MAPS

Mitigation Action Plans & Scenarios

ENSURING CONSISTENCY

in Multi-Sector Energy and Emissions Models

TECHNICAL // Consistency

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By Adrian Stone

This brief explains how modellers and users of multi-sector energy models can ensure consistent application of system rules, conservation of quantities, and adherence to logic in their work.

Introduction: an historical perspective

In the days leading up to D-Day, General Dwight D Eisenhower agonised over the uncertainty and variability of expert weather reports (Beevor, 2009). An impending storm threatened to derail the entire enterprise and thus a degree of certainty on the weather was key to making the call on whether to commit allied forces or not. With today's technology, his logisticians could have timed weather limited operations to the hour with over 90% certainty on a 5-day advance window using a free public resource. Water-sports fanatics will all be familiar with the advent, about 10 years ago, of public data from the United States Fleet Numerical Meteorology and Oceanography Center (FNMOC) that for the first time enabled an internet user to peer into the future a week in advance for any stretch of coastline on the globe. This image of the future was no longer fuzzy but rendered in fine detail with the lustrous colour of animated isopleth[1] charts and accompanied by hard data of wind speeds and swell heights resolved to a scale of hours.

It might be argued that raw computing power has contributed to the accurate projection of that most

1 An isopleth is a line or curve joining areas of equal values on a chart or graph

Key points

- There are a number of basic consistency checks that a modeller can perform for energy-emissions models
- Model parameters like energy demand are typically projected by sector, sometimes by separate teams in different locations. It is particularly important that where assumptions like drivers of demand are common between sectors, e.g. GDP and population growth, common data sets are employed in the separate exercises to ensure consistency
- Consistency needs to be ensured when quantities are passed between sectors to prevent double counting
- Models that make projections must be calibrated against at least one base year to ensure that assumptions have a coherent starting point
- It is useful to have an evolving future net load curve when modelling electricity demand, as different economic sectors have different load profiles and grow at different rates
- When the modeller has information that refutes official energy balance data for consumption of an energy carrier by an individual sector, suitable adjustments need to be made such that the total final consumption for all sectors added together is consistent with the energy balance across all energy carriers
- In bottom-up energy models it is preferable to redistribute unallocated energy pro-rata across sectors rather than creating a discrete balancing item e.g. 'Other' or 'Unknown'

historically elusive of phenomena, the weather, as much as meteorological science has done. Consistently increasing computing power and the increasingly elaborate software it facilitates have become a constant for two generations of technical professionals, changing the way we view information and complexity.

A plethora of public internet sites now deliver the FNMOC weather data with their own front ends, even enhancing it with in-house post-processing analysis. It is tempting to credit computer engineering with these almost magical achievements, but computing power can only leverage whatever state of science exists and the care with which it is applied. The GIGO law of computing or "garbage in equals garbage out" is a fundamental principle of logic that will perhaps pass into eternity long after Moore's Law of computing[2] is forgotten. In the case of weather, the modern prediction systems rest on a mass of accurate data collection and millennia of scientific endeavour on the problem at hand. Weather prediction is also subject to unambiguous and fairly immediate validation so prediction systems evolve rapidly in response to error.

Modelling efforts to project the long-term demand for energy and its associated emissions, on the other hand, often rely on weak data inputs which cannot be honed by regular validation. A model projection, relying as it does on long-term general trends may appear to be highly inaccurate over as long a period as five years and yet prove to have been a useful guide to the future over decades, as the variability inherent in economic cycles averages out. Energy models have also leveraged computing power and become more granular and complex. Now they typically capture the entire energy chain - from extraction to transformation to conversion to useful energy service - through an array of technologies, themselves represented in great technical detail. Depending on the model, the technologies in the demand or supply sectors or both might be represented. Given that these sectors interact at different levels, a high level of system complexity can evolve and with it the potential for error. Furthermore, models are an abstraction of reality and the method of abstraction is the modeller's art, always subject to improvement, embellishment and controversy. It is therefore of paramount importance that the methodology of abstraction is applied consistently throughout a model so that the model delivers results that are at least true to the underlying concepts and assumptions. The responsibility for this does not rest only with the designers and programmers of the models, but also extends to the users of tested models.

