energies

Article

Combining Behavioral Approaches with Techno-Economic Energy Models: Dealing with the Coupling Non-Linearity Issue

Francesco Moresino [1,*] and Emmanuel Fragnière [2,3]

1 Geneva School of Business Administration, University of Applied Sciences Western Switzerland (HES-SO Genève), Carouge 1227, Switzerland
2 Service Design Lab (IEM), University of Applied Sciences Western Switzerland (HES-SO Valais), Sierre 3960, Switzerland; emmanuel.fragniere@hevs.ch
3 School of Management, University of Bath, Bath BA2 7AY, UK
* Correspondence: francesco.moresino@hesge.ch; Tel.: +41-22-388-18-82

Received: 6 June 2018; Accepted: 4 July 2018; Published: 7 July 2018

Abstract: Consumer behaviour is often complex and even sometimes not economically rational. Wrongly, the first techno-economic energy planning models assumed the economic rationality hypothesis and, therefore, represented consumers' behaviour incorrectly. Nevertheless, the current trend is to couple these models with behavioural approaches that were specially developed to describe the real consumer choices. A novel approach was recently proposed, where a classical energy model is coupled with a share of choice model. This new approach has however two weaknesses. First, the share of choice increases the computational complexity as it necessitates additional binary variables for the modelling. Second, for complex models, the inclusion of the share of choice can lead to non-linearity and hence to severe computational problems. In the present paper, we propose to improve this method by externalizing the share of choice. Doing so, the number of binary variable will be reduced and the linearity property will be kept even for complex models.

Keywords: consumer behaviour; energy and environmental planning model; mathematical programming; optimization; share of choice model; hybrid energy model; behavioural operational research

1. Introduction

In the 1970s, the first oil shock followed by a second forced governments and agencies to reconsider their energy policies as they were too dependent on oil. In this context, decisions makers required the help of energy models in order to evaluate the economic impact of the policies they envisaged to implement [1]. As it was a vital issue, this contributed to the rapid development of energy modelling [2]. Two decades later, while the oil shocks were a distant memory, the interest in energy modelling decreased. However, at the same time, in order to fight against global warming, countries envisaged reducing their greenhouse gas emissions, which led, among others, to the Kyoto Protocol and later the Paris Agreement [3,4]. Consequently, after a small stagnation, a net regain of interest in energy models arose as the flourishing literature shows (see for example [5–7] for recent reviews).

Put simply, at the beginning of the development of energy models, two approaches were envisaged. On one side, engineers built bottom-up models driven by technologies, whereas on the other side, economists built top-down models driven by aggregate macroeconomic variables. The family of models that were originally bottom-up includes, among others, MARKAL (Market Allocation) [8,9] and TIMES (The Integrated MARKAL-EFOM System) [10,11] developed under the aegis of the International

Energy Agency; MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) [12] developed by the International Institute for Applied Systems Analysis; and OSeMOSYS (Open Source Energy Modelling System) [13,14] a quite recent open source model that has spread rapidly since its launch. The top-down family is comprised of, among others, DICE (Dynamic Integrated Climate-Economy) and RICE (Regional Integrated Climate-Economy) [15,16] developed by Nordhaus or EPPA (Emissions Prediction and Policy Analysis) [17] developed at the MIT Joint Program on the Science and Policy of Global Change. Of course, both approaches have their strengths and weaknesses. The main weakness of the top-down approach is the lack of precision in the technology description. It makes policies grounded on aggregate technologies that do not represent the reality in the field. However, this approach has the advantage of proposing overall and integrated policies. For the bottom-up approach, relying on perfect economy rationality axioms (perfect economy rationality axioms should be read in the sense that each actor maximizes his/her long-term profit), which do not correspond to the actual consumer behaviour, is a significant weakness since the resulting policies are not practical for decision making. This approach has, on the other hand, the advantage of handling a huge amount of technical data, which makes possible a direct link between the proposed policy and the decision maker. The debate between both models was mainly focused on the energy efficiency gap, i.e., the unexploited potential for energy efficiency that is economically rational [18–21]. Indeed, bottom-up models tend to underestimate the energy efficiency gap, whereas top-down models tend to overestimate it [22]. More generally, the ideal energy model should perform well with regard to three criteria : the technological explicitness, the microeconomic realism and the macroeconomic completeness [22]. As a matter of fact, hybrid models, which integrate both top-down and bottom-up logics, are the only ones that perform well along all three dimensions, and nowadays, the debate between top-down and bottom-up models is obsolete as there is a consensus for hybrid modelling. This context stimulated the development of Integrated Assessment Models (IAM) that combine knowledge from different domains into a single framework [23]. The family of IAM includes, among others, IGSM (Integrated Global System Model) [24,25] developed at the MIT Joint Program on the Science and Policy of Global Change; WEM (World Energy Model) [26] developed at the International Energy Agency; or GCAM (Global Change Assessment Model) [27,28] developed at the University of Maryland. In this trend to combine techniques from different domains, it is worth noting the increasing use of behavioural economics approaches to understand consumers' real choices regarding energy consumption (see for instance [29–33] for recent applications). For the modelling of the production, transformation and distribution of energy, techniques coming from the domain of the supply chain are widely used. Among the recent publications concerning supply chain optimization with applications to energy, we can mention: [34], where the production of biogas and electricity is optimized; [35] for an optimization of district heating systems with thermal energy storages; [36], where the extraction and transformation of shale gas into gas and electricity is optimized; [37] for an optimization of the transformation of biomass into heat and electricity. For recent reviews, we can mention, among others: [38], where they investigate the new methods of operations research in supply chain optimization; [39] for a focus on supply chain network design under uncertainty; and [40], where they concentrate on sustainable supply chain management.

