Coupling techno-economic energy models with behavioral approaches

Abstract

Classical energy planning models assume that consumers are rational, which is obviously rarely the case. This paper proposes an original method to take into account the consumer's real behavior in an energy model. This new hybrid model combines technical methods from operations research with behavioral approaches from social sciences and couples a classical energy model with a Share of Choice model.

Keywords: Consumer behavior, energy and environmental planning model, Share of Choice

1. Introduction

For decades, energy and environmental planning models such as MARKAL (Abilock and Fishbone (1979) and Fishbone and Abilock (1981)), TIMES (Loulou et al. (2005) and Amorim et al. (2014)) or more recently OSeMOSYS (Howells et al. (2011) and Welsch et al. (2014)) have helped policy makers to take their long-term decisions.

However, these classical models have a serious weakness: they assume that all actors are perfectly rational and that markets are perfect. To mimic approximatively irrational behaviors, artificial constraints are introduced in the model.

The field of optimization applied to sustainable development is indeed very important and numerous studies have been published to improve the quality of models (see for instance the special issue edited by Maros et al. (2009)).

1.1. Bottom-up models in energy and environmental planning

TIMES and MARKAL are well known long-term energy and environmental models. They are called techno-economic models and correspond to bottom-up frameworks. It means that all detailed Reference Energy System data points are ultimately fully aggregated. Through an optimization process solely least cost technologies are chosen. Many model extensions have been included over the years. For instance, Kannan (2011) integrates in the model a very detailed temporal dimension in the model. This contribution is beneficial in particular for electricity technologies that require a far more granular time description to take into account electricity peaks and address electricity storage for demand and supply side issues.

DEA techniques (Data envelopment analysis) also fall in the bottom-up category. For instance, it has been employed to compare effort of regions or cities towards better energy and environmental performance (Wu et al. (2015)).

However, the resulting energy policies provided by bottom-up models do not take into account the typical non-rational consumption behaviors of end users. These policies correspond to over-optimistic forecasts regarding energy conservation as well as emission reduction (Murphy and Jaccard (2011)).

1.2. Rationality of energy and technology choices

Rational choice theory is underlying the investment philosophy of most energy and environmental planning models. In reality most actors of the reference energy system are departing from this rationality. This phenomenon is called behavioral failure. These issues are explored today by scientists (see for instance to see how classical planning models could benefit from recent developments in behavioral economics (Shogren and Taylor (2008)).

Scientific literature from environmental psychology (see for instance Sundstrom et al. (1996) for a literature review of the field as well as elements of attitude change by Arbuthnott (2009) in sustainable development) can also teach us many insights regarding non rational behaviors of energy consumers. Many kinds of stressors (temperature, noise) can deeply affect the energy consumer behavior. We learn for instance that a strong goal intention does not guarantee goal achievement (Gollwitzer and Sheeran (2006)). This can be explained by psychological phenomena such as unwanted influences and disengagement from failing courses of action.

Technology diffusion is typically gradual due to market failures (e.g. information problems, agent slippage and unobserved costs) as well as non-market failures (e.g. heterogeneity among potential adopters). As shown by Jaffe and Stavins (1994) this phenomenon corresponds to a paradox considering the cost effectiveness nature of energy-conservation technologies.

1.3. Hybrid models coupling bottom-up and top-down frameworks

A new category of models has emerged to overcome the main drawbacks attached to bottom-up models. They are called hybrid models. The purpose of hybrid models is to simulate consumer and firm behavior at the technological level (Rivers and Jaccard (2005)). Policy tools like incentives or information programs can be more relevantly assessed. Indeed, energy and environmental models can be divided in two categories: bottom up and top down models. Unfortunately, scholars from these two worlds do not work together. Hybrid energy and environmental models attempt to take into account the peculiarities of the two modeling philosophies: bottom-up and top-down.

Bottom-up models are known to describe precisely the dynamics of technology while top down models better address the logic of economic systems. For instance, Giraudet et al. (2012) have coupled Res-IRF, a bottom-up module of energy consumption for space heating, with IMACLIM-R which is a general equilibrium model. Cayla and Maïzi (2015) have added new modeling features in TIMES in order to better capture the household behavior. It has been done through a detailed disaggregation representation of households behaviors. Ramea et al. (2013) has soft-linked TIMES with MA^3T, a nested multinomial logit model of market shares to represent the actual market share of different transport modes. A different approach has been chosen in Daly et al. (2014) and Daly et al. (2015) where two demands, short distance and long distance travel, and a new variable, Travel Time Investment (TTI) have been introduced into TIMES model together with a constraint Travel Time Budget (TTB). That way, instead of usual competition of technologies within the transport modes they belong to, transport technologies compete across modes and more expensive transportation modes are chosen if using the cheaper ones falls beyond the TTB.

