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ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure

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Abstract In this first part of a two-part article, the principal characteristics of the TIMES model and of its global incarnation as ETSAP-TIAM are presented and discussed. TIMES was conceived as a descendent of the MARKAL and EFOM paradigms, to which several new features were added to extend its functionalities and its applicability to the exploration of energy systems and the analysis of energy and environmental policies. The article stresses the technological nature of the model and its economic foundation and properties. The article stays at the conceptual and practical level, while a companion article is devoted to the more detailed formulation of TIMES equations. Special sections are devoted to the description of four optional features of TIMES: lumpy investments, endogenous technology learning, stochastic programming, and the climate module. The article ends with a brief description of recent applications of the ETSAP-TIAM model.

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1 Introduction

The ETSAP TIMES model (an acronym for The Integrated MARKAL-EFOM System), was developed and is maintained by the Energy Technology Systems Analysis Programme (ETSAP), an implementing agreement under the aegis of the International Energy Agency (IEA). The TIMES integrated assessment model (ETSAP-TIAM) is the global multiregional incarnation of the TIMES model generator.

TIMES is a model generator for local, national or multi-regional energy systems, which provides a technology rich basis for estimating energy dynamics over a long-term, multiple period time horizon. It is usually applied to the analysis of the entire energy sector, but may also applied to study in detail single sectors (e.g., the electricity and district heat sector).

In TIMES, reference case projections of end-use energy service demands (e.g., car road travel, residential lighting, steel production and the like) are provided by the user for each region. In addition, the user provides estimates of the existing stock of energy related equipment in all sectors in the base year, and the characteristics of available future technologies, as well as present and future sources of primary energy supply and their potentials. Using these as inputs, the model aims to supply energy services at minimum global cost (more accurately at minimum loss of total surplus) by simultaneously making decisions on equipment investment, equipment operation, primary energy supply, and energy trade. TIMES is thus a vertically integrated model of the entire extended energy system.

The scope of the model extends beyond purely energy related issues, to the representation of environmental emissions, and perhaps materials, related to the energy system. The model is well suited to the analysis of energy-environmental policies, which may be represented with accuracy thanks to the explicitness of the representation of technologies and fuels in all sectors.

In TIMES, the quantities and prices of the various commodities are in equilibrium, i.e., their prices and quantities in each time period are such that the suppliers produce exactly the quantities demanded by the consumers. This equilibrium has the property that the total surplus (consumers plus producers surpluses) is maximized.

In addition, TIMES includes a climate module that calculates the impact of energy decisions on greenhouse gas emissions and concentration, as well as on the resulting changes in atmospheric forcing, and in global temperature. The Climate Module is especially useful in global incarnations of TIMES, such as TIAM.

TIMES was developed as a successor of the MARKAL (Fishbone and Abilock 1981; Fishbone et al. 1983; Berger et al. 1992), and EFOM (Finon 1974; van der Voort et al. 1984) bottom-up energy models, and incorporates the features of these ancestors, plus several new features. From MARKAL, TIMES inherits the detailed description of technologies, the RES concept, and the equilibrium properties. From EFOM, TIMES inherits the detailed representation of energy flows at the technology level. In addition, TIMES has specific features that were not present in the ancestor models (at least in their earlier incarnations), as follows:

- Variable length periods;
- Vintaged technologies;
- Detailed representation of cash flows in the objective function;
- Technologies with flexible inputs and flexible outputs;
- Stochastic programming with risk aversion;
- Climate module;
- Endogenous energy trade between regions.

Most of these features are discussed in the rest of the article and in *Part II: The Mathematical Programming Formulation*.

Section 2 describes the inputs and outputs of TIMES. Section 3 provides a general overview of the representation in TIMES of the Reference Energy System (RES) of a typical region or country, focusing on its basic elements, technologies and commodities. Section 4 discusses the economic rationale of the model, and Sect. 5 describes three model options: Lumpy Investments (LI), Endogenous Technological Learning (ETL), and Stochastic Programming (SP). Section 6 focuses on the climate module of TIMES. Section 7 concludes this article.

Part II: The Mathematical Programming Formulation describes in more technical details the mathematical formulation of TIMES. An even more complete technical description of TIMES appears in the full documentation available on the ETSAP web site at www.etsap/org/documentation

2 Inputs and outputs of TIMES

2.1 The TIMES input scenario

The TIMES model is particularly suited to the *exploration* of possible long term energy futures based on contrasted *scenarios*. Given the long horizons simulated with TIMES (up to 2100 in the current versions of the model), the scenario approach is really the only choice. Scenarios, unlike forecasts, do not pre-suppose advance knowledge of the main drivers of the energy system. Instead, a scenario consists of a set of *coherent assumptions* about the future trajectories of these drivers, leading to a coherent organization of the system under study. A scenario builder must therefore carefully test the assumptions made for internal coherence, via a credible *storyline*. In TIMES, a complete scenario consists of four types of input: energy service demands, primary resource potentials, a policy setting, and the descriptions of a set of technologies. We now present a few comments on each of these four components.

2.1.1 The demand component of a TIMES scenario

In TIMES, the set of demand trajectories is obtained by first specifying the values of several *demand drivers* (population, GDP, sector outputs, etc.), which are obtained externally, via other models (such as GEMINI-E3) or from accepted external sources. The divers consist of: GDP, sector outputs, and population in the various regions. Note that GEMINI-E3 itself uses other drivers as inputs in order to derive its own results, e.g. assumptions on technical progress, population, and trade regime. For population and household projections, typical sources include IPCC, Nakicenovic (2000); Moomaw and Moreira (2001). Other approaches may be used to derive TIMES drivers, whether via models or other means. The versions of TIAM operated from 2004 to 2006 used GEM-E3 instead of GEMINI-E3 to derive its demand drivers.

Once the drivers for TIMES are determined and quantified, the construction of the reference demand scenario requires computing a set of *energy service demands* over the horizon. This is done by choosing *elasticities of demands to their respective driver*s, in each region, using the following general formula:

$$\text{Demand} = \text{Driver}^{\text{Elasticity}}.$$

The elasticities of demands to their respective drivers reflect the degree of decoupling between the drivers and the demands.

The demands are provided by the user only for the reference scenario. When the model is run for alternate scenarios (for instance for an emission constrained case, or for a set of alternate technological assumptions), it is likely that the demands will be affected. TIMES has the capability of estimating the response of the demands to the changing conditions of an alternate scenario. To do this, the model requires still another set of inputs, namely the assumed *elasticities of the demands to their own prices*. TIMES is then able to endogenously adjust the demands to the alternate cases. In fact, TIMES is driven not by demands but by *demand curves*.

2.1.2 The supply component of a TIMES scenario

The second constituent of a scenario is a set of *supply curves* for primary energy and material resources. Multi-stepped supply curves can be easily modeled in TIMES, each step representing a certain potential of the resource available at a particular cost. In some cases, the potential may be expressed as a cumulative potential over the model horizon (e.g., reserves of gas, crude oil, etc), as a potential over the resource base (e.g., available areas for wind converters differentiated by velocities, available farmland for biocrops, roof areas for photovoltaic installations) and/or as an annual potential (e.g., maximum extraction rates, or annual available wind, biomass, or hydro potentials). Note that the supply component also includes the identification of trading possibilities.