In the 1950s and 1960s, the development of mathematical psychology [41–43] permitted making a breakthrough in the modelling of consumers' behaviour, which opened the door to the development of conjoint analysis. Since the first approach to describe consumers' preference [44], conjoint analysis has become an important and popular tool in marketing science (see [45] for a recent literature review). The first product design optimizer using the paradigm of conjoint analysis was proposed by [46]. This model, which will be named later the share of choice, maximizes the share of preference and is formulated as a mixed integer linear program. In order to take into consideration some production aspects, [47] augmented the share of choice model. Inspired by this work, to take into account in a realistic way the production constraints, [48] proposed to couple the share of choice model with a production model. The method was then used to solve problems in different domains [49–51]. Following this idea, [52] combined a classical energy model with the share of choice model. This approach, which combines a behavioural method with operational research, has however two drawbacks. First, the share of choice model contains many additional binary variables, which, in turn, increases the computational complexity of the energy model. Second, the linearity property is not preserved for models where the market share may vary over time. Indeed, to couple the share of choice model with the energy model, decision variable from this latter model have to be multiplied by market shares (i.e., variables), which leads to non-linear modelling.

The present paper proposes an extension of this method by externalizing the share of choice model. Our new approach enables us to bypass both drawbacks. First, it reduces the number of binary variables and, consequently, the computational complexity. Second, the linearity property is preserved even for models where the market share may vary over time. For instance, contrary to the old approach, this new approach allows one to model cases where the consumers' behaviour evolves in time. Practically, this method has three steps. Firstly, using standard techniques of conjoint analysis, the consumers' utility functions are estimated with a survey. Secondly, with the help of a share of choice model, the consumers' behaviour is quantified into market share data. Thirdly, the market shares are input into the energy model using a specific modelling. Figure 1 schematizes the approach presented in this paper as opposed to the one proposed in [52].

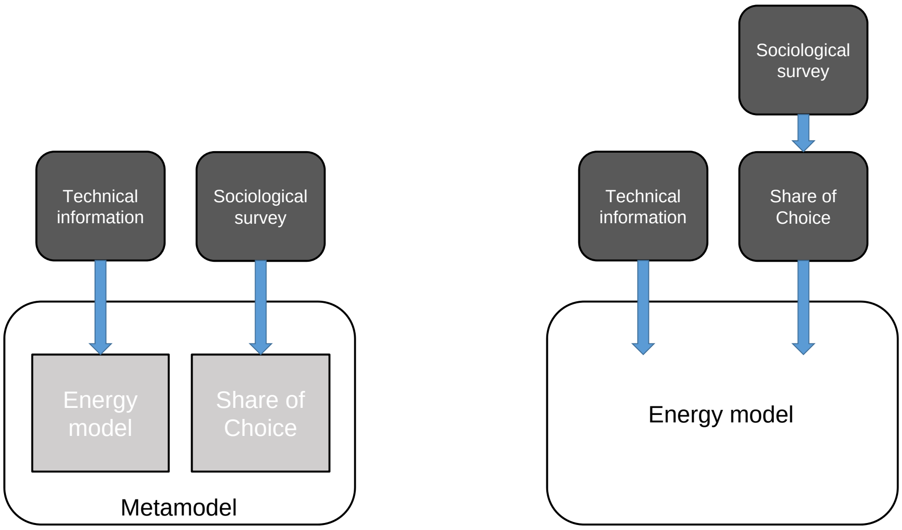

Figure 1. Coupling techno-economic energy models with behavioural approaches. On the left, the method proposed in [52]. On the right, the method proposed in the present paper.

To illustrate how the proposed method can be implemented, we use a case study. This case study explores the consumer preferences between fluorescent and Light-Emitting Diode (LED) bulbs under different government policies and combines the energy model UTOPIA [13] and a survey evaluating the consumers' preference between both bulbs [52]. The aim of this case study is not to provide the reader with elements of energy policy, but rather to demonstrate the feasibility of the concept first and then to show what kinds of results the method can offer.

The paper is organized as follows. In Section 2, we first introduce the case study, which will illustrate the method. Then, we present the method that externalizes the share of choice model from the techno-economic model. In Section 3, we present and discuss the case study results. Finally, in Section 4, we conclude and give further research directions.

2. Proposed Method

2.1. The Case Study

The principal aim of this case study is to show how the method proposed in the present paper can be implemented. For this purpose, we use the same case study as [52]. This case study explores the consumer preferences between fluorescent and LED bulbs under two different government policies, namely an information campaign and a subvention campaign promoting the more efficient LED bulb. Case studies focusing on light bulbs are very practical to illustrate in a simple way economic irrationality. Indeed, if consumers were rational, they would only buy LED bulbs and not fluorescent bulbs, which is obviously not the case in reality. The case study combines the energy model UTOPIA [13] and a survey evaluating the consumers' preference between fluorescent and LED bulbs [52]. UTOPIA describes the complete energy system of a fictive country and is implemented with the open source code OSeMOSYS. The survey was conducted in Romania and estimates the Willingness To Pay (WTP) for the LED bulbs before an information campaign, as well as the WTP after an information campaign. Details about the case study and the survey can be found in [52].

2.2. Externalizing the Share of Choice

The method implemented to externalize the share of choice has two steps. First, using the share of choice model, the market share is computed for all possible designs (in our example, the designs of all possible campaigns). Second, these market shares are introduced in the energy model as parameters. To do so, different constraints are added to the energy model, in order to include the share of choice information. We will describe this modelling by taking a simple example as an illustration. Suppose we have to design a service with only one salient attribute and where a single attribute level must be chosen. The possible levels for this attribute are denoted with the discrete parameter $i \in I$. We denote with $l(i)$ the market share, given the design i is chosen. The market shares $l(i)$ are calculated directly from the survey based on conjoint analysis techniques. Then, we incorporate in our model the binary decision variables $k(i)$, where $k(i) = 1$ if the service design takes i as the attribute level and $k(i) = 0$ otherwise. Of course, as one and only one design must be chosen, we have to add the constraint $\sum_i k(i) = 1$. The market share writes then $l = \sum_i l(i) \cdot k(i)$. Unfortunately, except for static models, the market share has to be multiplied with another variable, and we consequently lose the linearity property. To avoid this issue, we propose an alternate solution. Suppose that in our model, we have to compute $p = n \cdot l$, where n is a variable. Instead of using this nonlinear equation, we will use the following equations:

$$p \leq n \cdot l(i) + M(1 - k(i)) \quad \forall i \in I, \tag{1}$$
$$p \geq n \cdot l(i) - M(1 - k(i)) \quad \forall i \in I, \tag{2}$$

where M is a big number. Indeed, if i is not the chosen level, we have $k(i) = 0$, and Equations (1) and (2) become:

$$p \leq n \cdot l(i) + M \quad \forall i \in I, \tag{3}$$
$$p \geq n \cdot l(i) - M \quad \forall i \in I. \tag{4}$$

If M is chosen big enough (i.e., $M > \max_i(|n \cdot l(i)|)$), these two constraints are never binding. In contrast, if the chosen level is i, we have $k(i) = 1$, and Equations (1) and (2) become:

$$p \leq n \cdot l(i) \quad \forall i \in I, \tag{5}$$
$$p \geq n \cdot l(i) \quad \forall i \in I, \tag{6}$$

which leads to the desired result preserving the linearity property.