1.4. Behavioral patterns of energy consumptions as a top down model

Early in the seventies, researchers from marketing science started to describe the consumers' behavior using techniques that were developed in the former decade by psychologists and statisticians (see Debreu (1960) and Luce and Tukey (1964)). In a seminal paper, Green and Rao (1971) proposed a first approach of conjoint analysis to describe the consumers' preference. Then, Srinivasan and Shocker (1973) formalized the consumers' preference problem as an optimization share-of-choice programming model. Albers and

Brockhoff (1977) show how the model can be formulated as a mixed integer program. Since then, as the growing literature shows, these techniques became standards. Some articles propose algorithms to improve the computation's efficiency for the Share of Choice problem (see Gruca and Klemz (2003), Camm et al. (2006) and Wang et al. (2009)). A multitude of articles are dedicated to empirical studies in a variety of different fields, using conjoint analysis (for recent examples see Kairu-Wanyoike et al. (2014), Oltman et al. (2014) and Wooliscroft and Ganglmair-Wooliscroft (2014)). Finally, numerous articles develop and improve the techniques of conjoint analysis (see Agarwal et al. (2015) for a recent literature review).

1.5. A hybrid model including energy consumptions end user preferences

As seen bottom-up models are good at describing the technological diffusion dynamics, however they do not capture the true market dynamics. Energy models have thus been often combined with a general equilibrium model (for instance the MERGE model by Manne et al. (1995)). In this particular case, the general equilibrium model (i.e. the top-down framework) provides a macro-economic coherence to the long-term technological diffusion dynamics.

In this research, we have developed a hybrid model that couples a bottom-up and a top-down model to address behavioral patterns of energy consumption. Practically, we have coupled OSeMOSYS with a Share of Choice model. The Share of Choice model integrates part-worths (i.e. utility functions) describing end users' preferences regarding their energy consumption. The coupling of the bottom-up and top-down approaches is hard-linked through an integer programming problem (i.e. discrete choice model). The Share of Choice is composed of the discrete choice model as well as the utility functions. The goal of our hybrid model is thus through the top-down framework (i.e. utility functions) to provide a coherence to the technology diffusion by integrating typical behavioral patterns of energy end users.

To model the irrationality of consumers in energy models, a first attempt has been made using virtual technologies (Fragnière et al. (2010), Nguene et al. (2011)). This approach offers an improvement but is not totally satisfactory: the consumers behavior is an exogenous data and appropriate modeling is thus not possible.

In the present paper, we apply these techniques and propose an original method which enables us to take endogenously into account the consumer's real behavior in an energy model. This method couples technical methods

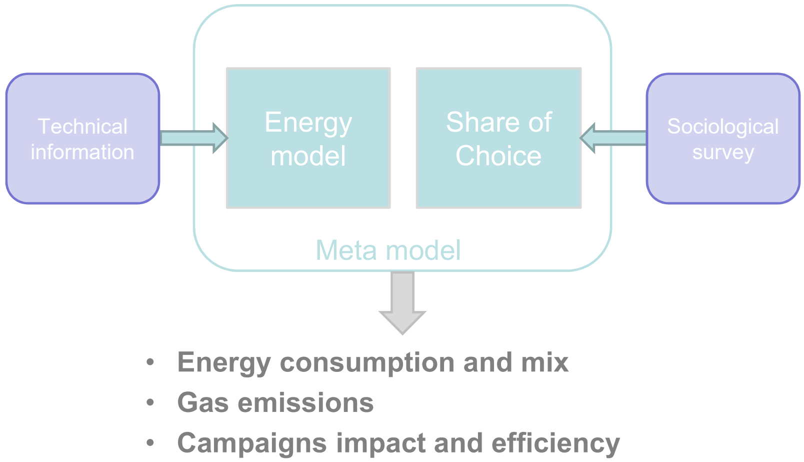

Figure 1: Coupling techno-economic energy models with behavioral approaches

from operations research with behavioral approaches from social sciences and is inspired by the method proposed in Fragnière et al. (2008) and Fragnière et al. (2012).

Roughly speaking, the main steps of this method are the following. First, the consumer's real behavior is estimated with a survey. Then the results of the survey are incorporated in a Share of Choice model which describes the consumers' preference. Finally, the Share of Choice model is coupled with a classical energy model. The resulting metamodel permits us to evaluate different possible energy policies. Figure 1 schematizes our method.

Section 2 introduces the case study and the survey conducted in Romania. Section 3 presents the metamodel and the set of data used for the numerical experiment. Numerical results are presented and discussed in Section 4. Finally, in Section 5, we conclude and indicate further research directions.

2. Method

2.1. The case study

The aim of this paper is to show how a classical energy model can be coupled with a Share of Choice model in order to take into account the consumers' real behavior. To illustrate our method, we take a case study where we put a focus on the consumer's behavior concerning bulbs. More precisely, we want to study the consumer's preference between fluorescent bulbs and

Light-Emitting Diode (LED) bulbs. For this case study, we suppose that the government can conduct two campaigns, namely an information campaign and a subvention campaign in favour of the more efficient LED bulbs. The final objective is to choose the optimal policy. For the energy model, we choose OSeMOSYS data set UTOPIA (Howells et al. (2011)). UTOPIA describes the whole energy system of a fictive country. It is a relatively small though complete energy model and is implemented with the open source OSeMOSYS code. In UTOPIA, we modify nothing except that we introduce a second lighting technology and the possibility of an information campaign and a subvention campaign. Then, we add to this energy model a Share of Choice model that describes the consumer's behavior regarding bulbs. To simplify modeling, we have assumed that the bulbs residual capacity is null. We did this small change in order to keep the model as simple as possible. Without this modification, we would have had to introduce new computed parameters in order be able to keep the linearity of the metamodel.

