Logit Market Share Allocation
Experimental TIMES Feature

1 Introduction

In standard TIMES, each agent maximizes its long-term discounted surplus, while being subject to marginal value pricing of all commodities, thus simulating far-sighted, competitive energy markets. This standard TIMES paradigm has been widely applied for many uses, including the assessment of technologies and of and public policies from a social viewpoint.

However, one can also well argue for the distinctive assumption that each agent is not willing or able to exactly maximize its surplus, either because the agent faces uncertain costs and prices, or because the agent's behavior is not that of a pure profit maximizer (e.g. there exist non-monetary costs that influence its investment decisions). This second characteristic of imperfect markets has been represented in several different ways in various simulation models. It can be modeled via a market sharing algorithm that attributes a non-zero market share to technologies that are not optimal but are in some way judged to be competitive and thereby close enough to the optimal choice(s) to deserve a share of the market. The closeness to competitiveness may be determined using a levelized cost measure or the dual information for each technology, together with adjustments incorporating intangible costs and preferences.

Because of the potential usefulness of such a market sharing mechanism in terms of simulating behaviorally more realistic economic choices, there is now (in v4.7.0) an experimental implementation available in TIMES for a basic logit market share allocation, briefly summarized here.

2 Design approach

2.1 Overview

The mechanism implemented allows the user to bound the market share that any single technology is allowed to capture in its own market, in a given time period. A typical example of an end-use market is the set of technologies providing the same demand segment in a given region at a specific time period (e.g., all residential space heating technologies in one region and period).

Without such a mechanism, it would be possible for the model to select a single technology to invest in, within any given time period (e.g. the conventional gas furnace might capture all new residential space heating demand in some periods and/or regions). That might happen even if the cost of the winner technology were only slightly lower than the cost of competing technologies. This winner-takes-all phenomenon, also called penny-switching or knife-edge effect, results from the linearity of the surplus expression in TIMES and other LP based models (Loulou et al. 2004).

In real markets, it is more often observed that the investment choices in a given end-use market are spread over several technologies, mainly for two reasons. The first is that individual end-users make investment decisions based on preferences other than pure financial costs (e.g. cleanliness, convenience, safety, etc.). The second reason is that there is more variety within a region than is captured by the model, and this variety (due to local conditions) introduces a cost differentiation that is ignored by the model (Rivers & Jaccard 2005). The latter reason is all the more pertinent if the region being modeled is large and includes several countries or provinces. These two causes, and perhaps others, make it unlikely that all end-users would select the same technology.

One commonly used remedy to this phenomenon is to introduce lower or upper bounds on the market shares of technologies in the same market (for instance, upper bounds on the share of gas-fired heaters, oil-fired heaters, and electric heaters in the residential space heating market at each time period, or lower bounds on solar heaters, or any combination of such). Market share bounds may be purely exogenous projections for the maximum/minimum realistic share of individual technologies or groups of technologies, but they may also be based on a more sophisticated method employing the relative costs of the competing technologies.

The first approach (exogenous constraints on market shares) may be implemented by any TIMES modeler via the market share attributes FLO_MARK/PRC_MARK, user constraints, or even with regular variable bounds. However, even though some flexibility may be introduced by constraints prescribing limits for "baskets" of similar technologies, in many cases this approach may appear too rigid, and hard bounds may still be needed for the "winners" if others in the group are to gain a share of the market. The second approach can be based on selecting among the technologies those that will be receiving some market share, and then allocating the market shares to them on the basis of their levelized costs, including tangible and intangible costs and agent preferences.

2.2 The Market Sharing Algorithm

The experimental market sharing mechanism implemented in TIMES follows more or less closely the approaches described in the GCAM model documentation (GCAM 2022), in the MARKAL-Sage documentation (Loulou et al. 2004), and those in the hybrid energy–economy equilibrium model CIMS (Axsen et al. 2009, Jaccard 2009, Mulholland et al. 2017, Mulholland et al. 2018).

The algorithm for implementing the mechanism comprises the following steps:

1. The modeler must first identify the groups of competing technologies, which we call the markets, denoted by m, and the related commodities C_m. For instance, the automobile market contains all passenger vehicles, which compete for satisfying the auto travel demand segment.

2. Initial model run: The model is fist solved using the standard formulation maximizing the long-term discounted surplus over all periods t. In the initial run we also impose small minimum market share bounds for each technology k in each market m, in order to be able to calculate levelized cost for each. From the solution, several quantities are recorded: first the total size of each market m, denoted $TOTMKT_m$, as the total amount of C_m produced by technologies k with investment decisions, and second, the levelized costs of the technologies k in each market (denoted by LEC_k for technology k), and third, the implied utilization factors IUF_k of each technology. From the standard levelized costs LEC_k (see TIMES documentation) we first compute the augmented levelized costs LEC_k^+

per activity, by adding the annualized intangible costs (where the exogenous parameter INT_k gives the intangible costs as a fraction of investment costs).

$$LEC^{+}_{k,t} = LEC_{k,t} + \left(\frac{INT_{k,t} \times INV_{k,t} \times CRF_{k,t}}{CAPACT_k \times IUF_{k,t}} \right) \tag{1}$$