2.3. The Model

To take into account the consumers' real preferences, we must convert the survey results into data for the model. In our example, the only information needed is the share of consumers choosing LED bulbs, given the policy chosen by the government. To keep the model as simple as possible, we suppose that the policy and the proportion of LED buyers cannot vary throughout the time horizon. Note that we could easily describe the more realistic case where the policy is not static and where the effect of the campaigns follows a dynamic process with inertia and erosion.

Before starting, let us mention that the notations used throughout the paper are given in Table 1.

Table 1. Notation for data and variables.

Data	**Notation**	**Notation in OSeMOSYS**
Year, period	$y \in Y$	y in YEAR
Information campaign level	$i \in I$	c in CAMPAIGN
Subvention level	$s \in S$	s in SUBVENTION
Cost of the information campaign	$c_{\text{cam}}(i)$	COST_CAMPAIGN[c]
Subvention's acceptance factor	a	ACCEPTANCE_SUBVENTION
Market share of LED bulbs	$l(i,s)$	SHARE[c,s]
Fluorescent bulb operational life	t_1	OperationalLife[,"RL1"]
LED bulb operational life	t_2	OperationalLife[,"RL2"]
Big number	M	BIGM
Decision variable	**Notation**	**Notation in OSeMOSYS**
Information campaign level	$k(i) \in \{0,1\}$	campaign[c]
Subvention level	$j(s) \in \{0,1\}$	subvention[s]
New capacity of fluorescent bulbs	$n_1(y)$	NewCapacity[,"RL1",y]
New capacity of LED bulbs	$n_2(y)$	NewCapacity[,"RL2",y]
Help variable	**Notation**	**Notation in OSeMOSYS**
Subvention's cost	c_{sub}	cost_subvention
Total LED bulbs bought	z	LED_bought

Though in our example, the choice for the information campaign is binary (we have either a campaign or no campaign), we will describe here the general case, where different campaign levels can be chosen. We denote with i the information campaign level and I the set of all possible campaign levels, where $i = 0$ means no campaign is conducted. The choice of the campaign is described with the binary variables $k(i)$, where $k(i)$ equals one if the chosen campaign level is i and zero otherwise. Of course, one and only one level has to be chosen, which translates into $\sum_{i \in I} k(i) = 1$.

For the subvention level, we take discrete values ranging from zero (i.e., no subvention) to the actual price of the LED bulb (i.e., LED bulbs are given for free). We denote with s the subvention level and S the set of all possible subvention levels. The choice of the subvention level is described with the binary variables $j(s)$, where $j(s)$ equals one if the chosen subvention level is s and zero otherwise. Of course, one and only one level has to be chosen, which translates into $\sum_{s \in S} j(s) = 1$.

We denote with $y \in Y$ the different possible periods in our model and with y_0 the first period. Subsequently, we will call the set Y the time horizon. Let $n_1(y)$ represent the new capacity of fluorescent bulbs and $n_2(y)$ the new capacity of LED bulbs. Let c_{sub} be the cost of the subvention campaign. Our model minimizes the overall cost for the society, and the subvention is paid by the government to consumers. Therefore, what is paid from one side is received by the other side, and the overall cost for the society is zero. In our model, the cost of the subvention should then be seen as an acceptance cost. Obviously, it should lie between zero and the total amount of expenses spent by the government. Indeed, the acceptance cost cannot be larger than the cost itself. In our model, we denote with a the percentage of the subvention that is accounted as an acceptance cost for the society.

Let x be the variables describing the activities in the classical energy model. Note that $n_1(y)$, $n_2(y)$, $k(i)$ and $j(s)$ belong to this vector. The energy model without taking the consumers' purchasing behaviour writes:

$$\min_x c \cdot x \tag{7}$$

subject to

$$A \cdot x \geq b. \tag{8}$$

In plain words, the model minimizes the overall costs subject to the energy supply chain constraints and belongs to the class of mixed integer programs. Then, in the extended model, we introduce the consumer purchasing behaviour in the following way. From the survey, we compute the market share of LED bulbs given a policy, and we denote with $l(i,s)$ these data. For the modelling, we make three logical assumptions. First, for the residual capacity replacement (i.e., the replacement of bulbs installed prior to the time horizon), the market share of LED bulbs is $l(i,s)$. Second, for new demand, the market share of LED bulbs is $l(i,s)$. Third, for the replacement of bulbs that were installed during the time horizon, each bulb is replaced with an identical one (i.e., consumers are consistent over time). This behaviour is introduced in the model as follows. We denote with t_1 (respectively t_2) the operational life of the fluorescent bulb (respectively LED bulb). During the first years, before the first bulbs installed during the time horizon have to be replaced (i.e., for $y - y_0 < t_1, t_2$), we have:

$$n_2(y) = (n_1(y) + n_2(y)) \sum_{i,s} l(i,s) \cdot k(i) \cdot j(s). \tag{9}$$

Unfortunately, this standard way does not preserve linearity. We therefore use the alternate modelling proposed in Equations (1) and (2) and impose that:

$$n_1(y) \leq n_2(y) \frac{1 - l(i,s)}{l(i,s)} + M(1 - k(i)) + M(1 - j(s)) \quad \forall i \in I \quad \forall s \in S, \tag{10}$$

$$n_1(y) \geq n_2(y) \frac{1 - l(i,s)}{l(i,s)} - M(1 - k(i)) - M(1 - j(s)) \quad \forall i \in I \quad \forall s \in S, \tag{11}$$

where M is a big number. For $t_1 \leq y - y_0 < t_2$, we have to take into account the replacement of fluorescent bulbs installed during the time horizon:

$$n_1(y) - n_1(y - t_1) \leq n_2(y) \frac{1 - l(i,s)}{l(i,s)} + M(1 - k(i)) + M(1 - j(s)) \quad \forall i \in I \quad \forall s \in S, \tag{12}$$

$$n_1(y) - n_1(y - t_1) \geq n_2(y) \frac{1 - l(i,s)}{l(i,s)} - M(1 - k(i)) - M(1 - j(s)) \quad \forall i \in I \quad \forall s \in S. \tag{13}$$