2.2. The survey

To evaluate the behavior of consumers concerning bulbs, we have conducted a survey in Romania and interviewed 120 persons. For such surveys, there exist four main techniques, namely the full-profile, the two-factor, the self-explicated and the hybrid approaches (see Green et al. (1993)). Each technique has advantages and limitations depending on the number of different products and the number of salient attributes studied. When few different products are evaluated and when no specific study is conducted on the salient attributes, the full-profile method is the most efficient one. As there is a need to evaluate the consumers' preference between only two bulbs and no need to evaluate the separate effect of the different attributes, we decided to employ the full-profile approach. More precisely, the survey relies on two steps and each one is divided in two questions.

The first step aims at evaluating the respondent preference before a possible information campaign. For this purpose, two cards are presented to the respondent (Figure 2). The first card describes the fluorescent bulbs and the second one the LED bulb. Both cards contain indications that can be found on the packaging. It includes the price, the life duration, the energy efficiency and the power of the bulb. First, we ask the respondent which bulb he would be willing to buy. If the respondent chooses the LED bulb, we go to the second step. If the respondent chooses the fluorescent bulb, we then evaluate if a possible subvention campaign could turn him into a LED bulbs

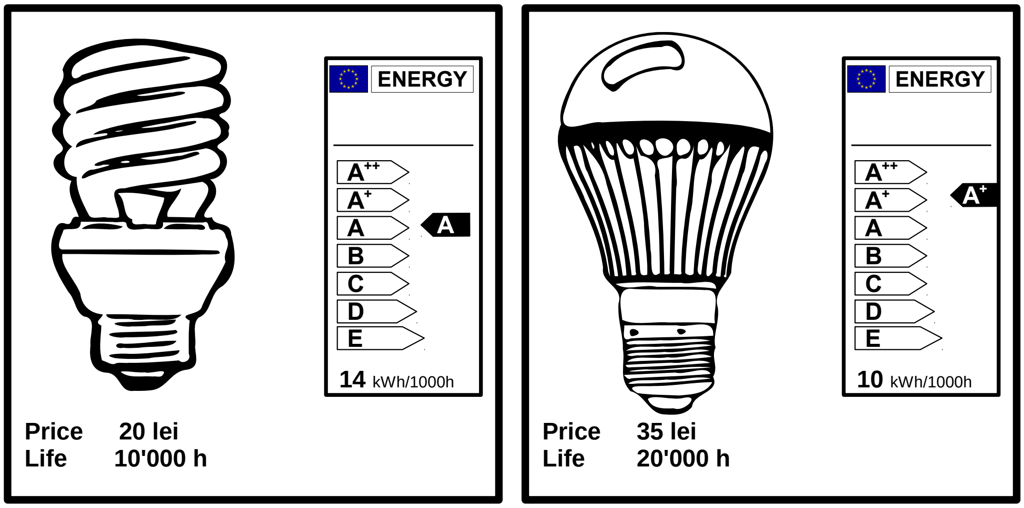

Figure 2: First cards presented to the respondents

buyer. For this purpose we ask a second question: "what is the maximal amount you are ready to pay for the LED bulb?". This provides us with the respondent's Willingness To Pay (WTP) for the LED bulb.

The second step aims at evaluating the respondent preference after the information campaign. For this purpose, two cards are presented to the respondent (Figure 3). Compared to the previous cards, these cards contain an additional information, namely the annual cost of utilization. The annual cost includes the depreciation cost and the electricity cost. It is based on a standard use of 1000 hours per year. Then, as in the first step, we ask the respondent the same questions to know his preference and his WTP for the LED bulb.

The WTP is not an easy notion for most respondents (see Homburg et al. (2005) and Kim et al. (2009)). In order not to confuse respondents, we decided to keep the survey as simple as possible. However, this decision has two drawbacks. First, the direct questions could influence respondents' declaration. Second, we have no control questions to evaluate the veracity of answers. The results obtained lead us to believe that the survey has a possible declaration bias. Indeed, the penetration of the LED bulbs is lower in reality than what the survey seems to show. This could be a bias or an issue of stated preferences vs. revealed preferences: a difference between