2.1.3 The policy component of a TIMES scenario

Insofar as some policies impact on the energy system, they may become an integral part of the scenario definition. For instance, a No-Policy scenario may perfectly ignore emissions of various pollutants, while alternate policy scenarios may enforce emission restrictions, or emission taxes, etc. The detailed technological nature of TIMES allows the simulation of a wide variety of both micro measures (e.g., technology portfolios, or targeted subsidies to groups of technologies), and broader policy targets (such as general carbon tax, or permit trading system on air contaminants). A simpler example might be a nuclear policy that limits the future expansion of nuclear plants. Another example might be the imposition of fuel taxes, or of industrial subsidies, etc.

2.1.4 The techno-economic component of a TIMES scenario

The fourth and last constituent of a scenario is the set of technical and economic parameters assumed for the transformation of primary resources into energy services. In TIMES, these techno-economic parameters are described in the form of technologies (or processes) that transform some commodities into others (fuels, materials, energy services, emissions). Some technologies may be forced and others may simply be available for the model to choose. The usefulness of a TIMES instance rests on a rich, well developed set of technologies, both current and future, for the model to choose from. The emphasis put on the technological database is one of the main distinguishing factors of the class of Bottom-up models, to which TIMES belongs.[1] Other classes of models will tend to emphasize other aspects of the system (e.g., interactions with the rest of the economy) and treat the technical system in a more succinct manner via aggregate production functions.

Remark Two scenarios may differ in all or in only some of their components. For instance, the same demand scenario may very well lead to multiple scenarios by varying the primary resource potentials and/or technologies and/or policies, insofar as the alternative scenario assumptions do not alter the basic demand inputs (Drivers and Elasticities). The scenario builder must always be careful about the overall coherence of the various assumptions made on the four components of a scenario.

2.2 TIMES outputs

For each scenario, TIMES produces two types of result. First, the primal solution of the Linear Program provides, at each time period and in each region:

- A set of investments in all technologies;
- The operating levels of all technologies;
- The imports and exports of each type of tradeable energy forms and materials;
- The extraction levels of each primary energy form and material;
- The flows of each commodity into and out of each technology;

[1] Although TIMES does not encompass the macroeconomic variables beyond the energy sector, accounting for price elasticity of demands captures a major element of feedback effects between the energy system and the economy.

- The emissions of each substance by each technology, sector, and total;
- The changes in concentration of the greenhouse gases;
- The radiative forcing induced by the atmospheric concentration of GHG in the atmosphere;
- The change in global temperature induced by the change in radiative forcing.

In addition, the dual solution of the Linear Program provides:

- The shadow price of each commodity present in the RES (energy form, demand, emission, material);
- The reduced cost of each technology in the RES, i.e., the required cost reduction to make that technology competitive.

3 The structure of the TIMES model

Operationally, a TIMES run configures the *energy system* (of a *set of regions*) over a certain *time horizon* in such a way as to *minimize the net total cost* (or equivalently *maximize the net total surplus*) of the system, while satisfying a number of *constraints*.

3.1 Structure versus data

It is useful to distinguish between a model's *structure* and a particular instance of its implementation. A model's structure exemplifies its fundamental approach for representing and analyzing a problem—it does not change from one implementation to the next. All TIMES models exploit an identical mathematical structure. However, each model instance will vary according to the data inputs. For example, in a multi-region model one region may have undiscovered domestic oil reserves, and accordingly, TIMES generates technologies and processes related to discovery and field development. If, alternatively a region does not have undiscovered oil reserves no such technologies and processes are generated by the model. Due to this property TIMES may also be called a *model generator* that, based on the input information provided by the modeler, generates an instance of a model.

The structure of TIMES is ultimately defined by variables and equations determined from the data input provided by the user. The database itself contains both qualitative and quantitative data. The *qualitative data* includes, for example, lists of energy carriers, the technologies that the modeler feels are applicable (to each region) over a specified time horizon, as well as the environmental emissions that are to be tracked. This information may be further classified into subgroups, for example energy carriers may be split by type (e.g., fossil, nuclear, renewable, etc). The *quantitative data,* in contrast, contains the technological and economic parameter values specific to each technology, region, and time period. When constructing multi-region models it is often the case that a technology may be available for use in two distinct regions; however, cost and performance assumptions may be different. This section discusses both qualitative and quantitative assumptions in the TIMES modeling system.

3.2 Time in TIMES

The time horizon is divided into a user-chosen number of time-periods, each model period containing an arbitrary, possibly different number of years. For TIMES all years in a given period are considered identical. [2] For all quantities such as capacities, commodity flows, operating levels, etc, any model input or output related to period *t* applies to each of the years in that period, with the exception of investment variables, which are usually made only once in a period.[3] In the TIAM case, a long horizon of 100 years is selected in order to properly reflect the long term nature of the climate phenomena.

The initial period is usually considered a past period, over which the model has no freedom, and for which the quantities of interest are all fixed by the user at their historical values. The initial period consists in most applications of a single year, in order to facilitate calibration to standard energy statistics. Calibration to the initial period is one of the important tasks required when setting up a new TIMES model. The main variables to be calibrated are: the capacities and operating levels of all technologies, and the extracted, exported, imported, produced, and consumed quantities for all energy carriers, and the emissions if modeled. Note carefully that the specification of existing capacities in the initial period influences the model's behavior over several future periods, since the existing capacities have a life that extends (sometimes far) into the subsequent periods.

In addition to time-periods, there are time divisions within a year, also called *time-slices,* which may be defined at will by the user. For instance, the user may want to define seasons, day/night, and/or weekdays/weekends. Time-slices are especially important whenever the mode and cost of production of an energy carrier at different times of the year are significantly different. This is the case for instance when the demand for an energy form fluctuates across the year and a variety of technologies may be chosen for its production. In such cases, the matching of supply and demand requires that the activities of the technologies producing and consuming the commodity be tracked in each time slice. Electricity and other non storable energy forms are prime candidates for time slicing.

3.3 The RES concept

The TIMES energy economy consists of three types of entity:

- *Technologies* (also called *processes*) are representations of physical devices that transform commodities into other commodities. Processes may be

[2] Except for the cost objective function which differentiates between payments in each year of a period, and for investment variables.

[3] There are exceptional cases when TIMES must assume that an investment is repeated more than once in a period. This occurs when the period is so long that it exceeds the technical life of the investment.

primary sources of commodities (e.g., mining processes, import processes), or transformation activities such as conversion plants that produce electricity, energy-processing plants such as refineries, end-use demand devices such as cars and heating systems, etc,

- *Commodities* consist of energy carriers, energy services, materials, monetary flows, and emissions. A commodity is generally produced by some process(es) and/or consumed by other process(es), and
- *Commodity flows* are the links between processes and commodities. A commodity flow is of the same nature as a commodity but is attached to a particular process, and represents one input or one output of that process. For instance, *heating oil* is a commodity, whereas *heating oil for residential oil furnace* is a commodity flow.

It is helpful to picture the relationships among these various entities using a network diagram, referred to as a Reference Energy System (RES). In TIMES, the RES processes are represented as boxes and commodities as vertical lines. Commodity flows are represented as horizontal links between process boxes and commodity lines. Each flow is oriented and links exactly one process node with one commodity node.