Finally, for $y - y_0 \geq t_1, t_2$, we have to take into account the replacement of both fluorescent and LED bulbs installed during the time horizon:

$$n_1(y) - n_1(y - t_1) \leq (n_2(y) - n_2(y - t_2)) \frac{1 - l(i,s)}{l(i,s)} + M(1 - k(i)) + M(1 - j(s)) \quad \forall i \in I \quad \forall s \in S, \tag{14}$$

$$n_1(y) - n_1(y - t_1) \geq (n_2(y) - n_2(y - t_2)) \frac{1 - l(i,s)}{l(i,s)} - M(1 - k(i)) - M(1 - j(s)) \quad \forall i \in I \quad \forall s \in S. \tag{15}$$

Let $z = \sum_y n_2(y)$ be the total amount of LED bulbs bought during the time horizon (to keep it simple, we omit the conversion factors encountered in OSeMOSYS). Applying the same alternate modelling preserving linearity, the subvention's acceptance cost must satisfy:

$$c_{\text{sub}} \leq a \cdot z \cdot s + M(1 - j(s)) \quad \forall s \in S, \tag{16}$$

$$c_{\text{sub}} \geq a \cdot z \cdot s - M(1 - j(s)) \quad \forall s \in S. \tag{17}$$

These two equations ensure that the acceptance cost equals the total costs of the subvention campaign (total LED bulbs bought multiplied by the subvention per bulb) multiplied by the acceptance factor a.

The model has been implemented using the open source OSeMOSYS code and is available as Supplementary Material. The files model.mod and model.dat contain the model and the data. The file model.run contains commands to run the optimization in the AMPL environment and save interesting results in a format readable by MATLAB or Octave. Here, in the core of the paper, we intentionally used compact notations to describe our model. Details of the the key points' implementation in OSeMOSYS can be found in Appendix A. Table 1 gives the correspondence between notations used throughout this paper and notations used in OSeMOSYS.

2.4. Data

Except two changes, we use the same dataset as in [52]. In their study, to simplify modelling, they made a change from the original UTOPIA model: they assumed that the bulbs' residual capacity was null. They did this small change in order to keep their model as simple as possible. Indeed, without this modification, it would have been necessary to introduce new computed parameters in order to be able to keep the linearity of their model. Our approach does not suffer from this problem, and we can take the same residual capacity as in the original UTOPIA model, namely 5.6 PJ/year. The second change concerns the information campaign cost. As explained in [52], the cost of the campaign is evaluated from observations based on the study in [53] and amounts to 20 million dollars for the whole horizon. Since this is an estimation, they also took a more pessimistic estimation of 40 million dollars as a second scenario. In the present paper, in light of discussions with specialists, we decided not to change the low scenario (20 million dollars), but to take a cost of 300 million dollars for the high scenario. This high range between both scenarios reflects the fact that these figures rely on rough estimations. Finally, following [52], we take for the subvention's acceptance factor $a = 50\%$ and, as this factor is extremely hard to estimate, conduct a marginal analysis for this parameter.

3. Results and Discussion

Though the model can be solved using the open source environment GNU MathProg, we used the solver Mosek in the AMPL environment. All files used for the experiment are provided as Supplementary Materials. We solved the model on an Intel Core i5-4590 computer with a CPU (central processing unit) of 3.3 GHz and 8 Go RAM (random-access memory). The model had 36,229 linear variables, 12 binary variables and 34,416 constraints. For this small model, the CPU time for the resolution was about 0.10 s. The principal aim of this numerical experiment was to show how our method externalizing the share of choice can be implemented. This case study also demonstrated the benefits of externalizing the share of choice model compared to the direct method proposed in [52]. As mentioned in the previous section, with our method, we were able to take into account residual capacities without introducing extra parameters, as is the case with the direct method. Moreover, our approach could easily take into account the more realistic case where the policy was not static and where the effect of the campaigns followed a dynamic process with inertia and erosion. This cannot be taken into account by the direct method of [52]. Indeed, due to coupling non-linearity issues, the resulting model would be a non-convex non-linear model for which no standard solving method is available. This provides a definitive argument in favour of our method. To explore the performance of the direct method (i.e., the method where the share of choice is not externalized), we took a simplified version of the case study where the residual capacities were null. This simplified model had 36,229 linear variables, 132 binary variables and 33,692 constraints. For this simplified model, the CPU time for the resolution was about 0.18 s, which is clearly higher than before.

A second aim of this case study was to illustrate the kind of results the method could provide. The rest of the section analyses the results obtained from the case study.

For the low scenario, we observe that it was optimal to run an information campaign and not to give a subvention. The total discounted cost over the whole horizon of 20 years was 27,545 million dollars. A marginal analysis showed that the threshold point for the subvention's acceptance factor was 2.2%. Indeed, below this point, it was optimal to give a subvention of four dollars per LED bulb and not to run an information campaign.

For the high scenario, it was optimal not to run an information campaign and not to give a subvention. The total discounted cost for the whole horizon was 27,554 million dollars. For the subvention's acceptance factor, the threshold was 3.3%. For a subvention acceptance factor lower than this point, it was optimal to give a subvention of four dollars per LED bulb and not to run an information campaign.

These results were comparable with those of [52], and we concluded that, for this dataset, a subvention campaign would probably not be accepted by the population. Finally, this case study shows the benefits of coupling a behavioural approach with a techno-economic model. Indeed, our model reflects perfectly the consumer purchasing behaviour estimated through the survey even if consumers are not economically rational. Actually, without the inclusion of the behavioural approach, the proportion of LED bulbs would have been 100%, as they are economically more efficient than fluorescent bulbs. For both scenarios, Figure 2 shows the bulbs' installed capacity, whereas Figure 3 shows the bulbs' penetration.