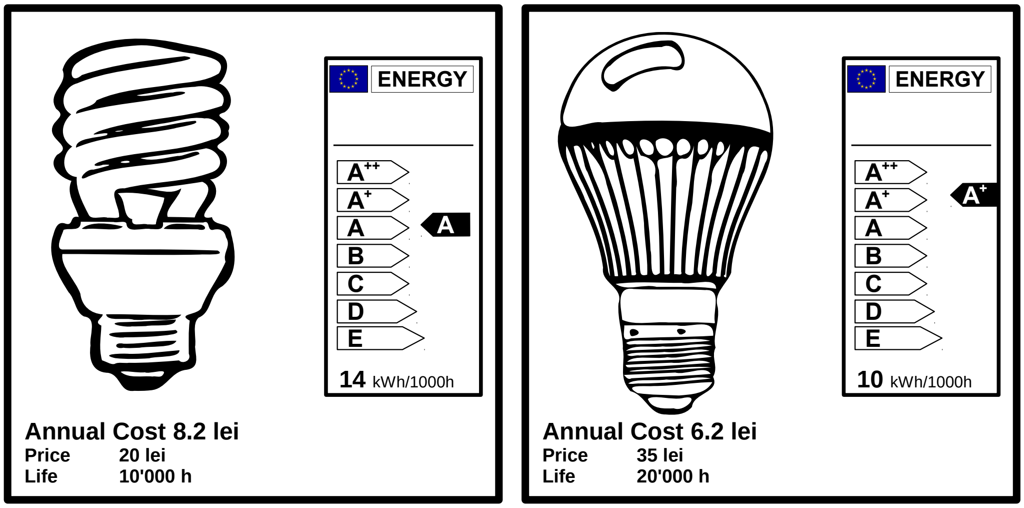

Figure 3: Second cards presented to the respondents

what people claim to intend to do in the future and what they have done in the past. To be complete, we must point out that incandescent bulbs will be banned in Romania. At the time the survey was conducted, incandescent bulbs were still allowed. The discrepancy could come from the fact that the incandescent bulbs are not incorporated in our survey. To be able to answer this question, a new control survey should be conducted. For our paper, as we use anyway the UTOPIA model, this is not an issue.

To sum up, the survey provides us with the following two kinds of information: the WTP when no additional information is given to the respondent and the WTP when he gets additional information. If the respondent chooses the LED bulb even if no subvention is given, the WTP is of course 35 lei, the actual price of the LED bulb.

3. Theory and calculation

3.1. The metamodel

In order to take into account the consumers' real preference, it is necessary to translate the survey's results into data for the Share of Choice model. Throughout the paper, we use the following notation:

Respondent	$r \in R$,
Year	$y \in Y$,
Subvention level per LED bulb	$s \geq 0$,
Information campaign level	$i \in \{0, 1\}$.

$i = 0$ means that no information campaign is conducted whereas $i = 1$ means that an information campaign is conducted. For each respondent r and both campaign level $i \in 0, 1$, the survey provides us with the WTP (denoted in the model with $w(i, r)$). To describe users' preference, we use an ordinal utility function. As this utility function can be calibrated as desired, we make the following choice. The utility function for the fluorescent bulb is 0, whatever the level of the campaign. For modeling purposes, we also converted lei in dollars using the exchange rate of 0.3. For instance, the price of the LED bulb is 10.5 dollars (35 lei). For each respondent, the utility function of the LED bulb is given by

$$U(0, r) \cdot (1 - i) + U(1, r) \cdot i + s, \tag{1}$$

where the part-worth are given by

$$U(i, r) = \begin{cases} 1 & \text{if } w(i, r) = 10.5, \\ \\ w(i, r) - 10.5 & \text{otherwise.} \end{cases} \tag{2}$$

Note that 10.5 in the function represents the price of the LED bulb in dollars. Given the campaign level and the subvention level, this utility function is positive if the LED bulb is preferred to the fluorescent bulb and negative if the fluorescent bulb is preferred. To describe the structure of the metamodel, we use the following notations. For data, we have

$d(y)$	forecasted annual demand for bulbs,
c_i	total discounted cost of the campaign,
c_s	total discounted cost of the subsides.

The first data point exists in the original UTOPIA, whereas the two other ones are added to the original model. For the decision variables, we use the following notation:

i	information campaign configuration: 1 if campaign is conducted and 0 otherwise,
$p(r)$	preference for respondent r: 1 if the respondent buys LED bulbs and 0 otherwise,
l	share of LED bulbs,
$z_2(y)$	installed capacity of LED bulbs,
$z_1(y)$	installed capacity of fluorescent bulbs,
x	variables describing the activities in the classical energy model ($d(y)$, $z_1(y)$, $z_2(y)$, i and s also belong to this vector).

Note that the first four variables do not belong to the original UTOPIA model. The energy model without the Share of Choice writes

$$\min_x c \cdot x \tag{3}$$

s.t.