This paper briefly explores the responsibilities for model consistency borne by users of multi-sector energy models. This will be attempted through a limited theoretical analysis supported by examples from the Energy Research Centre's (ERC) South African TIMES Model (SATIM) and other references. The paradigm of the optimisation family of energy models as currently used by the ERC informs the approach and so it may be only partially relevant to researchers using other types of models.

Economic sectors typically considered in energy models

It is useful in energy models to distinguish between the technologies and agents involved in the supply of energy (supply-side) and those involved in the demand for energy (demand-side). Energy models are also typically further organised by economic sector because of consistencies in structure and technology along those lines and because data is typically reported by economic sector.

SUPPLY-SIDE SECTORS	DEMAND-SIDE SECTORS
Extraction of primary energy[3]	Industry
Electricity Production	Commercial
Liquid Fuels Production	Agriculture
	Transport
	Residential

TIMES, a bottom-up optimisation platform for generating so-called 3E models (engineering, economy, environment), includes both supply-side and demand-side sectors. The demand for energy on the supply sectors are an exogenous input to the model. MESSAGE, a free-for-use optimisation model, is usually only used because of practical limitations to optimise the technologies active in the supply sectors to

2 Moore's Law states that the number of transistors that can fit on to an affordable computer chip will double every two years (The Economist, 2011)

3 including the extraction and supply of all fuels not transformed (for instance coal for heating)

meet an exogenous demand. In either case, the included sectors are interrelated in the physical world and within the model abstraction. Consistency therefore needs to be ensured in the passing of quantities between sectors and the prevention of double counting of parameter values.

Definition of internal consistency

In the literature the term "internal consistency" is more commonly applied to the statistical reliability of questionnaires, as measured by a test like Cronbach's alpha (Chiclana, Herrera, & Herrera-Viedma, 2002), rather than to 'models' in a general sense. Cronbach's alpha is a measure of the reliability with which a set of questions together measure a single construct. A questionnaire is of course a type of model, and while a test like Cronbach's alpha may indicate that a set of questions are probably measuring a common construct, there is no guarantee that it is the intended construct and hence the consistency established by the test is only internal. There is thus a direct parallel with other types of models and as will be discussed, internal consistency checks can and should be part of energy modelling exercises. While, the term 'internal consistency' seems to find some formal use amongst economic modellers (Wren-Lewis, 2012; Davies, 2012), a formal definition does not readily present itself. For the purposes of this paper the following definition of the requirements of model internal consistency will be adopted:

The assumptions and mechanics of a model, must, within itself and to the extent of its boundaries:

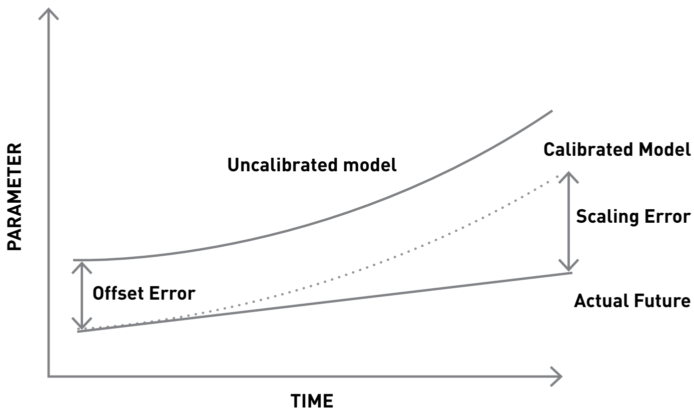
- Be consistent in its adherence to logic.
- Be consistent in the application of its system rules, unless a logical argument exists to the contrary.
- Be consistent in terms of the conservation of quantities such as energy, mass (where Newtonian physics applies) and money such that basic accounting practices are observed.

Given this, errors are at least limited to validity of the underlying principles of the model and the reliability of exogenous data.

Avioding scaling errors

One of the fundamental steps in building any model that makes projections into the future is that of base-year calibration. We can't predict the future so we start our model in the past where we can calibrate it to produce an output that has been measured, ideally by an official source. In an energy model the aggregate consumption of energy would usually be calibrated against the national energy balance published by the relevant government department, or else the International Energy Agency (IEA) energy balance. In this way our projection begins from a point in which we have some confidence, and our outputs characterising the future will be subject to scaling error arising from our assumptions and not compounded by significant offset error as shown in Figure 1 below.