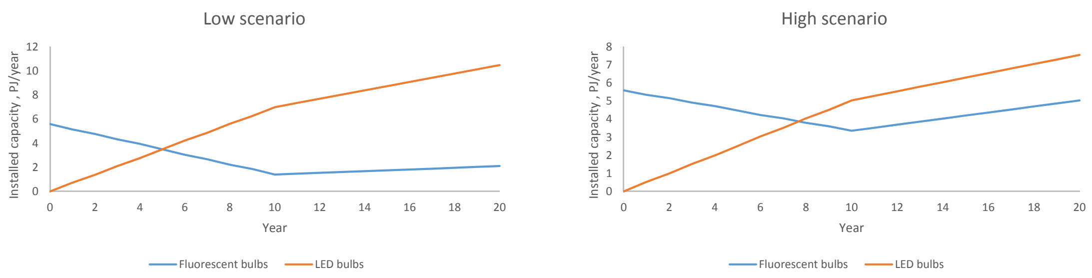

Figure 2. Installed capacity for both scenarios.

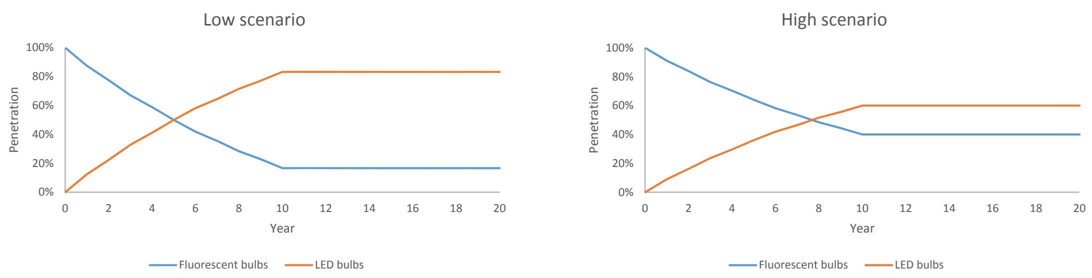

Figure 3. Bulbs' penetration for both scenarios.

4. Conclusions

In the present paper, we proposed a new method that permits one to represent the real consumer's behaviour in an energy model even if this behaviour is not economically rational. This method combines conjoint analysis with a techno-economic energy model and improves the method proposed in [52] by externalizing the share of choice model. This new approach offers two advantages compared to the old one. First, it reduces the number of binary variables and, hence, the computational complexity. Second, it allows us to keep the linearity property even for more complex models. We particularly think about models where the consumer's choice follows a dynamic process. For this class of model, the old approach would lead to a non-convex non-linear model for which no standard solving method is available.

We illustrated the methodology with the same case study as [52]. The case study explored the consumer preferences between fluorescent and LED bulbs under two different government policies, namely an information campaign and a subvention campaign promoting the more efficient LED bulb. It was implemented with the open source code OSeMOSYS and is available as Supplementary Material. As such, all developments in this research were based on open source tools so that other energy modellers can also integrate behavioural approaches in their models.

The method proposed in the present paper is versatile and can easily be adapted to other problems. In our view, nothing limits nor constrains the use of our approach for other datasets, other types of techno-economic energy models or other problems. In this paper, the analysis has focused on a single behavioural factor, which is the consumers' behaviour with regard to light bulbs. The method can be implemented to take into account simultaneously other factors such as the consumers' behaviour with regard to heating and transportation. In this study, we focused on the design of government policies, but the method can be used for designing new products or services. For instance, the method can be used for the design of a car sharing service, i.e., to chose the best characteristic of the service taking into account economic constraints and the impacts on the traffic and the environment.

To conclude, in the trend of hybrid modelling, the present paper contributes to better integrating real consumers' behaviour in the techno-economic model. In further research, we intend to develop a model where the government policies can vary and where the effect of the campaigns follows a dynamic process with inertia and erosion.

Supplementary Materials: Supplementary Materials are available online at http://www.mdpi.com/1996-1073/11/7/1787/s1.

Author Contributions: F.M. and E.F. conceived of and designed the experiments. F.M. performed the experiments and analysed the data. F.M. and E.F. wrote the paper.

Funding: This research was funded by Schweizerischer Nationalfonds zur Förderung der Wissenschaftlichen Forschung grant number IZERZO_142217.

Acknowledgments: This work was supported by the Swiss Enlargement Contribution in the framework of the Romanian-Swiss Research Programme (Grant IZERZO_142217).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

LED	Light-Emitting Diode
WTP	Willingness To Pay
PJ	Petajoule
GHG	Greenhouse Gas
MARKAL	Market Allocation
TIMES	The Integrated MARKAL-EFOM System
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impact
OSeMOSYS	Open Source Energy Modelling System
DICE	Dynamic Integrated Climate-Economy
RICE	Regional Integrated Climate-Economy
EPPA	Emissions Prediction and Policy Analysis
IAM	Integrated Assessment Model
IGSM	Integrated Global System Model
WEM	World Energy Model
GCAM	Global Change Assessment Model
CPU	Central Processing Unit

LED	Light-Emitting Diode
WTP	Willingness To Pay
PJ	Petajoule
GHG	greenhouse gas
MARKAL	Market Allocation
TIMES	The Integrated MARKAL-EFOM System
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impact
OSeMOSYS	Open Source Energy Modelling System
DICE	Dynamic Integrated Climate-Economy
RICE	Regional Integrated Climate-Economy
EPPA	Emissions Prediction and Policy Analysis
IAM	Integrated Assessment Model
IGSM	Integrated Global System Model
WEM	World Energy Model
GCAM	Global Change Assessment Model
CPU	Central Processing Unit
RAM	Random-Access Memory
GHz	Gigahertz
Go	Giga Octets
NEMS	The National Energy Modeling System