$$A \cdot x \geq b. \tag{4}$$

Roughly speaking, the model tries to minimize the costs respecting production and demand constraints. Then in the metamodel we have to introduce the Share of Choice as follows. For each respondent $r \in R$, the following two inequalities must hold

$$U(0,r) \cdot (1-i) + U(1,r) \cdot i + s \geq (p(r)-1) \cdot M, \tag{5}$$

$$U(0,r) \cdot (1-i) + U(1,r) \cdot i + s \leq p(r) \cdot M, \tag{6}$$

where i and $p(r)$ are binary variables and M is a big number. In these two equations, we recognize the utility function described in Equation (1). For each respondent r, these two equations insure that if the utility of the LED bulb is greater than or equal to the utility of the fluorescent bulb, then the respondent is counted as a LED bulbs buyer ($p(r) = 1$). If the utility of the LED bulb is smaller than the utility of the fluorescent bulb, the respondent is counted as a fluorescent bulbs buyer ($p(r) = 0$). Then, the proportion of LED bulbs writes

$$l = \frac{\sum_{r \in R} p(r)}{\mathrm{card}(R)}, \tag{7}$$

where $\mathrm{card}(R)$ is the number of respondents. Finally, we must include in the metamodel the following constraints, where capacity and demand are put in relation:

$$z_1(y) = d(y) \cdot (1-l), \tag{8}$$

$$z_2(y) = d(y) \cdot l. \tag{9}$$

These two equations insure that the installed capacity of both bulbs matches the proportion computed with the Share of Choice. In OSeMOSYS, these two constraints contain capacity factors and activity to capacity factors not presented here.

Here, in the core of the paper, we intentionally used general notation to describe our metamodel. Details of the implementation for the key points can be found in Appendix A. Furthermore, the full model with data can be found in the supplementary data (see Appendix B).

	Fluorescent bulb	LED bulb
OSeMOSYS symbol	RL1	RL2
InputActivityRatio from ELC	1	0.7143
OutputActivityRatio to RL	1	1
FixedCost	9.46	4.73
CapitalCost	100	200
ResidualCapacity	0	0
AvailabilityFactor	1	1
OperationalLife	10	20
VariableCost	0	0
CapacityToActivityUnit	1	1
CapacityFactor	1	1

Table 1: Bulbs characteristics

Year	0	10	20
SpecifiedAnnualDemand	5.6	8.4	12.6

Table 2: Demand for residential light (PJ/year)

3.2. Data

Our goal is to show how it is possible to couple an energy model with a Share of Choice model. In order not to modify the original energy model, we decided to use the existing bulb from UTOPIA though it doesn't have exactly the same price characteristics as the real bulbs ones such as indicated in our survey. Indeed, the ratio between the price of electricity and the price of bulbs is lower in UTOPIA than in Romania. In UTOPIA, the existing bulb, namely RL1, corresponds to the fluorescent bulb. We introduced a new bulb, namely RL2, which corresponds to the LED bulb. Data for both bulbs can be found in Table 1. As explained before, except for the residual capacity, all data for RL1 are the same as in the original UTOPIA model. Data for the residential light are given in Table 2. These data points are the same as in the original model UTOPIA.

For the whole horizon, the total discounted cost of the campaign is evaluated from observations based on the study from Fragnière et al. (2010) and is set as 20 million dollars. As this is a rough estimation, we also take a more pessimistic estimation (40 million dollars). The first estimation provides us with a low scenario and the second one with a high scenario.

Our model tries to minimize the global costs for the society. Expenses related to subventions are paid by the government to individuals. Seen from the point of view of an accountant, this means that the cost for the society is zero: what is paid from one side is received by the other side. In our model, the cost of the campaign should be seen as an acceptance cost. Obviously it should lie between zero and the expenses spent by the government. Indeed, the acceptance cost cannot be larger than the cost itself or lower than zero. For our experiment, we let this cost vary, but took as basis scenario an acceptance cost equal to 50% of the total subvention.

As mentioned above, some parameters cannot easily be estimated. To deal with this problem we can use a scenario approach and/or do some marginal analysis. For the cost of the information campaign we decided to take the scenario approach. We could indeed rely on precise data coming from the LEM, which is the market survey insitute of our school (2 authors of the paper are the directors of the LEM). On the other had, for the cost of the subvention we have used the marginal analysis approach. In this latter case, reduced costs of the optimization tell if the corresponding variables are competitive at the optimum.

4. Results and discussion

We solved the metamodel using Mosek solver in the AMPL environment. Note that it is also possible to solve the metamodel using the open source environment GNU MathProg.

Our metamodel shows that for the low scenario, it is optimal to run an information campaign and not to give a subvention. For the whole horizon (20 years), the total discounted cost is 27'860 million dollars. This amount represent the overall costs in the UTOPIA model. If we let the subvention acceptance cost to be lower than our basis scenario, we see that the break-even point lies around 2.1% of the total subvention. For an acceptance cost lower than this point, it is optimal to give a subvention of 3 dollars per LED bulb and not to run an information campaign.