FIGURE 1:
OFFSET AND SCALING ERROR IN MODELS THAT ESTIMATE FUTURE PARAMETER VALUES



It is of course possible to calibrate a single year with a false set of assumptions because, depending on the underlying equations of the model, a value X for an output parameter can often be attained with a number of permutations of input assumptions, some of which may result in poor estimates of future values. It is therefore useful to have a number of calibration years, given that the available data and the structure of the model allow this, particularly where there are a number of unknown input parameters. An example are models of energy demand from the transport sector where the model demand for gasoline and diesel can be dependent on assumptions of annual vehicle mileage, vehicle fuel economy, scrap rates of vehicles and the price elasticity of demand, all of which may be unknown or partially known. Using a number of calibration years enables the modeller to refine these assumptions relative to one another and reduce the risk of scaling error due to errors in assumed values.

Consistency of Total Final Consumption

Generally the aggregate Total Final Consumption (TFC) of an energy carrier, gasoline for instance, published by the national energy balance is fairly reliable, given reasonably functional national institutions and enterprises. This is because aggregate TFC is typically derived from the quantity of retail sales of the energy carrier, and in most economies money flows are fairly accurately accounted for in their totality for auditing and management purposes.

The allocation of TFC to sectors is dependent on the effort made by the entity collecting the data to classify their customers by sector and as such is not necessarily accurate. Therefore modellers building a set of assumptions may in certain cases allocate a base year consumption of an energy carrier to a sector that differs markedly from that listed in the energy balance because they have first-hand information from that sector or dominant companies in that sector, or a different interpretation of the source data. By our principle above, the difference from the energy balance or other source would need to be reallocated to another sector or sectors such that the TFC of all sectors together is consistent with the energy balance on a per energy carrier basis.

Ideally, equally verifiable information would present itself that would indicate a positive error in one sector's consumption to balance the negative error in another sector. In practice this rarely happens and a strategy for distributing the excess or deficit needs to be decided on. The simplest is a pro-rata distribution amongst the sectors for which there is no compelling evidence that the energy balance is wrong. Other strategies, for instance attributing excess or deficit consumption to the sector with the highest consumption, thus diluting it, might suggest themselves based on the prevailing circumstances. It is therefore evident that the decision to deviate from the allocation of TFC to a sector in the energy balance is a trade-off between correcting that one sector and giving rise to errors in the other sectors that need to be adjusted to keep the total TFC of all sectors consistent.

Energy balances typically have a balancing item, called 'Other' or 'Unknown', to which any remaining consumption after allocation to the economic sectors is assigned. The retail sales data from the primary source may itself have an 'Unknown' category. This is the case, for example, with the data published by the South African National Electricity Regulator (NERSA) which allocated 35 PJ of electricity sales or 5% to the category 'General' in 2006 (NERSA, 2006), more than the allocations to the Agriculture (3%) and Transport Sectors (2%). It is undesirable to try and deal with this in a bottom-up energy model by creating a dummy sector or similar. Better is to redistribute the energy pro-rata between sectors or dilute it in some way in high consuming sectors. In this way we hold to the principle of consistency through balancing the aggregate consumption in the model with the energy balance or other

Basic consistency checks

- The assumption of fuel-based emission factors should be consistent between sectors. This means, for example, that an adoption of an emissions factor of say 95 ton CO_2 /TJ for coal should be applied to all sectors unless it can be verified that a different grade of coal with a different emission factor prevails in a given sector.
- Carbon should balance between model CO_2 emissions and the consumption of primary fuels in the model across sectors. This is typically a validation performed on model results.
- Energy supplied by the supply sectors should balance that consumed by the demand sectors.
- If the Electricity-Supply Sector is represented in the model and emissions from electricity production are accounted for in that module, they should not be double counted by linking emissions to the consumption of electrical energy by the demand sectors.
- The total consumption or production of a fuel in the base year for all the sectors together should add up to a sensible and verifiable number. This means that sector aggregate checks are required.

primary source for the base year.

Other critical data assumptions that are typically acquired from external official sources are GDP and population projections which need to be consistently handled are discussed below.

Consistency of GDP and population assumptions

Complex projects seem to have a way of stumbling on the small and the simple. The space industry provides some of the most extreme examples with the Challenger mid-air explosion thought to be due to O-ring failure (Gladwell, 2009) or the Mars Climate Orbiter crash allegedly due to two design teams using different systems of units and not reconciling (CNN, 1999). Sectoral energy models tend to be quite complex undertakings because a large amount of difficult to acquire data needs to be collected and modelling the energy structure of each sector requires the development of a high-level of specific expertise. This often gives rise to separate teams, sometimes in different locations, working on the different sectors and this can cause problems in the consistency of common assumptions.