Appendix A. Modifications in the OSeMOSYS Code

This section presents the major modification made in UTOPIA's OSeMOSYS code in order to implement our method. Table 1 gives the correspondence between notations used throughout this paper and notations used in OSeMOSYS. The following modifications are made in the modelling file:

```
set CAMPAIGN;
set SUBVENTION;
param COST_CAMPAIGN{c in CAMPAIGN};
param ACCEPTANCE_SUBVENTION;
var campaign{c in CAMPAIGN} binary;
var subvention{s in SUBVENTION} binary;
var cost_subvention;
var LED_bought; # million LED bulbs bought
param BIGM;
param SHARE{c in CAMPAIGN, s in SUBVENTION};

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

subject to E_LED_bought:
LED_bought =
(sum {r in REGION, t in TECHNOLOGY, y in YEAR: t = 'RL2'}NewCapacity[r,t,y])*278/14 ;

subject to E1_cost_subvention{s in SUBVENTION}:
cost_subvention <=
ACCEPTANCE_SUBVENTION *LED_bought*s + BIGM* (1-subvention[s]);

subject to E2_cost_subvention{s in SUBVENTION}:
cost_subvention >=
ACCEPTANCE_SUBVENTION *LED_bought*s - BIGM* (1-subvention[s]);
```

```
subject to normalisation1:
sum {c in CAMPAIGN} campaign[c]=1;

subject to normalisation2:
sum {s in SUBVENTION} subvention[s]=1;

subject to share_a1{r in REGION, y in YEAR, c in CAMPAIGN,
s in SUBVENTION: y<first(YEAR)+ OperationalLife[r,"RL1"]}:
NewCapacity[r,"RL1",y] <=
NewCapacity[r,"RL2",y]*((1-SHARE[c,s])/SHARE[c,s])
+ BIGM *(1-subvention[s])+ BIGM *(1- campaign[c]) ;

subject to share_1b1{r in REGION, y in YEAR, c in CAMPAIGN,
s in SUBVENTION: y<first(YEAR)+ OperationalLife[r,"RL1"]}:
NewCapacity[r,"RL1",y]>=
NewCapacity[r,"RL2",y]*((1-SHARE[c,s])/SHARE[c,s])
- BIGM *(1-subvention[s])- BIGM *(1-campaign[c]) ;

subject to share_a2{r in REGION, y in YEAR, c in CAMPAIGN, s in SUBVENTION:
y>=first(YEAR)+ OperationalLife[r,"RL1"] and
y< first(YEAR)+ OperationalLife[r,"RL2"] }:
NewCapacity[r,"RL1",y] -
NewCapacity[r,"RL1",y-OperationalLife[r,"RL1"]] <=
NewCapacity[r,"RL2",y]*((1-SHARE[c,s])/SHARE[c,s])
+ BIGM *(1-subvention[s])+ BIGM *(1-campaign[c]) ;

subject to share_b2{r in REGION, y in YEAR, c in CAMPAIGN, s in SUBVENTION:
y>=first(YEAR)+ OperationalLife[r,"RL1"] and
y< first(YEAR)+ OperationalLife[r,"RL2"] }:
NewCapacity[r,"RL1",y] -
NewCapacity[r,"RL1",y-OperationalLife[r,"RL1"]] >=
NewCapacity[r,"RL2",y]*((1-SHARE[c,s])/SHARE[c,s])
- BIGM *(1-subvention[s])- BIGM *(1-campaign[c]) ;

subject to share_a3{r in REGION, y in YEAR, c in CAMPAIGN, s in SUBVENTION:
y>= first(YEAR)+ OperationalLife[r,"RL2"]}:
NewCapacity[r,"RL1",y] -
NewCapacity[r,"RL1",y-OperationalLife[r,"RL1"]] <=
(NewCapacity[r,"RL2",y]
-NewCapacity[r,"RL2",y-OperationalLife[r,"RL2"]])
*((1-SHARE[c,s])/SHARE[c,s])
+ BIGM *(1-subvention[s])+ BIGM *(1-campaign[c]) ;

subject to share_b3{r in REGION, y in YEAR, c in CAMPAIGN, s in SUBVENTION:
y>= first(YEAR)+ OperationalLife[r,"RL2"]}:
NewCapacity[r,"RL1",y] -
NewCapacity[r,"RL1",y-OperationalLife[r,"RL1"]] >=
(NewCapacity[r,"RL2",y]
-NewCapacity[r,"RL2",y-OperationalLife[r,"RL2"]])
```

```
*((1-SHARE[c,s])/SHARE[c,s])
- BIGM *(1-subvention[s])- BIGM *(1-campaign[c]) ;
```

The following modifications are made in the data file:

```
set CAMPAIGN:= 0 1;
set SUBVENTION:= 0 1 2 3 4 5 6 7 8 9;

param COST_CAMPAIGN:= 0 0 1 20;
param ACCEPTANCE_SUBVENTION:= 0.5;
param BIGM:=9999;

param SHARE:=
0 0 0.600
0 1 0.600
.
.
.
1 8 0.983
1 9 0.992
;
```