For the high scenario, it is optimal not to run an information campaign and not to give a subvention. The total discounted cost is 27'872 million dollars. For the acceptance cost, the break-even point is around 3.5% of the total subvention. For an acceptance cost lower than this point, it is optimal

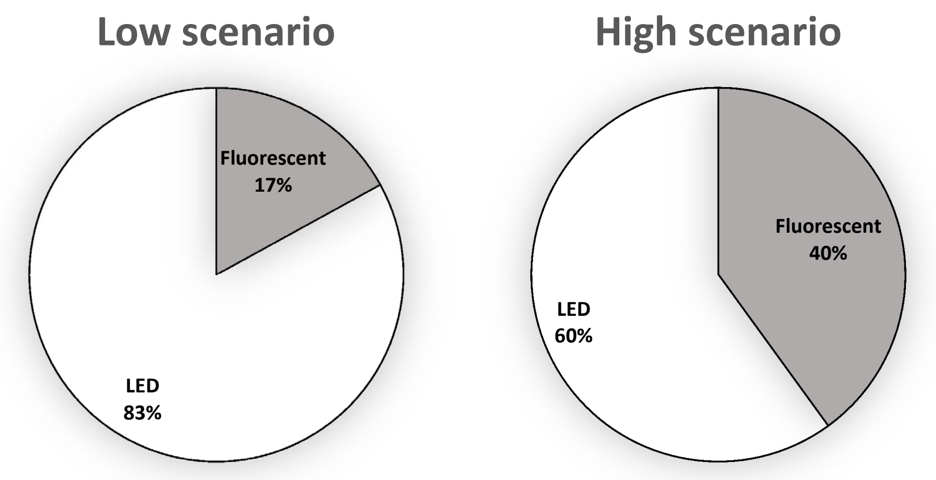

Figure 4: Bulbs penetration for both scenarios

to give a subvention of 3 dollars per LED bulb and not to run an information campaign.

From these results, we can conclude that an efficient subvention campaign will probably not be accepted by the population as the acceptance cost break-even points are far from the estimated basis scenario. A marginal analysis shows that the information campaign should be run if its costs are lower than 32 million dollars.

Besides these results, it is important to note that the share of LED bulbs mimics the consumers' behavior estimated through the survey. Note that without a Share of Choice model taking into account the irrationality of consumers, this proportion would have been 100%. Indeed, it is economically rational to solely buy LED bulbs. Figure 4 shows the proportion of fluorescent and LED bulbs for both scenarios. As mentioned earlier, in our survey, we are probably facing a declaration bias, the share of LED bulbs could be lower in reality.

This case study shows how it is possible to take into account the consumers' real behavior in an energy model. It also shows the type of recommendation that can be provided to decision makers. The recommendation can take into account uncertainties about parameters using scenarios and marginal analysis.

5. Conclusion

We have proposed an original method which enables us to take into account the consumer's real behavior in an energy model. This method couples technical methods from operations research with behavioral approaches from social sciences. In a further development, we aim to externalize the Share of Choice model. This will have two advantages. First, it will reduce the number of binary variables, which in turn, will reduce drastically the computational complexity of the model. Second, it will simplify the modeling. Indeed, it will be possible to keep linearity properties for more complex models. For instance, in our current model, we have computed the acceptance cost a posteriori. With the new approach this will be an endogenous data. This prototype has been prepared in OSeMOSYS framework because access to internal model structure was needed, but TIMES model is well suited for soft-linking. The Share of Choice model can be kept external.

As mentioned earlier, we admit that our survey has a possible declaration bias. In the future, we aim to conduct a new survey with verification questions.

This approach is definitively inductive and requires numerous surveys to properly model the demand side of the related RES (Reference Energy System). Nevetheless, this is the strengh of these energy and environmental models to be very detailed. So far, they have a good granularity regarding the technology coefficients. We can expect the same in the future about the behavioral coefficients.

Moreover, most long term energy and environmental planning models are based on a fixed structure where demand side technologies are competing together solely for a given useful (e.g. lighting). Based on our hybrid modeling structure (OSeMOSYS coupled with a Share of Choice model), "behavioral" kinds of trade-offs (e.g. between different final energy demands, like transportation and lighting) could be addressed directly at the level of the model structure.

Appendix A. Additions and modifications in the OSeMOSYS code

In the present section, we present the principal additions and modifications that were done in UTOPIA's OSeMOSYS code in order to obtain our metamodel. Table A.3 gives the correspondence between notations used throughout this paper and notations used for the modeling in OSeMOSYS. In the modeling file, the following additions or modifications were done:

```
set CAMPAIGN := 0..1;
param COST_CAMPAIGN;
param COST_SUBVENTION;
var campaign binary;
var subvention >=0;
param NB_RESPONDENT;
set RESPONDENT:= 1..NB_RESPONDENT;
param BIGM;
param U{c in CAMPAIGN,r in RESPONDENT};
var preference{r in RESPONDENT} binary;
var share;

minimize cost: (sum{r in REGION, y in YEAR} TotalDiscountedCost[r,y])
+ COST_CAMPAIGN * campaign
+ COST_SUBVENTION * subvention ;

subject to share_of_choice_1 {r in RESPONDENT}:
U[0,r] * (1-campaign) + U[1,r] * campaign + subvention
>= (preference[r]-1)* BIGM;

subject to share_of_choice_2 {r in RESPONDENT}:
U[0,r] * (1-campaign) + U[1,r] * campaign + subvention
<= preference[r]* BIGM;

subject to total_share:
   share= sum{r in RESPONDENT} preference[r]/NB_RESPONDENT;

subject to share1 {y in YEAR} :
TotalCapacityAnnual ["UTOPIA", "RL1", y]  =
(1-share) * SpecifiedAnnualDemand["UTOPIA", "RL", y];

subject to share2 {y in YEAR} :
TotalCapacityAnnual ["UTOPIA", "RL2", y]  =
share * SpecifiedAnnualDemand["UTOPIA", "RL", y];
```

In the data file, the following additions were done:

```
param COST_CAMPAIGN := 20;
param COST_SUBVENTION := 6.2;
```

```
param BIGM:= 99;
param NB_RESPONDENT := 120;

param U:=
0 1 1
0 2 1
0 3 1
0 4 -4.5
0 5 1
0 6 -6
.
.
.
1 118 -5.1
1 119 1
1 120 1
;
```

To keep this section readable, modifications done for the introduction of the LED bulbs are not displayed here and can be found in the supplementary data.