The drivers of energy demand in most economic sectors include GDP and population and the modelling team should use a common assumption of future values for these drivers across sectors so that the model is consistent. This is of particular importance when demand is an exogenous input to the model and the analysis of drivers is being pre-processed in a number of spreadsheets.

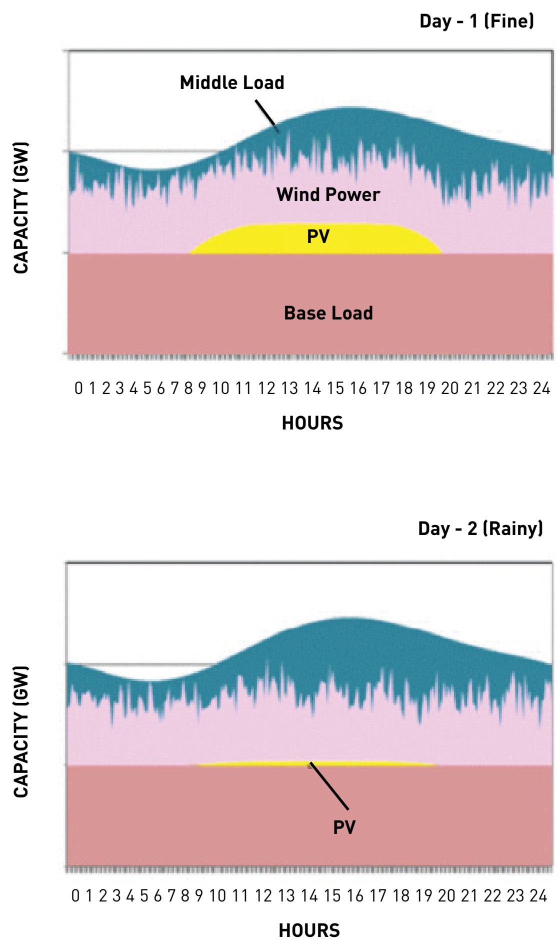
Load profile of electricity demand

The load profile of demand for electricity is a critical consideration in the technology mix decision to supply the electricity grid. A distinction is generally drawn between base load, the lowest continuous power demand that must be met by a network, and peak loads at times of high net demand. Knowledge of the load profile becomes even more critical when integrating intermittent renewable supply into the grid using stochastic analysis as illustrated in Figure 2 in the output from an IEA modelling study on load issues (IEA, 2010).

The load profiles of individual sectors are of course different, with industry, classically, having a flatter profile and the residential sector having a morning and evening peak. In a hot country, the commercial sector and even the residential sector might have a midday peak due to air-conditioner load. As these sectors may grow at different rates, it is useful if the model accounts for this in the evolution of a future net load curve, not just a net demand for electrical energy. There needs to be consistency between sectors as follows:

- The integral of the demand curve is the net consumption of electrical energy and this value needs to match the demand estimate on a per sector basis.
- The sum of the sector demands needs to match net sales by the utilities for the base year.

FIGURE 2:
MODELLING SIMULATION OF DAILY BALANCE OF DEMAND AND SUPPLY ON TWO TYPICAL DAYS - (IEA, 2010)



Combined heat and power plants

Combined heat and power (CHP) plants that supply the industry sector need to be dealt with in the model in a consistent manner, representing an interaction between the industry sector and the electricity production sector. For example, the solution adopted in the ERC's SATIM model (ERC, 2012) is that their heat component is modelled as an energy service to industry and the associated data is input as part of the array of Industry Sector assumptions while their electricity production is modelled as an energy supply to industry and the associated data is input in the array of Electricity Production Sector assumptions.

Coordinating the supply and demand sides of the model

In many energy models the demand for energy is an exogenous input that reflects the growth in energy services. Optimisation models will derive a least cost mix of demand-side technologies to meet those energy services but also a least cost mix of supply-side technologies to meet the net demand for energy. The technologies modelled for the liquid fuels and electricity sectors clearly then need to have the capacity to meet demand in the base year or else imports need to be available to make up the shortfall.