Figure 1 depicts a small portion of a hypothetical RES containing a single energy service demand, namely residential space heating. There are three end-use space heating technologies using the gas, electricity, and heating oil energy carriers (commodities), respectively. These energy carriers in turn are produced by other technologies, represented in the diagram by one gas plant, three electricity-generating plants (gas fired, coal fired, oil fired), and one oil refinery. To complete the production chain on the primary energy side, the diagram also represents an extraction source for natural gas, an extraction source for coal, and two sources of crude oil (one extracted domestically and then transported by pipeline, and the other one imported). This simple RES has a total of 13 commodities and 13 processes. Note that in the RES every time a commodity enters/leaves a process (via a particular flow) its name is changed (e.g., wet gas becomes dry gas, crude becomes pipeline crude). This simple rule enables the inter-connections between the processes to be properly maintained throughout the network.

To organize the RES, and inform the modeling system of the nature of its components, the various technologies, commodities, and flows may be classified into *sets*. Each TIMES set regroups components of a similar nature. The same item may appear in multiple technology or commodity sets. The set membership conveys the nature of the individual components and is often more relevant to post-processing (reporting) than for influencing the model structure itself. This is because in TIMES most processes are endowed with essentially the same attributes (with the exceptions of storage and inter-regional exchange processes), and unless the user decides otherwise (e.g., by providing values for some attributes and ignoring others), they have the same variables attached to them, and must obey similar constraints.

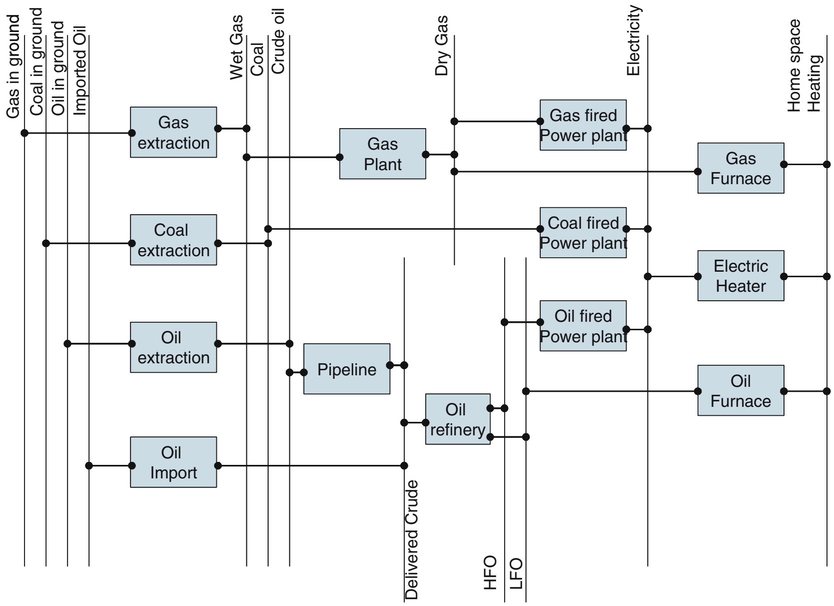

Fig. 1 Partial view of a simple Reference Energy System (all arcs are oriented left to right)

In contrast, the TIMES commodities are classified into several *Major Groups*. There are five such groups: energy carriers, materials, energy services, emissions, and monetary flows. The use of these groups is essential in the definition of some TIMES constraints, as discussed in Part II.

Figure 2 sketches the more complete RES of the TIAM model, applicable to each of the 15 TIAM regions.[4] The main elements of TIAM's RES are now briefly described:

- *Energy supply sector:* Each primary energy form is extracted from multiple layers of reserves (fossil, biomass) or of resource potentials (non-fossil energy such as wind, hydro, shallow, deep and very deep geothermal, etc.), each with a potential and a specific unit cost. This constitutes a supply curve for each energy form. The primary energy resources and forms modeled in TIAM are: coal (4 resources, 2 forms), crude oil (21 resources, 4 forms), natural gas (11 resources, 1 form), and solid biomass (8 resources, 6 forms).
- *Energy trade:* The following types of energy are endogenously traded between the 15 TIAM regions: coal (brown and hardcoal), crude oil, refined petroleum products (gasoline, diesel, heavy fuel oil and naphta), natural gas, liquefied natural gas, and atmospheric emissions (see below). The prices of these energy forms are therefore endogenously computed by the model;

[4] Africa, Australia, New-Zealand, Canada, Central and South America, China, Eastern Europe, Former Soviet Union, India, Japan, Mexico, Middle-East, Other Developing Asia, So-Korea, USA, Western Europe.

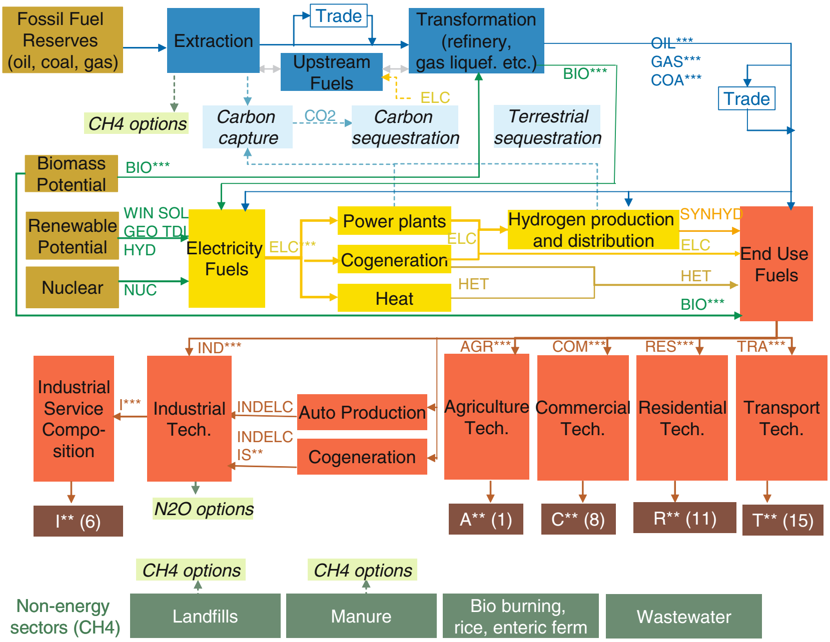

Fig. 2 Sketch of the TIAM model's RES

the impact of environmental policies on energy and permit trade is thus taken into account.

