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Integration of behavioral effects from vehicle choice models into long-term energy systems optimization models

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ABSTRACT

Long-term energy systems models have been used extensively in energy planning and climate policy analysis. However, specifically in energy systems optimization models, heterogeneity of consumer preferences for competing energy technologies (e.g., vehicles), has not been adequately represented, leading to behaviorally unrealistic modeling results. This can lead to policy analysis results that are viewed by stakeholders as clearly deficient. This paper shows how heterogeneous consumer behavioral effects can be introduced into these models in the form of perceived disutility costs, to more realistically capture consumer choice in making technology purchase decisions. We developed a novel methodology that incorporates the theory of a classic consumer choice model into a commonly used long-term energy systems modeling framework using a case study of light-duty vehicles. A diverse set of consumer segments (thirty-six) is created to represent observable, identifiable differences in factors such as annual driving distances and attitude towards risks of new technology. Non-monetary or "disutility" costs associated with these factors are introduced to capture the differences in preferences across consumer segments for various technologies. We also create clones within each consumer segment to capture randomly distributed unobservable differences in preferences. We provide and review results for a specific example that includes external factors such as recharging/refueling station availability, battery size of electric vehicles, recharging time and perceived technology risks. Although the example is for light-duty vehicles in the US using a specific modeling system, this approach can be implemented more broadly to model the adoption of consumer technologies in other sectors or regions in similar energy systems modeling frameworks.

1. Introduction

Energy systems models have been used to understand the interactions between supply and demand, the role of new technologies, and the impacts of policies under various long-term scenarios. The model paradigm incorporates features from several areas such as energy, economics, engineering, and environment. Since the 1970s, several kinds of energy systems models have been developed that employ different types of mathematical methods such as linear programming (MARKAL, Loulou et al., 2004; TIMES, Loulou et al., 2005) accounting (LEAP, Heaps, 2016), and simulation (WEM, IEA, 2016).

Models based on a linear programming framework (commonly refer to as ESOM (Energy System Optimization Model)) identify least-cost investment pathways under different long-term scenarios. They represent technologies in great detail, but have been criticized for producing results that are an unrealistic representation of market behavior (Schäfer, 2012) . This problem of a highly simplified representation of consumer behavior in long-term integrated assessment energy models has been long recognized (Wilson and Swisher, 1993) . Many identify this lack of a realistic depiction of consumer behavior as one of the major challenges that ESOM must address to build a complete climate policy analysis framework, as concerns about achieving climate goals increase over time (Brosch et al., 2016; DeCarolis et al., 2017; Pfenninger et al., 2014).

1.1. Energy Systems Optimization Model (ESOM)

ESOMs are one of the most commonly used modeling frameworks where optimal solutions are obtained using an objective function

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List of acronyms

MARKAL	Market Allocation
TIMES	The Integrated MARKAL-EFOM System
EFOM	Energy Flow Optimization Model
ESOM	Energy Systems Optimization Model
COCHIN	Consumer Choice Integration
MA^{3}T	Market Allocation of Advanced Automotive Technologies
MNL	Multinomial Logit (discrete choice model)
NMNL	Nested Multinomial Logit (discrete choice model)
DSL	conventional diesel vehicle
G.Hyb	gasoline hybrid vehicle
D.Hyb	diesel hybrid vehicle
BEV	battery electric vehicle
PHEV	plug-in hybrid vehicle
FCV	fuel cell vehicle
VMT	vehicle miles traveled
ITAX	investment tax (a TIMES model attribute)
GAMS	General Algebraic Modeling System
SM	supplementary material