Future technologies that form part of the input assumptions of demand-side sectors might use fuels not in common use currently at scale like methanol or hydrogen. Supply-side technologies that can supply these new demand-side technologies need to be added to the model, including assumptions of costs and emissions factors, so that the costs of the energy chain can be estimated and its emissions compared to any constraints.

Consistent rules for projecting the demand for energy

The projection of demand for energy may be approached in a number of ways but for long-term energy models, the demand for an energy service, for instance light or heat, or a commodity like steel, is typically linked to economic drivers like GDP and these are projected over the study period. The demand for energy is then in turn linked to the service or commodity in the model by technologies like boilers or steel plants. In certain cases an intermediate indicator may be linked to GDP for example, the demand for energy services by commercial buildings will be proportional to floor area so this can serve as a useful indicator. The total floor area of commercial enterprises may be linked to GDP as follows:

$$FA_i = FA_{i-1} \times \left[1 + \text{elasticity} \times \left(\frac{GDPI_i}{GDPI_{i-1}} - 1 \right) \right]$$

Where:

FA_i	=	Floor Area in year i
$GDPI_i$	=	Indexed GDP of tertiary Commercial Sector in year i
elasticity	=	% change in floor area / % change in indexed GDP as indicated by historical data

The assumed elasticity would generally be less than 1 reflecting that the economy adds more value per square metre of office space as it grows and this should be evident from past trends. The demand for freight (ton-km) will similarly be unlikely to grow in direct proportion to GDP as the share of services in the economy grows relative to transport intensive activities. The demand for coking coal on the other hand may be related to steel production, but an elasticity of 1 may be more appropriate because the consumption of coke per unit of output should be more or less constant. The projection of demand for energy services and commodities should therefore be consistent with observed economic and process phenomena and the approach should be harmonised between teams working on different sectors. This has important implications for emissions calculations in particular and could have a large impact on the behaviour of an emissions constrained model.

Other MAPS' modelling publications

MAPS has produced a number of papers and technical briefs that explore various modelling approaches. These publications aim to support modellers through providing overviews of approaches currently in use.

- **Guidelines for the selection of long-range energy systems modelling platforms**
  Support paper giving guidance in the selection of modelling platforms to analyse mitigation actions in the energy sector.
- **Marginal Abatement Cost Curves as mitigation decision tools**
  Support paper explaining different approaches to using MAC curves as a mitigation decision tool.
- **Review of linked modelling of low-carbon development and mitigation**
  Review of linked modelling approaches used in the assessment of mitigation actions and low carbon development strategies.
- **The challenges of linking sectoral and economy-wide models**
  Technical brief providing a synopsis of the challenges in linking sectoral and economy-wide models.
- **Summary of the South African Times Model (SATIM) methodology**
  Overview of how the SATIM methodology is used in analysing seven key sectors of the South African economy.
- **Modelling in the South African Long Term Mitigation Scenarios**
  Outline of some of the sectoral modelling approaches used during the South African Long Term Mitigation Scenarios.

Conclusion

Energy modellers are being asked to produce models of ever greater complexity. This is driven by the growing diversity and size of energy systems, but also by increased pressure to identify areas where externalities, like climate change, can be mitigated. This places ever greater demands on modellers to validate the consistency of their models. Many of these checks are simple, but as such are easily forgotten. In such cases they can rob models, that otherwise represent a great deal of human effort and ingenuity, of their power and usefulness. Energy models require a great deal of effort in data collection and separate teams or individuals often assume responsibility for the sectors in the model. This increases the danger of overall consistency being overlooked, which makes rigorous validation essential with this type of modelling.

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MORE ABOUT MAPS

Mitigation Action Plans and Scenarios (MAPS) is a collaboration among developing countries aimed at establishing an evidence base for long-term transition to robust climate-compatible economies that aligns economic development with poverty alleviation. Through its collaboration MAPS offers an opportunity to establish synergies and share lessons with participating developing countries as well as the wider climate-change and development community, using the in-country processes as 'living laboratories'.

Central to MAPS is the facilitated interaction between key stakeholders and in-country research teams. This interaction takes place primarily in Scenario Building Meetings. Here inputs to models and results are discussed and agreed upon. The rigour of information generated by research and the involvement of stakeholders, produces results that are credible, legitimate and relevant. These results provide a sound basis with which to answer key policy questions. MAPS is currently active in Brazil, Chile, Colombia and Peru.

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