- *Energy transformation:* crude oil is transformed into 15 RPP's via refinery processes; solid biomass may be transformed into alcohols; coal and natural gas may be transformed into hydrogen via gasification or reforming (hydrogen might also be produced by electrolysis); natural gas is liquefied and LNG is gasified and via appropriate processes.
- *Energy conversion:* Electricity is produced by a large number of technologies, each of which takes as input one or more primary resources, such as coal, gas, heavy oil, wind, hydro, etc.
- *Energy consumption sectors:* End-use sectors include Residential, Commercial, Industry and Transportation. Each has several independent demands for energy services, shown in Table 1 . Each energy service may be satisfied by an array of end-use technologies in competition.
- *Emissions and emission reduction options:* TIAM models emissions of the following greenhouse gases (GHG): CO_2 from energy consumption, CH_4 from energy consumption (including leakages) as well as from some non-energy sectors (landfills, manure, wastewater, non-energy biomass burning, enteric fermentation and rice cultivation) and N_2O from energy consumption as well as from adipic and nitric acid industries. All GHGs emissions are also merged into a single CO_2-equivalent emission, based on their global warming potential, and used as input into the climate module (see Sect. 6). Emission mitigation may be accomplished in a number of ways:

Table 1 End-use demands in TIAM

	Code	Unit
Transportation segments (15)		
Autos	TRT	Billion vehicle-km/year
Buses	TRB	Billion vehicle-km/year
Light trucks	TRL	Billion vehicle-km/year
Commercial trucks	TRC	Billion vehicle-km/year
Medium trucks	TRM	Billion vehicle-km/year
Heavy trucks	TRH	Billion vehicle-km/year
Two wheelers	TRW	Billion vehicle-km/year
Three wheelers	TRE	Billion vehicle-km/year
International aviation	TAI	PJ/year
Domestic aviation	TAD	PJ/year
Freight rail transportation	TTF	PJ/year
Passengers rail transportation	TTP	PJ/year
Internal navigation	TWD	PJ/year
International navigation (bunkers)	TWI	PJ/year
Non-energy uses in transport	NEU	PJ/year
Residential segments[a] (11)		
Space heating	RH1, RH2, RH3, RH4	PJ/year
Space cooling	RC1, RC2, RC3, RC4	PJ/year
Hot water heating	RWH	PJ/year
Lighting	RL1, RL2, RL3, RL4	PJ/year
Cooking	RK1, RK2, RK3, RK4	PJ/year
Refrigerators and freezers	RRF	PJ/year
Cloth washers	RCW	PJ/year
Cloth dryers	RCD	PJ/year
Dish washers	RDW	PJ/year
Miscellaneous electric energy	REA	PJ/year
Other energy uses	ROT	PJ/year
Commercial segments[a] (8)		
Space heating	CH1, CH2, CH3, CH4	PJ/year
Space cooling	CC1, CC2, CC3. CC4	PJ/year
Hot water heating	CHW	PJ/year
Lighting	CLA	PJ/year
Cooking	CCK	PJ/year
Refrigerators and freezers	CRF	PJ/year
Electric equipments	COE	PJ/year
Other energy uses	COT	PJ/year
Agriculture segment (1)		
Agriculture	AGR	
Industrial segments[b] (6)		
Iron and steel	IIS	Millions tonnes
Non ferrous metals	INF	Millions tonnes
Chemicals	ICH	PJ
Pulp and paper	ILP	Millions tonnes
Non metal minerals	INM	PJ
Other industries	IOI	PJ
Other segment (1)		
Other non specified energy consumption	ONO	PJ/year

[a] RLi, RCi, RLi, RKi, CHi, CCi represent the demands for sub-regions available in some regions (e.g., USA, CAN)
[b] Industrial energy services are made up of a "recipe" of more detailed services: steam, process heat, machine drive, electrolytic service, other, and feedstock

  - Via energy substitutions;
  - Via improved efficiency of installed devices;
  - Via specific non-CO_2 abatement devices (e.g., CH_4 flaring or utilization for electricity production, suppression of leakages at natural gas transmission level, N_2O thermal destruction, anaerobic digestion of wastes with gas recovery, etc.);
  - Via sequestration (CO_2 capture and underground storage, biological carbon sequestration);
  - Via demand reductions (in reaction to increased carbon prices).

  Note also although agricultural GHG emissions are accounted for, some of them have no abatement options (i.e., CH_4 emissions from wastewater, biomass burning, enteric fermentation, and rice paddies). Endogenous trade of all emissions is available, so that permit trade can be easily represented within the model.
- Due to its detailed technological nature, TIAM is able to simulate almost any type of emission abatement measure, be it a regulation, a tax, a cap-and-trade system, a portfolio standard, etc.
- Finally, the initial year of the database is calibrated to the energy balances provided by the International Energy Agency, and the characteristics of the technologies and reserves are based on literature or expert knowledge (IPCC reports, US-Environmental Protection Agency, IEA-Energy Technology Perspectives, US-Department of Energy, US Geological Survey, World Energy Council, etc.).

3.4 Overview of the TIMES attributes (sets and parameters)

We provide below only succinct comments on the types of attribute attached to each entity of the RES or to the RES as a whole.

Attributes may be cardinal (e.g., numbers) or ordinal (e.g., sets). Most sets are defined for processes to describe subsets of flows that are then used to construct specific flow constraints. The cardinal attributes are usually called *parameters*. We give below a brief description of the types of parameters available in the TIMES model generator.

3.4.1 Parameters associated with processes

Process-oriented parameters fall into three general categories.

- *Technical parameters* include efficiency, availability factor(s), commodity consumptions per unit of activity, shares of fuels per unit activity, technical life of the process, construction lead time, dismantling lead-time and duration, amounts of the commodities consumed (respectively released) by the construction (respectively dismantling) of one unit of the process, and contribution to the peak equation. The efficiency, availability factors, and commodity inputs and outputs of a process may be defined in several flexible ways depending on the desired process flexibility, on the time-slice resolution chosen for the process and on the time-slice resolution of the commodities involved. Certain parameters are only relevant to special processes, such as storage processes or processes that implement trade between regions.

- *Economic and policy parameters* include a variety of costs attached to the investment, dismantling, maintenance, and operation of a process. In addition, taxes and subsidies may be defined in a very flexible manner. Other economic parameters are the economic life of a process (which is the time during which the investment cost of a process is amortized, which may differ from the operational lifetime) and the process specific discount rate, also called *hurdle rate,* both of which serve to calculate the annualized payments on the process investment cost.
- *Bounds* (upper, lower, equality) may be imposed on the investment, capacity, and activity of a process.

Note that many process parameters may be *vintaged* (i.e., dependent upon the date of installation of new capacity), and furthermore may be defined as being dependent on the *age* of the technology. For instance, the annual maintenance cost of an automobile could be defined to remain constant for say 3 years and then increase in a linear manner each year after the third year.

3.4.2 Parameters associated with commodities

Commodity-oriented parameters also fall into three categories.

- *Technical parameters* associated with commodities: overall efficiency (for instance grid efficiency), and the time-slices over which that commodity is to be tracked. For demand commodities, in addition the annual projected demand and load curves (if the commodity has a sub-annual time-slice resolution) can be specified.
- *Economic parameters* include additional costs, taxes, and subsidies on the production of a commodity. In the case of a demand service, additional parameters are: the demand's own-price elasticity, the total allowed range of variation of the demand value, and the number of steps to use for the discrete approximation of the curve.
- *Policy based parameters* bounds (at each period or cumulative) on production of a commodity, or on the imports or exports of a commodity by a region.

3.4.3 Parameters attached to commodity flows into and out of processes

A commodity flow (more simply, a *flow*) is an amount of a given commodity produced or consumed by a given process. Some processes have several flows entering or leaving it, perhaps of different types (fuels, materials, demands, or emissions). Each flow has a variable attached to it, as well as several attributes.

- *Technical parameters* permit full control over the maximum and/or minimum share a given input or output flow may take within the same commodity group. For instance, a flexible turbine may accept oil or gas as input, and the modeler may use a parameter to limit the share of oil to at most 40% of the total fuel input. Other parameters and sets define the amount of certain outflows in relation to certain inflows (e.g., efficiency, emission rate by fuel, etc.). For instance, in an oil refinery a parameter may be used to set the total amount of refined products equal to 92% of the total amount of inputs into the refinery, or to calculate certain emissions as a fixed proportion of the amount of oil consumed.