References

1. Kohl, W.L. *After the Second Oil Crisis: Energy Policies in Europe, America, and Japan*; Lexington Books: Lanham, MD, USA, 1982.
2. Pfenninger, S.; Hawkes, A.; Keirstead, J. Energy systems modeling for twenty-first century energy challenges. *Renew. Sustain. Energy Rev.* **2014**, *33*, 74–86. [CrossRef]
3. Springer, U. The market for tradable GHG permits under the Kyoto Protocol: A survey of model studies. *Energy Econ.* **2003**, *25*, 527–551. [CrossRef]
4. Luhmann, H.J.; Arens, C. Von den flexiblen Mechanismen des Kyoto Protokolls zu den kooperativen Ansatzen des Ubereinkommens von Paris. *Z. Umweltpolit. Umweltr./J. Environ. Law Policy* **2016**, *39*, 95–101.
5. DeCarolis, J.; Daly, H.; Dodds, P.; Keppo, I.; Li, F.; McDowall, W.; Pye, S.; Strachan, N.; Trutnevyte, E.; Usher, W.; et al. Formalizing best practice for energy system optimization modelling. *Appl. Energy* **2017**, *194*, 184–198. [CrossRef]
6. Riva, F.; Tognollo, A.; Gardumi, F.; Colombo, E. Long-term energy planning and demand forecast in remote areas of developing countries: Classification of case studies and insights from a modelling perspective. *Energy Strategy Rev.* **2018**, *20*, 71–89. [CrossRef]
7. Wiese, F.; Hilpert, S.; Kaldemeyer, C.; Pleßmann, G. A qualitative evaluation approach for energy system modelling frameworks. *Energy Sustain. Soc.* **2018**, *8*, 13. [CrossRef]
8. Fishbone, L.G.; Giesen, G.; Goldstein, G.; Hymmen, H.A.; Stocks, K.J.; Vos, H.; Wilde, D.; Zoelcher, R.; Balzer, C.; Abilock, H. User's guide for MARKAL (BNL/KFA Version 2. 0). A multi-period, linear-programming model for energy systems analysis. 1983. Available online: https://www.osti.gov/biblio/5419690 (accessed on 5 July 2018).
9. Fishbone, L.G.; Abilock, H. MARKAL, a linear-programming model for energy systems analysis: Technical description of the BNL version. *Int. J. Energy Res.* **1981**, *5*, 353–375. [CrossRef]
10. Loulou, R.; Remme, U.; Kanudia, A.; Lehtila, A.; Goldstein, G. Documentation for the TIMES Model. 2016. Available online: https://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-I_July-2016.pdf (accessed on 5 July 2018).
11. Loulou, R.; Labriet, M. ETSAP-TIAM: The TIMES integrated assessment model Part I: Model structure. *Comput. Manag. Sci.* **2008**, *5*, 7–40. [CrossRef]
12. Schrattenholzer, L. *The Energy Supply Model MESSAGE*; International Institute for Applied Systems Analysis (IIASA): Laxenburg, Austria, 1981. Available online: http://pure.iiasa.ac.at/id/eprint/1542/ (accessed on 5 July 2018).

13. Howells, M.; Rogner, H.; Strachan, N.; Heaps, C.; Huntington, H.; Kypreos, S.; Hughes, A.; Silveira, S.; DeCarolis, J.; Bazillian, M.; et al. OSeMOSYS: The open source energy modeling system: An introduction to its ethos, structure and development. *Energy Policy* **2011**, *39*, 5850–5870. [CrossRef]
14. Gardumi, F.; Shivakumar, A.; Morrison, R.; Taliotis, C.; Broad, O.; Beltramo, A.; Sridharan, V.; Howells, M.; Hörsch, J.; Niet, T.; et al. From the development of an open-source energy modelling tool to its application and the creation of communities of practice: The example of OSeMOSYS. *Energy Strategy Rev.* **2018**, *20*, 209–228. [CrossRef]
15. Nordhaus, W.D. An Optimal Transition Path for Controlling Greenhouse Gases. *Science* **1992**, *258*, 1315–1319. [CrossRef] [PubMed]
16. Nordhaus, W.D. *Managing The Global Commons: The Economics of Climate Change*; MIT Press: Cambridge, MA, USA, 1994.
17. Babiker, M.B.; Reilly, J.M.; Mayer, M.; Eckaus, R.S.; Wing, I.S.; Hyman, R.C. The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Revisions, Sensitivities, and Comparisons of Results. 2001. Available online: https://globalchange.mit.edu/publication/14577 (accessed on 5 July 2018).
18. Hirst, E.; Brown, M. Closing the efficiency gap: Barriers to the efficient use of energy. *Resour. Conserv. Recycl.* **1990**, *3*, 267 –281. [CrossRef]
19. Jaffe, A.B.; Stavins, R.N. The energy-efficiency gap What does it mean? *Energy Policy* **1994**, *22*, 804–810. [CrossRef]
20. Gillingham, K.; Palmer, K. Bridging the Energy Efficiency Gap: Policy Insights from Economic Theory and Empirical Evidence. *Rev. Environ. Econ. Policy* **2014**, *8*, 18–38. [CrossRef]
21. Solnørdal, M.T.; Foss, L. Closing the Energy Efficiency Gap—A Systematic Review of Empirical Articles on Drivers to Energy Efficiency in Manufacturing Firms. *Energies* **2018**, *11*, 518. [CrossRef]
22. Hourcade, J.C.; Jaccard, M.; Bataille, C.; Ghersi, F. Hybrid Modeling: New Answers to Old Challenges Introduction to the Special Issue of The Energy Journal. *Energy J.* **2006**, *SI2006*. [CrossRef]
23. Helgesen, P.I. *Top-Down and Bottom-Up: Combining Energy System Models and Macroeconomic General Equilibrium Models*; Technical Report; Trondheim Norwegian University of Science and Technology: Trondheim, Norway, 2013.
24. Prinn, R.G. Development and application of earth system models. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 3673–3680. [CrossRef] [PubMed]
25. Sokolov, A.P.; Schlosser, C.A.; Dutkiewicz, S.; Paltsev, S.; Kicklighter, D.W.; Jacoby, H.D.; Prinn, R.G.; Forest, C.E.; Reilly, J.; Wang, C.; et al. The MIT Integrated Global System Model (IGSM) Version 2: Model Description and Baseline Evaluation. 2005. Available online: http://web.mit.edu/globalchange/www/MITJPSPGC_Rpt124.pdf (accessed on 5 July 2018).
26. IEA. *World Energy Model, Documentation*; Technical Report; International Energy Agency: Paris, France, 2017.
27. Edmonds, J.; Wise, M.; Pitcher, H.; Richels, R.; Wigley, T.; Maccracken, C. An integrated assessment of climate change and the accelerated introduction of advanced energy technologies. *Mitig. Adapt. Strateg. Glob. Chang.* **1997**, *1*, 311–339. [CrossRef]
28. Kim, S.H.; Edmonds, J.; Lurz, J.; Smith, S.J.; Wise, M. The ObjECTS Framework for Integrated Assessment: Hybrid Modeling of Transportation. *Energy J.* **2006**, *27*, 63–91. [CrossRef]
29. Benartzi, S.; Beshears, J.; Milkman, K.L.; Sunstein, C.R.; Thaler, R.H.; Shankar, M.; Tucker-Ray, W.; Congdon, W.J.; Galing, S. Should Governments Invest More in Nudging? *Psychol. Sci.* **2017**, *28*, 1041–1055. [CrossRef] [PubMed]
30. Siebert, L.C.; Sbicca, A.; Aoki, A.R.; Lambert-Torres, G. A Behavioral Economics Approach to Residential Electricity Consumption. *Energies* **2017**, *10*, 768. [CrossRef]
31. Frederiks, E.R.; Stenner, K.; Hobman, E.V. Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renew. Sustain. Energy Rev.* **2015**, *41*, 1385–1394. [CrossRef]
32. Andor, M.A.; Fels, K.M. Behavioral Economics and Energy Conservation—A Systematic Review of Non-price Interventions and Their Causal Effects. *Ecol. Econ.* **2018**, *148*, 178–210. [CrossRef]
33. Delgado, L.; Shealy, T. Opportunities for greater energy efficiency in government facilities by aligning decision structures with advances in behavioural science. *Renew. Sustain. Energy Rev.* **2018**, *82*, 3952–3961. [CrossRef]