Equation variables and units

D	end-use demand in year y (miles)
y	model year
n	Vehicle technology
C	annualized cost per mile ($/mile)
F	price per unit energy fuel ($/GJ)
E	vehicle efficiency (miles/GJ)
f	fuel
M	annual miles traveled (miles)
g	consumer
i	clone
r	random number
μ	scale factor
U	indirect utility
V	observable utility
ε	random error term
A	available alternatives

that minimizes the discounted total system cost over the entire model horizon. For example, MARKAL and TIMES developed by the International Energy Agency and Energy Technology Systems Analysis Programme (IEA-ETSAP, 2001) have been used widely to conduct in-depth analyses of energy pathways for long-term scenarios (UK-MARKAL, Kannan et al., 2007; CA-TIMES, Yang et al., 2015; US-TIMES, Babaee et al., 2014). These models assume a single, social decision maker whose decision is based solely on cost minimization. Because linear programming leads to corner solutions, this yields all or nothing outcomes on technology investments. Specifically, solving the model yields a decision to invest in a single technology in a given year (rather than a mix of technologies), but may switch to an entirely different technology in the next year. This is also referred to as "knife-edge" behavior as small changes in costs can lead to a complete shift from one technology to another.

1.2. Recent developments in incorporating consumer behavior in ESOM frameworks

Modelers have typically overcome this behavior by imposing "ad-hoc" constraints such as limits on market shares and sales growth rates (Mundaca et al., 2010) . Modeling "tricks," i.e., methods and values that lack strong theoretical underpinnings and coherent empirical observations, such as hurdle rates, market share constraints, and technology growth rate constraints have been commonly introduced to make the scenarios of the adoption rate of technologies look more realistic. These shortcomings have long been recognized and to some extent have undermined the validity of ESOM and their ability to make credible scenarios and policy evaluations.

Progress has been made in recent years to improve the behavioral realism of ESOM as detailed in DeCarolis et al. (2017). Table 1 summarizes the philosophies of recent ESOM studies incorporating consumer behavior realism in TIMES models. The most common approach is to create different consumer segments to represent the heterogeneity in consumer demand level and/or consumer choice (Bunch et al., 2015; Cayla and Maïzi, 2015; Daly et al., 2014; McCollum et al., 2016; Nguene et al., 2011; Ramea, 2016) . Additionally, disutility costs have been introduced to represent perceived "non-monetary" costs (e.g., inconvenience cost or lack of new vehicle model availability), time cost, risk attitude, or market barriers (e.g., lack of awareness) (Nguene et al., 2011) . Behavioral constraints, such as time budget constraints (Daly et al., 2014; Tattini et al., 2018) and household budget constraints (Cayla and Maïzi, 2015) have also been considered in some models.

In general, these studies point to the fact that consumer investment decisions are often dominated by non-monetary costs, and there is significant heterogeneity in consumer demand and preferences. This paper extends the theoretical work laid out in Bunch et al. (2015) by adding a case study and comparing the results with the original consumer choice model that this model is based on. These are explained in more detailed in the following sections.

1.3. A novel approach: incorporating a consumer choice model within an ESOM framework

The term "consumer choice" refers to the purchase decisions of consumers, and in many social science fields discrete choice models (such as multinomial logit and nested-multinomial logit) are used to compute the purchase probability of each choice alternative for a given consumer (or group of consumers with a specified set of explanatory variables) (Koppelman and Bhat, 2006; Train, 2009) . An important unifying behavioral framework (random utility maximization [RUM]) assumes that each individual consumer chooses the alternative that maximizes her utility (Train, 2009) . However, these utilities are unobservable and randomly distributed from the perspective of the analyst. A general representation of the RUM framework is:

$$U_{m,j} = V\,(x_j, d_m; \beta) + \varepsilon_{m,j} \textit{ for all } j \in A \tag{1}$$

where $U_{m,j}$ is interpreted in economic theory as consumer m's (indirect) utility (conditional on choosing alternative j), and A is the set of all available alternatives. The function $V()$ is a model for the mean of utility as a function of its arguments, the vectors d_m and x_j denote consumer characteristics and attributes of choice alternative j, respectively, β is a vector of parameters (weights) that represent consumer preferences, and $\varepsilon_{m,j}$ is a random disturbance term. In this framework, the probability of consumer m choosing alternative a is given by $P_{m,a}$ = Probability ($U_{m,a} \geq U_{m,j}$, for all j in A).

For practical behavioral modeling, researchers typically assume a linear-in-parameters functional form for $V()$. For purposes of this paper, we assume that a segmentation scheme for consumers has been developed based on specific observable characteristics. Assume there are G segments, and let $g(m)$ denote the segment to