- *Economic parameters* include delivery and other variable costs, taxes and subsidies attached to an individual process flow.

3.4.4 Parameters attached to the entire RES

These parameters include currency conversion factors (in a multi-regional model), region-specific time-slice definitions, region-specific values of capital and labor (influencing the costs of technologies), a region-specific general discount rate, and reference year for calculating the discounted total cost (objective function). In addition, certain switches control the activation of the data interpolation procedure as well as special model features to be employed (see last three sections).

3.5 Managing and running a TIMES model

The construction and maintenance of a TIMES database is greatly helped by the VEDA_FE (front end) interface that allows the user to construct, access, browse, and generally maintain the model's database, as well as order a series of model runs. A companion back end interface, VEDA_BE, facilitates the exploration of the solution and the construction of result tables and graphics. The descriptions of the VEDA interfaces are available at http://www.kanors.com/software.htm

The TIMES database is transformed into a Linear Programming matrix via a computer program (matrix generator) written in the GAMS language. The LP is then solved by a commercial optimizer such as CPLEX or EXPRESS. When mixed integer programming (MIP) is required (see Sects. 5.1 and 5.2), the GAMS program automatically activates the MIP feature of the optimizer.

4 Economic rationale of TIMES

This section provides an economic interpretation of the TIMES and other partial equilibrium models based on maximizing total surplus. Partial equilibrium models have one common feature: they simultaneously configure the production and consumption of commodities (i.e., fuels, materials, and energy services) and their prices. The price of producing a commodity affects the demand for that commodity, while at the same time the demand affects the commodity's price. A market is said to have reached an equilibrium at prices p^* and quantities q^*

when no consumer wishes to purchase less than q^* at price p^* and no producer wishes to produce more than q^* at price p^*. Both p^* and q^* are vectors whose dimension is equal to the number of different commodities being modeled. As explained below, when all markets are in equilibrium the total economic surplus is maximized.

Earlier and simpler Bottom-up models had fixed energy service demands, and thus were limited to minimizing the cost of supplying these demands (e.g. the early incarnations of MARKAL, see Fishbone and Abilock 1981; Berger et al. 1992 though MARKAL has since been extended beyond these early versions). In contrast, the TIMES demands for energy services are themselves elastic to their own prices, thus allowing the model to compute a *bona fide* supply-demand equilibrium. This feature is a fundamental step toward capturing the main feedback from the economy to the energy system.

Section 4.1 discusses the central economic rationale of the TIMES model. Section 4.2 describes the details of how price elastic demands are modeled in TIMES, and Sect. 4.3 provides additional discussion of the economic properties of the model.

4.1 The TIMES paradigm

In brief, TIMES is a *technology explicit, multi-regional, partial equilibrium* model, that assumes *price elastic demands, competitive markets, and perfect foresight* (resulting in *Marginal value Pricing*) . We now proceed to flesh out each of these properties.

4.1.1 A technology explicit model

As already presented in Sect. 2, each technology is described in TIMES by a number of technical and economic parameters. A mature TIMES model may include several thousand technologies in all sectors of the energy system (energy procurement, conversion, processing, transmission, and end-uses) in each region. Thus TIMES is not only technology explicit, it is technology rich. Furthermore, the number of technologies and their relative topology may be changed at will, purely via data input specification, without the user ever having to modify the model's equations. The model is thus to a large extent *data driven*.

4.1.2 Multi-regional feature

Some existing TIMES models covering the entire energy system include up to 15 regional modules, while some existing sectoral TIMES models consist of up to 30 regions. The number of regions in a model is limited only by the difficulty of solving LP's of very large size. The individual regional modules are linked by energy and material trading variables, and by emission permit trading variables, if desired. The trade variables transform the set of regional modules into a single multi-regional (possibly global) energy model, where actions taken in one region may affect all other regions. This feature is of course essential when global or regional energy and emission policies are being simulated.

4.1.3 Partial equilibrium properties

As explained above, TIMES computes a partial equilibrium on energy markets. This equilibrium feature is present at every stage of the energy system: primary energy forms, secondary energy forms, and energy services. A supply-demand equilibrium has the property of maximizing the total surplus, defined as the sum of suppliers and consumers surpluses. The TIMES equilibrium possesses in fact three fundamental properties: *linearity, maximization of surplus,* and *competitiveness of energy markets*. These properties in turn result in two additional features: *marginal cost pricing,* and the *profit maximization* property. We describe each property in some detail below.

4.1.3.1 Linearity A linear input-to-output relationship means that each technology may be implemented at any capacity, continuously from a lower limit to some upper limit, without economies of scale. In a real economy, a given technology is usually available in discrete sizes, rather than on a continuum (for instance a nuclear power plant, or a hydroelectric project). In such cases, it may happen that the model's solution shows some technology's capacity at an unrealistically small size. However, in most applications, such a situation is relatively infrequent and often innocuous, since the scope of application is at the country or region's level, and thus large enough so that small capacities are unlikely to occur.[5]

The fact that TIMES's equations are linear, *does not mean that production functions behave in a linear fashion*. Indeed, the TIMES production functions are usually highly non-linear (but convex), representing non-linear functions as a stepped sequence of linear functions. As a simple example, a supply of some resource may be represented as a sequence of linear segments, each with rising unit cost. Thus, diseconomies of scale are frequently present in TIMES and are easily accommodated.

The linearity property allows the TIMES equilibrium to be computed using Linear Programming. Part II contains a streamlined version of the variables, constraints, and objective function of the TIMES L.P. In the case where economies of scale or some other non-convex relationship is important to the problem being investigated, the optimization program would no longer be linear or even convex. We shall examine such a case in Sect. 4 when discussing Endogenous Technology Learning.

4.1.3.2 Maximization of total surplus: price equals marginal value The *total surplus* of an economy is the sum of the suppliers' and the consumers' surpluses. In TIMES, the suppliers of a commodity are technologies that procure a given

[5] There are situations where plant size matters, for instance when the region being modeled is very small. In such cases, it is possible to enforce a rule by which certain capacities are allowed only in multiples of a given size (e.g., build or not a gas pipeline), by introducing integer variables. This option, referred to as Lumpy Investment (LI) is available in TIMES and is discussed in Sect. 4.

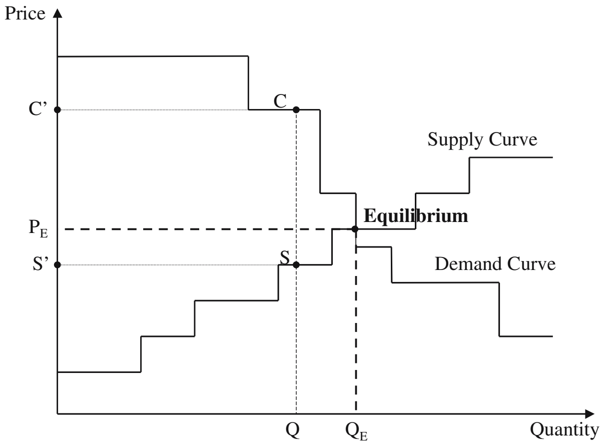

Fig. 3 Equilibrium in the case of an energy form: the model implicitly constructs both the supply and the demand curves

commodity, and the consumers of a commodity are technologies or demands that consume a given commodity. Many technologies are both suppliers and consumers, but not of the same commodity (a technology never has the same commodity as input and output, with the exception of storage technologies). Therefore, for each commodity the RES defines a set of suppliers and a set of consumers.