34. Jensen, I.G.; Münster, M.; Pisinger, D. Optimizing the supply chain of biomass and biogas for a single plant considering mass and energy losses. *Eur. J. Oper. Res.* **2017**, *262*, 744–758. [CrossRef]
35. Balaman, Ş.Y.; Selim, H. Sustainable design of renewable energy supply chains integrated with district heating systems: A fuzzy optimization approach. *J. Clean. Prod.* **2016**, *133*, 863–885. [CrossRef]
36. Chen, Y.; He, L.; Guan, Y.; Lu, H.; Li, J. Life cycle assessment of greenhouse gas emissions and water-energy optimization for shale gas supply chain planning based on multi-level approach: Case study in Barnett, Marcellus, Fayetteville, and Haynesville shales. *Energy Convers. Manag.* **2017**, *134*, 382–398. [CrossRef]
37. Murphy, F.; Sosa, A.; McDonnell, K.; Devlin, G. Life cycle assessment of biomass-to-energy systems in Ireland modelled with biomass supply chain optimisation based on greenhouse gas emission reduction. *Energy* **2016**, *109*, 1040–1055. [CrossRef]
38. Pourhejazy, P.; Kwon, O.K. The New Generation of Operations Research Methods in Supply Chain Optimization: A Review. *Sustainability* **2016**, *8*, 1033. [CrossRef]
39. Govindan, K.; Fattahi, M.; Keyvanshokooh, E. Supply chain network design under uncertainty: A comprehensive review and future research directions. *Eur. J. Oper. Res.* **2017**, *263*, 108–141. [CrossRef]
40. Rajeev, A.; Pati, R.K.; Padhi, S.S.; Govindan, K. Evolution of sustainability in supply chain management: A literature review. *J. Clean. Prod.* **2017**, *162*, 299–314. [CrossRef]
41. Debreu, G. Representation of a Preference Ordering by a Numerical Function. In *Decision Processes*; Thrall, R.M., Coombs, C.H., Davis, R.L., Eds.; John Wiley & Sons: New York, NY, USA, 1954; pp. 159–165.
42. Debreu, G. Topological Methods in Cardinal Utility Theory. In *Mathematical Methods in the Social Sciences, 1959*; Arrow, K.J., Karlin, S., Suppes, P., Eds.; Stanford University Press: Stanford, CA, USA, 1960; pp. 16–26.
43. Luce, R.; Tukey, J.W. Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement. *J. Math. Psychol.* **1964**, *1*, 1–27. [CrossRef]
44. Green, P.E.; Rao, V.R. Conjoint Measurement for Quantifying Judgmental Data. *J. Mark. Res.* **1971**, *8*, 355–363. [CrossRef]
45. Agarwal, J.; Desarbo, W.S.; Malhotra, N.K.; Rao, V.R. An Interdisciplinary Review of Research in Conjoint Analysis: Recent Developments and Directions for Future Research. *Cust. Needs Solut.* **2015**, *2*, 19–40. [CrossRef]
46. Zufryden, F.S. A Conjoint Measurement-Based Approach for Optimal New Product Design and Market Segmentation. In *Analytic Approaches to Product and Marketing Planning: Proceedings of Workshop*; Shocker, A., Ed.; Marketing Science Institute: Cambridge, MA, USA, 1977; pp. 100–114.
47. Easton, F.F.; Pullman, M.E. Optimizing Service Attributes: The Seller's Utility Problem. *Decis. Sci.* **2001**, *32*, 251–276. [CrossRef]
48. Fragnière, E.; Heitz, C.; Moresino, F. The Concept of Shadow Price to Monetarize the Intangible Value of Expertise. In Proceedings of the 2008 IEEE International Conference on Service Operations and Logistics, and Informatics, Beijing, China, 12–15 October 2008; pp. 1736–1741.
49. Fragnière, E.; Moresino, F.; Zheng, N. Development of Pricing Models for Intangible Services Based on Conjoint Analysis and Mathematical Programming: A Case Study About the Design of Credit Card Services in China. In Proceedings of the 2011 Service Research and Innovation Institute Conference, San Jose, CA, USA, 29 March–2 April 2011; pp. 653–662.
50. Fragnière, E.; Moresino, F.; Shen, Y. Application of Share of Choice Model in Insurance Industry Based on Conjoint Analysis and Mathematical Programming. In Proceedings of the 2012 IEEE International Conference on Service Operations and Logistics, and Informatics, Suzhou, China, 8–10 July 2012; pp. 404–409.
51. Fragnière, E.; Lombardi, A.; Moresino, F. Designing and Pricing Services Based on Customer-Perceived Value: An Airline Company Feasibility Study. *Ser. Sci.* **2012**, *4*, 320–330. [CrossRef]
52. Fragnière, E.; Kanala, R.; Moresino, F.; Reveiu, A.; Smeureanu, I. Coupling techno-economic energy models with behavioural approaches. *Oper. Res.* **2017**, *17*, 633–647.
53. Fragnière, E.; Kanala, R.; Lavigne, D.; Moresino, F.; Nguene, G. Behavioral and Technological Changes Regarding Lighting Consumptions: A MARKAL Case Study. *Low Carbon Econ.* **2010**, *1*, 8–17. [CrossRef]