ Jan Duerinck, Assessing and improving methodologies for GHG projections, 13th and 14th of October 2008, Brussels, VITO/Öko/IEEP
- Presentation of project progress to the follow up committee meetings

7. PUBLICATIONS

Following publications have been written (sept 2011):

Nijs W., Van Regemorter D., (2008), "EU-objectives on climate change and renewable energy for 2020 in Belgium" VITO, CES K.U.Leuven, working paper, 2008 (see Annex 1)

Proost S., Delhaye E., Nijs W., Van Regemorter D.,(2009) "Will a radical transport pricing reform jeopardize the ambitious EU climate change objectives ?", Energy Policy, Volume 37, Issue 10, October 2009, Pages 3863-3871, Center for Economic Studies, Catholic University of Leuven, Belgium, Transport & Mobility Leuven, VITO.

Nijs W., Van Regemorter D. (2010), EU-objectives on climate change and renewable energy for 2020 in Belgium . In J. Eyckmans, G. Pepermans, S. Proost (Ed.), *Climate change and Energy Perspectives* (p.105-126). ISBN 9789081586702

Duerinck J. (2011), Electricity and fuel consumption in Europe: A panel error correction model for residential demand elasticities, Die politische Förderung des Stromsparens in Privathaushalten, Doris Fuchs, ISBN 978-3-8325-2895-9

Duerinck J., Van Regemorter D. (2011), Residential energy demand elasticities: what lessons can be learned from bottom-up and top-down methodologies, IEW 2011, Stanford. (see Annex 2)

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