The set of suppliers of a commodity is characterized by its *inverse production function* (or *supply curve*) plotting the marginal production cost of the commodity as a function of the quantity supplied. In TIMES, as in other technological models, the supply curve of a commodity is not explicitly specified, but rather implicitly (*endogenously*) derived by the model itself. It is a standard result of Linear Programming theory that the inverse supply function is step-wise constant and increasing in each factor (see Fig. 3) for the case of a single commodity). Each horizontal step of the inverse supply function indicates that the commodity is produced by a certain set of technologies in a strictly linear fashion. As the quantity produced increases, one or more resources in the mix is exhausted, and therefore the system must start using a different (more expensive) set of technologies. Thus, each change in production mix generates one step of the staircase production function with a value higher than the preceding step.

In a symmetrical manner, each TIMES instance defines a series of *inverse demand functions* (i.e., *demand curves*). For demands, two cases are distinguished. First, if the commodity in question is an energy carrier whose production and consumption are endogenous to the model, then its demand curve is implicitly constructed within TIMES, and is a step-wise constant, decreasing function of the quantity demanded, as illustrated in Fig. 3. If on the other hand the commodity is a demand for an energy service, then its demand curve is exogenously defined by the user via the specification of the own-price elasticity of that demand, and the curve is in this instance a smoothly decreasing curve

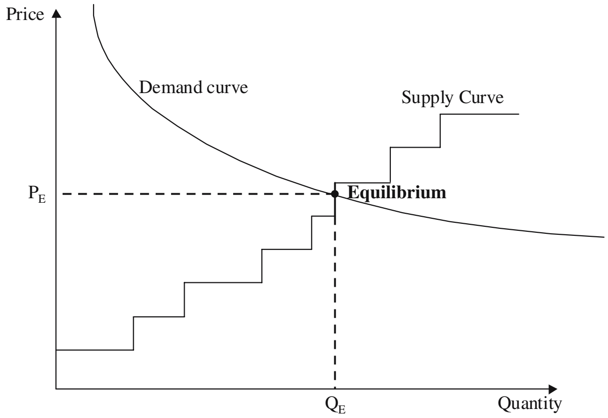

Fig. 4 Equilibrium in the case of an energy service: the user explicitly provides the demand curve, usually using a simple functional form

as illustrated in Fig. 4.[6] In TIMES, each energy service demand is assumed to have a constant own price elasticity function of the form: $D/D0 = (P/P0)^E$, where $\{D_{0,}P_0\}$ is a reference pair of demand and price values for that energy service over the forecast horizon (obtained from solving a reference scenario), and E is the own price elasticity of that energy service demand chosen by the user (note that though not shown by the notation, this price elasticity may vary over time).

The supply-demand equilibrium is at the intersection of the supply function and the demand function, and corresponds to an equilibrium quantity Q_E and an equilibrium price P_E.[7] At price P_E, suppliers are willing to supply the quantity Q_E and consumers are willing to buy that same quantity Q_E. Of course, the TIMES equilibrium concerns many commodities, and the equilibrium is a multi-dimensional analog of the above, where Q_E and P_E are now vectors rather than scalars.

Using Fig. 3 as an example, the definition of the suppliers' surplus corresponding to a certain point S on the inverse supply curve is the net revenue attached to a given commodity, i.e., the area between the horizontal segment SS′ and the inverse supply curve. Similarly, the consumers' surplus for a point C on the inverse demand curve, is defined as the area between the segment CC′ and the inverse demand curve. This area is the opportunity gain of all consumers who purchase the commodity at a price lower than the price they would have been willing to pay. For a given quantity Q, the total surplus (suppliers' plus consumers') is thus the area comprised between the two inverse curves and located at the left of Q. It is seen from Fig. 3 that the total surplus is maximized

[6] This smooth curve will be discretized later for computational purposes, as described in Part II.

[7] As may be seen in Fig. 3, the equilibrium is not necessarily unique. In the case shown in Fig. 3, any point on the vertical segment containing the equilibrium is also an equilibrium, with the same Q_E but a different P_E. In other cases, the multiple equilibria may have the same price and different quantities.

exactly when Q is equal to the equilibrium quantity Q_E. Therefore, we may state (in the single commodity case) the following Equivalence Principle:

> *"The supply-demand equilibrium is reached when the total surplus is maximized"*

In the multi-dimensional case, the proof of the above statement is less obvious, and requires a certain *integrability property* (Samuelson 1952; Takayama and Judge 1971). One sufficient condition for the integrability property to be satisfied is realized when the cross-price elasticities of any two energy forms are equal, viz.

$$\frac{\partial P_j}{\partial Q_i} = \frac{\partial P_i}{\partial Q_j} \quad \text{for all } i, j.$$

In the case of commodities that are energy services, these conditions are trivially satisfied in TIMES because we have assumed zero cross price elasticities. In the case of an energy carrier, where the demand curve is implicitly derived, it is also easy to show that the integrability property is always satisfied.[8] Thus the equivalence principle is valid in all cases. This is a remarkably useful result that provides a simple method for computing the equilibrium, as is explained in detail in Part II.

In summary, the equivalence principle guarantees that the TIMES supply-demand equilibrium maximizes total surplus.The total surplus concept has long been a mainstay of social welfare economics because it takes into account both the surpluses of consumers and of producers.[9]

Remark In early versions of MARKAL, and in several other least-cost bottom-up models, energy service demands are exogenously specified by the modeler, and only the cost of supplying these energy services is minimized. In such a case the "inverse demand curve" is a vertical line.

4.1.3.3 Competitive energy markets with perfect foresight Competitive energy markets are characterized by perfect information and by multiple agents that do not exercise market power. It is a standard result of microeconomic theory that the assumption of competitive markets entails that the market price of a commodity is equal to its marginal value in the economy. This property holds in the TIMES economy, as discussed in the next subsection.

In TIMES, the perfect information assumption extends to the entire planning horizon, so that each agent has perfect foresight, i.e., complete knowledge of the market's parameters, present and future. Hence, the equilibrium is computed by maximizing total surplus in one pass for the entire set of periods. Such a

[8] This results from the fact that in TIMES each price P_i is the shadow price of a balance constraint (see Part II), and may thus be (loosely) expressed as the derivative of the objective function F with respect to the right-hand-side of a balance constraint, i.e., $\partial F/\partial Q_i$. When that price is further differentiated with respect to another quantity Q_j, one gets ,$\partial^2 F/\partial Q_i \cdot \partial Q_j$, which, under mild conditions is always equal to $\partial^2 F/\partial Q_j \cdot \partial Q_i$, as desired.

[9] See e.g., Samuelson and Nordhaus (1977)

farsighted equilibrium is also called an *inter-temporal, dynamic* or *clairvoyant* equilibrium.

However, the perfect foresight assumption may be relaxed by assuming that some parameters are uncertain. This assumption is at the basis of the Stochastic Programming option of TIMES (Sect. 5.3). Another variant of TIMES assumes that agents have a limited foresight (e.g., over one or a few periods rather than the full horizon).