Appendix B. Supplementary data

Supplementary data to this article can be found in the attached file metamodel.zip. It contains three files. The files metamodel.mod and metamodel.dat contain the modeling and the data. The file metamodel.run contains the commands (AMPL environment) to run the optimization and retrieve the interesting results. Results can then be viewed with Matlab or Octave.

References

Abilock, H., Fishbone, L. G., 1979. User's Guide for MARKAL (BNL Version). BNL 27075.

Agarwal, J., Desarbo, W. S., Malhotra, N. K., Rao, V. R., 2015. An interdisciplinary review of research in conjoint analysis: Recent developments and directions for future research. Customer Needs and Solutions 2, 19–40.

Data	notation	notation in OSeMOSYS
Respondent	$r \in R$	r in RESPONDENT
Year	$y \in Y$	y in YEAR
Cost of campaign	c_i	COST_CAMPAIGN
Cost of subventions	c_s	COST_SUBVENTION
Part-worth	$U(i, r)$	U[c,r]
Big number	M	BIGM
Forecasted annual demand	d(y)	SpecifiedAnnualDemand[,"RL",y]

Variable	notation	notation in OSeMOSYS
Information campaign level	$i \in \{0, 1\}$	campaign
Subvention level	$s \geq 0$	subvention
Preference	$p(r) \in \{0, 1\}$	preference
LED bulbs' share	l	share
Fluorescent bulbs' capacity	$z_1(y)$	TotalCapacityAnnual [,"RL1",y]
LED bulbs' capacity	$z_2(y)$	TotalCapacityAnnual [,"RL2",y]

Table A.3: Notation for data and variables.

Albers, S., Brockhoff, K., 1977. A procedure for new product positioning in an attribute space. European Journal of Operational Research 1 (4), 230–238.

Amorim, F., Pina, A., Gerbelová, H., da Silva, P. P., Vasconcelos, J., Martins, V., 2014. Electricity decarbonisation pathways for 2050 in Portugal: A TIMES (The Integrated MARKAL-EFOM System) based approach in closed versus open systems modelling. Energy 69, 104–112.

Arbuthnott, K. D., 2009. Education for sustainable development beyond attitude change. International Journal of Sustainability in Higher Education 10 (2), 152–163.

Camm, J. D., Cochran, J. J., Curry, D. J., Kannan, S., 2006. Conjoint optimization: An exact branch-and-bound algorithm for the share-of-choice problem. Management Science 52 (3), 435–447.

Cayla, J.-M., Maïzi, N., 2015. Integrating household behavior and heterogeneity into the times-households model. Applied Energy 139, 56 – 67.

Daly, H. E., Ramea, K., Chiodi, A., Yeh, S., Gargiulo, M., 2014. Incorporating travel behaviour and travel time into TIMES energy system models. Applied Energy 135, 429–439.

Daly, H. E., Ramea, K., Chiodi, A., Yeh, S., Gargiulo, M., Ó Gallachóir, B., 2015. Modal Shift of Passenger Transport in a TIMES Model: Application to Ireland and California. Vol. 30 of Lecture Notes in Energy. Springer, pp. 279–291.

Debreu, G., 1960. Topological methods in cardinal utility theory. In: Arrow, K. J., Karlin, S., Suppes, P. (Eds.), Mathematical Methods in the Social Sciences. Vol. 73. University Press, Stanford, pp. 16–26.

Fishbone, L. G., Abilock, H., 1981. MARKAL, a linear-programming model for energy systems analysis: Technical description of the BNL version. International Journal of Energy Research 5 (4), 353–375.

Fragnière, E., Heitz, C., Moresino, F., 2008. The concept of shadow price to monetarize the intangible value of expertise. In: Proceedings of the IEEE International Conference on Service Operations and Logistics, and Informatics, 2008. IEEE, pp. 1736–1741.

Fragnière, E., Kanala, R., Lavigne, D., Moresino, F., Nguene, G., 2010. Behavioral and Technological Changes Regarding Lighting Consumptions: A MARKAL Case Study. Low Carbon Economy 1 (1), 8–17.

Fragnière, E., Lombardi, A., Moresino, F., 2012. Designing and pricing services based on customer-perceived value: An airline company feasibility study. Service Science 4 (4), 320–330.

Giraudet, L.-G., Guivarch, C., Quirion, P., 2012. Exploring the potential for energy conservation in french households through hybrid modeling. Energy Economics 34 (2), 426 – 445.