3. Output market shares: For each market m, we now compute the market share for each candidate technology as a fraction of the total market $TOTMKT_m$ of the produced commodity (using an exogenous heterogeneity parameter v, and an exogenous preference parameter $\boldsymbol{\alpha}_k$), by employing a logit choice formulation:

$$MSO_{k,t} = \frac{\alpha_{k,t}\left(LEC^{+}_{k,t}\right)^{-v}}{\sum_{i=1}^{N_m}\left\{\alpha_{i,t}\left(LEC^{+}_{i,t}\right)^{-v}\right\}} \tag{2}$$

4. Capacity market shares: For each market m, we finally compute the market share for the new capacity of each candidate technology as a fraction the total new capacity market. This conversion implies simply the division of the market shares by the implied utilization factors and normalization:

$$MSC_{k,t} = \frac{\dfrac{MSO_{k,t}}{IUF_{k,t}}}{\sum_{i=1}^{N_m}\left\{\dfrac{MSO_{i,t}}{IUF_{i,t}}\right\}} \tag{3}$$

5. Re-run of the model, where the new capacity market shares (3) are now implemented in terms of upper bounds. The constraints are, however, implemented with dummy variables relaxing each constraint at a given penalty cost (user-definable, in proportion to investment costs), to avoid possible infeasibilities due to other constraints in the model that might prevent the model from being able to satisfy all the market share constraints.

Note that although the final market shares are in terms of new capacity, they are in the activity unit. The market shares are applied by generating a constraint for each market m, technology k and period t, requiring that the new capacity of technology k is at most the fraction of $MSC_{k,t}$ of the total new capacity in market m in period t, in activity units.

There are also some additional considerations implemented, for example, related to adjusting the market shares in case the actual winners in the initial solution happen to be inconsistent with the winners in the calculated markets shares, implying that there are some other constraints also at play. The details of these additional refinements are omitted here [but may be inserted later].

If found useful, the feature might be subsequently improved and enhanced with additional refinements (or removed if not considered useful) according to the feedback from TIMES users.

2.3 Input attributes

There are only two exogenous input parameters to be specified by the user for using the market sharing mechanism, and they are the following:

- COM_MSHGV(reg,year, com) = <value> :
  Defines commodity com as a market where the market sharing mechanism is to be applied. The parameter value defines the heterogeneity parameter v (cf. Eq. 2).
- NCAP_MSPRF(reg,year,com,prc,lim) = <value> :
  - lim = 'N' : Defines the preference weights α_k in the logit market share formulation for the market com, and technology prc. Default value = 1.
  - lim = 'LO' : Defines the intangible costs as a fraction of the investment costs for the market com, and technology prc. Default value = 0.
  - lim = 'UP' : Defines the dummy penalty costs in proportion to the capacity-related costs for the market com, and technology prc. Default value = 2.

The heterogeneity parameter (COM_MSHGV, also called the logit exponent) represents the key input specification for the market share formulation. The value of the logit exponent determines how large the ratio must be to produce a significant difference in market share. A traditional linear programming optimization model would have $v = \infty$, where the cheapest technology captures 100% of the market – a completely homogeneous market. Considering an example with just two competing technologies A and B, with technology A being 15% more expensive than B, at v = 10, B captures 85% of the market, but at v = 1, B only captures 55% of the market. The second case is considered a more heterogeneous market, and the first case a more homogeneous market. The GCAM documentation (GCAM 2022) describes the logit exponent −3 as providing moderate switching behaviour for the electricity sector choice function. For the passenger car market, a much larger heterogeneity value (15) has been used in the CIMS model and in the Irish CarSTOCK model (Kamiya 2005, Mulholland et al. 2017), but another study with CIMS states the optimal v values for the car market were found ranging from 3.9 to 6.1 (Axsen et al. 2009).

The preference weight parameter (NCAP_MSPRF(...,'N') or α in Eq. 2) defines the share weights, which serve two purposes. First, they can be used to calibrate the model to observed historical values. With such a calibration procedure regionally specific preferences for particular choice alternatives (arising, from societal preferences, existing infrastructure, barriers to market entry, etc.) can be taken into account in the share weight parameters. Share weights may also be used for gradually phasing in new technologies, by setting the weights to low values in the first year the technologies are available, and gradually increasing them to a neutral values in later years.

The intangible cost parameter (NCAP_MSPRF(...,'LO')) provides another way of capturing choice preferences. Intangible costs can account for hidden costs associated with a new technology, such as consumer perceptions of quality, reliability, availability, social desirability or popularity. In particular, it may be a useful method for capturing the effects of consumer hesitation towards purchasing new technologies and range anxiety. Intangible costs may also be chosen to account for any consumer preferences for each technology when also calibrated using current market shares, and in that case the preference weight parameters can be left completely unused.

2.4 Limitations

The design and implementation of the market sharing mechanism is currently experimental only and has notable limitations, which mostly arise from the fact that it requires re-solving the model. Most importantly, it can cannot be used together with the following extensions:

- Any of the stochastic / tradeoff analysis features (STAGES/SENSIS)
- The time-stepped (myopic) algorithm (TIMESTEP)
- The standard TIMES MACRO or the MACRO-MSA formulation

3 Implementation

The feature has been implemented as a TIMES extension ECB (for Economic Choice Behavior), which can be activated as follows:

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$SET ECB YES
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