4.1.3.4 Marginal value pricing The fact that the TIMES equilibrium occurs at the intersection of the inverse supply and inverse demand curves implies directly that the equilibrium price is equal to the marginal system value of the commodity. From a different angle, the duality theory of Linear Programming indicates that for each constraint of the TIMES linear program there is a dual variable. This dual variable (when an optimal solution is reached) is also called the constraint's *shadow price,* and is equal to the marginal change of the objective function per unit increase of the constraint's right-hand-side. For instance, the shadow price of a demand constraint is the price of the corresponding energy service.

Duality theory does not necessarily indicate that the marginal value of a commodity is equal to the marginal cost of *producing* that commodity. For instance, in Fig. 3 the price does not correspond to *any* marginal supply cost, since it is located at a discontinuity of the inverse supply curve. In this case, the price is determined by demand rather than by supply, and the phrase *marginal cost pricing* (so often used in the context of optimizing models) is incorrect. The phrase *marginal value pricing* is more appropriate.

4.1.3.5 Profit maximization: the invisible hand An interesting property may be derived from the assumptions of competitiveness. While the avowed objective of the TIMES model is to maximize the total surplus, it is also true that each economic agent in TIMES maximizes its own 'profit'. This property is akin to the famous 'invisible hand' property of competitive markets, and may be established rigorously. This property is important inasmuch as it provides an alternative justification for the class of equilibria based on the maximization of total surplus. It is now possible to shift the model's rationale from a global, societal one (surplus maximization), to a local, decentralized one (individual utility maximization). Of course, this equivalence is valid only insofar as the marginal value pricing mechanism is strictly enforced—that is, neither individual producers nor individual consumers have market power.

5 Three optional features of TIMES

5.1 The lumpy investment option

5.1.1 Description

In some cases, the linearity property of the TIMES model may become a drawback for the accurate modeling of certain investment decisions. Consider for example a TIMES model for a relatively small community such as a city. For such a scope the *granularity* of some investments may have to be taken into account. For instance, the size of an electricity generation plant proposed by the model would have to conform to an implementable minimum size (it would make no sense to decide to construct a 50 MW nuclear plant). Another example for multi-region modeling might be whether or not to build cross-region electric grid(s) or gas pipeline(s) in discrete size increments. Processes subject to investments of only specific size increments are described as “lumpy” investments.

For other types of investments, size does not matter: for instance the model may decide to purchase 10,950.52 electric cars, which is easily rounded to 10,950 without any serious inconvenience. The situation is similar for a number of residential or commercial heating devices, or for the capacity of wind turbines or industrial boilers, or for any technologies with relatively small minimum feasible sizes. Such technologies would not be candidates for treatment as “lumpy” investments.

It is the user’s responsibility to decide that certain technologies should (or should not) respect the minimum size constraint, weighing the pros and cons of so doing. This section explains how the TIMES LP is transformed into a Mixed Integer Program (MIP) to accommodate minimum or multiple size constraints, and states the consequences of so doing on computational time and on the interpretation of duality results.

The lumpy investment option available in TIMES is slightly more general than the one described above. It insures that investment in technology k is equal to one of a finite number N of pre-determined sizes: $0, S_1(t), S_2(t), \ldots, S_N(t)$. As implied by the notation, these discrete sizes may be different at different time periods. Note that by choosing the N sizes as the successive multiples of a fixed number S, it is possible to invest (perhaps many times) in a technology with fixed standard size.

Imposing such a constraint on an investment is unfortunately impossible to formulate using standard LP constraints and variables. It requires the introduction of *integer variables* in the formulation. The optimization problem resulting from the introduction of integer variables into a Linear Program is called a Mixed Integer Program (MIP).

5.1.2 Formulation and solution of the mixed integer linear program

Typically, the modeling of a lumpy investment involves Integer Variables, i.e. variables whose values may only be non-negative integers (0, 1, 2, ...). The mathematical formulation is as follows

$$NCAP(p,t) = \sum_{i=1}^{N} S_i(p,t) \times Z_i(p,t) \qquad \text{each } t = 1, \ldots, T$$

with

$$Z_i(p,t) = 0 \text{ or } 1$$
and
$$\sum_{i=1}^{N} Z_i(p,t) \leqslant 1.$$

The second and third constraints imply that at most one of the Z variables is equal to 1. Therefore, the first constraint now means that $NCAP$ is equal to one of the preset sizes or is equal to 0, which is the desired result.

Although the formulation of lumpy investments *looks* simple, it has a profound effect on the resulting optimization program. Indeed, MIP problems are notoriously more difficult to solve than LPs, and in fact many of the properties of linear programs discussed in the preceding sections do not hold for MIPs, including duality theory, complementary slackness, etc. Note that the constraint that $Z(p,t)$ should be 0 or 1 departs from the *divisibility* property of linear programs. This means that the *feasibility domain* of integer variables (and therefore of some investment variables) is no longer contiguous, thus making it vastly more difficult to apply purely algebraic methods to solve MIP's. In fact, practically all MIP solution algorithms make use (at least to some degree) of partial enumerative schemes, which tend to be time consuming and less reliable[10] than the algebraic methods used in LP.

5.1.3 Important remark on the MIP dual solution (*shadow prices*)

Using MIP rather than LP has an important impact on the interpretation of the TIMES shadow prices. Once the optimal MIP solution has been found, it is customary for MIP solvers to fix all integer variables at their optimal (integer) values, and to perform one additional iteration of the LP algorithm, so as to obtain the dual solution (i.e., the shadow prices of all constraints). However, the interpretation of these prices is different from that of a LP. Consider for instance the shadow price of the natural gas balance constraint: in a pure LP, this value represents the price of natural gas. In MIP, this value represents the price of gas *conditional on having fixed the lumpy investments at their optimal integer values.* What does this mean? We shall attempt an explanation via one example: suppose that one lumpy investment was the investment in a gas pipeline; then, *the gas shadow price will not include the investment cost of the pipeline, since that investment was fixed when the dual solution was computed.*

In conclusion, when using MIP, only the primal solution is fully reliable. In spite of this major caveat, modeling lumpy investments may be of paramount

[10] A TIMES LP program of a given size tends to have fairly constant solution time, even if the database is modified. In contrast, a TIMES MIP may show some erratic solution times. One may observe reasonable solution times (although significantly longer than LP solution times) for most instances, with an occasional *very* long solution time for some instances. This phenomenon is predicted by the theory of complexity as applied to MIP, see Papadimitriou and Steiglitz (1982).

importance in some instances, and may thus justify the extra computing time and the partial loss of dual information.

5.2 Endogenous technological learning (*ETL*)

5.2.1 Introduction

In a long-term dynamic model such as TIMES the characteristics of many of the future technologies are almost inevitably changing over the sequence of future periods due to *technological learning*.

In some cases it is possible to forecast such changes as a function of time, and thus to define a time-series of values for each parameter (e.g., unit investment cost, efficiency). In such cases, technological learning is *exogenous* since it depends only on time elapsed and may thus be specified outside the model.

In other cases there is evidence that the pace at which some technological parameters change is dependent on the *experience* acquired with this technology. Such experience is not solely a function of time elapsed, but typically depends on the cumulative investment in the technology. In such a situation, technological learning is *endogenous,* since the future values of the parameters are no longer a function of time elapsed alone, but depend on the cumulative investment decisions taken by the model (which are unknown before running the model). Thus, the evolution of technoeconomic parameters may no longer be established outside the model, since it depends on the model's results. ETL is also named *Learning-By-Doing* (LBD) by some authors.