Gollwitzer, P. M., Sheeran, P., 2006. Implementation intentions and goal achievement: A metaanalysis of effects and processes. Vol. 38 of Advances in Experimental Social Psychology. Academic Press, pp. 69 – 119.

Green, P. E., Krieger, A. M., Agarwal, M. K., 1993. A cross validation test of four models for quantifying multiattribute preferences. Marketing Letters 4 (4), 369–380.

Green, P. E., Rao, V. R., 1971. Conjoint measurement for quantifying judgmental data. Journal of Marketing Research, 355–363.

Gruca, T. S., Klemz, B. R., 2003. Optimal new product positioning: A genetic algorithm approach. European Journal of Operational Research 146 (3), 621–633.

Homburg, C., Koschate, N., Hoyer, W. D., 2005. Do satisfied customers really pay more? a study of the relationship between customer satisfaction and willingness to pay. Journal of Marketing 69 (2), 84–96.

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., Hughes, A., Silveira, S., DeCarolis, J., Bazillian, M., Roehrl, A., 2011. OSeMOSYS: the open source energy modeling system: an introduction to its ethos, structure and development. Energy Policy 39 (10), 5850–5870.

Jaffe, A. B., Stavins, R. N., 1994. The energy paradox and the diffusion of conservation technology. Resource and Energy Economics 16 (2), 91 – 122.

Kairu-Wanyoike, S. W., Kaitibie, S., Heffernan, C., Taylor, N. M., Gitau, G. K., Kiara, H., McKeever, D., 2014. Willingness to pay for contagious bovine pleuropneumonia vaccination in Narok South District of Kenya. Preventive Veterinary Medicin 115 (3-4), 130–142.

Kannan, R., 2011. The development and application of a temporal MARKAL energy system model using flexible time slicing. Applied Energy 88 (6), 2261 – 2272.

Kim, J.-Y., Natter, M., Spann, M., 2009. Pay what you want: A new participative pricing mechanism. Journal of Marketing 73 (1), 44–58.

Loulou, R., Remme, U., Kanudia, A., Lehtila, A., Goldstein, G., 2005. Documentation for the TIMES Model.

Luce, R. D., Tukey, J. W., 1964. Simultaneous conjoint measurement: a new scale type of fundamental measurement. Journal of Mathematical Psychology 1 (1), 1–27.

Manne, A., Mendelsohn, R., Richels, R., 1995. Merge: A model for evaluating regional and global effects of GHG reduction policies. Energy Policy 23 (1), 17 – 34.

Maros, I., Arabatzis, G., Sifaleras, A., 2009. Special issue on optimization models in environment and sustainable development. Operational Research 9 (3), 225–227.

Murphy, R., Jaccard, M., 2011. Energy efficiency and the cost of GHG abatement: A comparison of bottom-up and hybrid models for the US. Energy Policy 39 (11), 7146 – 7155.

Nguene, G., Fragnière, E., Kanala, R., Lavigne, D., Moresino, F., 2011. Socio-MARKAL : Integrating energy consumption behavioral changes in the technological optimisation framework. Energy for Sustainable Development 15 (1), 73–83.

Oltman, A. E., Jervis, S. M., Drake, M. A., 2014. Consumer attitudes and preferences for fresh market tomatoes. Journal of Food Science 79 (10), S2091–S2097.

Ramea, K., Yang, C., Yeh, S., Bunch, D., Ogden, J., June 2013. Incorporation of consumer demand in energy systems models and their implications for climate policy analysis. International Energy Workshop 2013, Paris.

Rivers, N., Jaccard, M., 2005. Combining top-down and bottom-up approaches to energy-economy modeling using discrete choice methods. The Energy Journal 26 (1), 83–106.

Shogren, J. F., Taylor, L. O., 2008. On behavioral-environmental economics. Review of Environmental Economics and Policy 2 (1), 26–44.

Srinivasan, V., Shocker, A. D., 1973. Linear programming techniques for multidimensional analysis of preferences. Psychometrika 38 (3), 337–369.

Sundstrom, E., Bell, P. A., Busby, P. L., Asmus, C., 1996. Environmental psychology 1989-1994. Annual Review of Psychology 47 (1), 485–512.

Wang, X. J., Camm, J. D., Curry, D. J., 2009. A branch-and-price approach to the share-of-choice product line design problem. Management Science 55 (10), 1718–1728.

Welsch, M., Deane, P., Howells, M., Ó Gallachóir, B., Rogan, F., Bazilian, M., Rogner, H.-H., 2014. Incorporating flexibility requirements into long-term energy system models a case study on high levels of renewable electricity penetration in Ireland. Applied Energy 135, 600–615.

Wooliscroft, B., Ganglmair-Wooliscroft, A., 2014. Improving conditions for potential New Zealand cyclists: An application of conjoint analysis. Transportation Research: Part A: Policy and Practice 69, 11–19.

Wu, J., Zhu, Q., Yin, P., Song, M., 2015. Measuring energy and environmental performance for regions in china by using dea-based malmquist indices. Operational Research, 1–21.