Whereas exogenous technological learning does not require any additional modeling, endogenous technological learning (ETL) requires specific features. In TIMES, there is a provision to represent the effects of endogenous learning on the unit investment cost of technologies. Other parameters (such as efficiency) are not currently treated.

5.2.2 The ETL challenge

For many technologies, empirical studies of their unit investment cost have been undertaken in several countries. Many of these studies find an empirical relationship between the unit investment cost of a technology at time $t, INVCOST_t$, and the cumulative investment in that technology up to time t, $C_t = \sum_{j=-1}^{t} VAR\_INV_j$.

A typical relationship between unit investment cost and cumulative investments is of the form:

$$\mathrm{INVCOST}_t = a \cdot C_t^{-b}, \tag{1}$$

where a is the initial unit investment cost (when C_t is equal to 1) and b is the learning index, representing the speed of learning.[11] As experience (represented by cumulative capacity) increases, the unit investment cost decreases, and this may make investments in the technology more attractive. It should be clear that near-sighted investors will not be able to detect the advantage of investing early in learning technologies, since they will only observe the high initial investment cost and (being near-sighted), will not anticipate the future drop in investment cost resulting from early investments. In other words, tapping the full potential of technological learning-by-doing requires far-sighted agents who accept making initially non-profitable investments in order to later benefit from the investment cost reduction.

With regard to actual implementation, simply using (1) as the objective function coefficient of VAR_INV_t will yield a non-linear, non-convex expression. Therefore, the resulting mathematical optimization is no longer linear, and requires special techniques for its solution. In TIMES, a Mixed Integer Programming (MIP) formulation is used, as described in Part II.

5.2.3 Endogenous versus exogenous learning: discussion

In this section, we formulate a few comments and warnings that may be useful to potential users of the ETL feature. We start by stating a very important caveat to the ETL formulation described in the previous subsections and in Part II: if a model is run with such a formulation, it is very likely that the model will select some technologies, and *will invest massively at some early period* in these technologies unless it is prevented from doing so by additional constraints. Why this is likely to happen may be qualitatively explained by the fact that once a learning technology is selected for investing in, two opposing forces are at play in deciding the optimal timing of the investments. On the one hand, the discounting provides an incentive for postponing investments. On the other hand, investing early allows the unit investment cost to drop immediately, and thus allows much cheaper investments in the learning technologies in the current and all future periods. Given the significant cost reduction that is usually induced by learning, the first factor (discounting) is unlikely to dominate, and hence the model will tend to invest massively and early in such technologies —or of course, not at all. What we mean by "massively" depends on the other constraints of the problem (such as the extent to which the commodity produced by the learning technology is in demand, the presence of existing technologies that compete with the learning technology, etc.). However, there is a clear danger that we may observe unrealistically large early investments in some learning technologies.

[11] It is usual to define, instead of b, another parameter, pr called the *progress ratio,* which is related to b via the following relationship:

$$pr = 2^{-b}.$$

Hence, $1 - pr$ is the cost reduction incurred when cumulative investment is doubled. Typical observed pr values are in a range of 0.75 to 0.95.

ETL modelers are well aware of this phenomenon, and they impose additional constraints to control the penetration of learning technologies. These constraints may take the form of upper bounds on the capacity of or the investment in the learning technologies at each time period, reflecting what is deemed realistic. These upper bounds play a determining role in the solution of the problem, and it is most often observed that the capacity of a learning technology is either equal to 0 or to the upper bound. This last observation indicates that the selection of upper bounds by the modeler is the predominant factor in controlling the penetration of successful learning technologies.

In view of the preceding discussion, a fundamental question arises: is it worthwhile for the modeler to go to the trouble of modeling *endogenous* learning (with all the attendant computational burdens) when the results are to a large extent conditioned by *exogenous* upper bounds? We do not provide a clear and unambiguous answer to this question; that is left for each modeler to evaluate.

However, given the above caveat, a possible alternative to ETL would consist in using exogenous learning trajectories. To do so, the same sequence of upper bounds on capacity would be selected by the modeler, and the values of the unit investment costs (INVCOST) would then be externally computed by plugging these upper bounds into the learning formula (1). This approach makes use of the same exogenous upper bounds as the ETL approach, but avoids the considerable computational burden of ETL. Of course, the running of exogenous learning scenarios is not entirely foolsafe, since there is no absolute guarantee that the capacity of a learning technology will turn out to be exactly equal to the assumed exogenous upper bound. If that were not the case, a modified scenario would have to be run, with upper bounds adjusted downward. This trial-and-error approach may seem inelegant, but it should be remembered that it (or some other heuristic approach) might prove to be necessary in those cases where the number of learning technologies and the model size are both large, thus making the rigorous ETL formulation computationally intractable.

5.3 Stochastic Programming

5.3.1 Introduction

Stochastic Programming is an approach for optimal decision making under risk. The risk consists of uncertainty regarding the values of some (or all) of the LP parameters (cost coefficients, matrix coefficients, RHS's). Each uncertain parameter is considered to be a random variable, usually with a discrete, known probability distribution. The objective function thus becomes also a random variable and a criterion must be chosen in order to make the optimization possible. Such a criterion may be expected cost, expected utility, or others (Kanudia and Loulou 1998).

Uncertainty on a given parameter is said to be *resolved* —either fully or partially, at the *resolution time,* i.e. the time at which the actual value of the parameter is revealed. Different parameters may have different times of resolution.

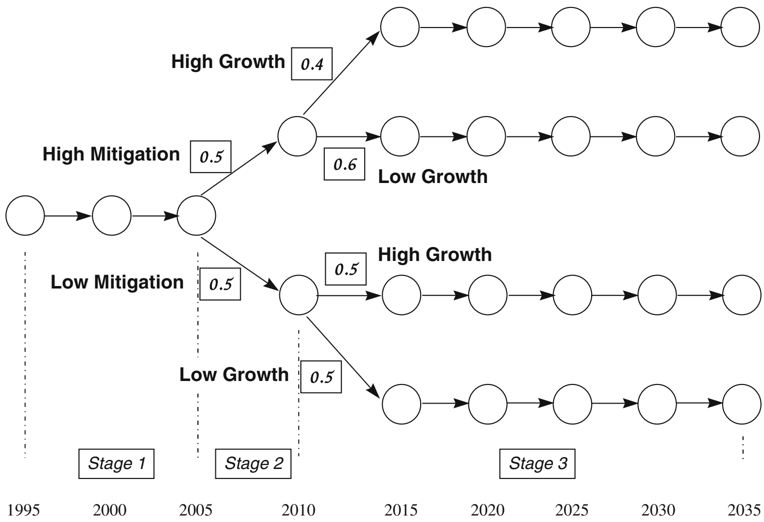

Fig. 5 Example of an event tree

Both the resolution times and the probability distributions of the parameters may be represented on an event tree, such as the one of Fig. 5, depicting a typical energy/environmental situation. In Fig. 5, two parameters are uncertain: mitigation level, and demand growth rate. The first may have only two values (High and Low), and becomes known in 2005. The second also may have two values (High and Low) and becomes known in 2010. The probabilities of the outcomes are shown along the branches. This example assumes that present time is 1995. This example is said to have three stages (i.e., two resolution times). The simplest non-trivial event tree has only two stages (a single resolution time).

5.3.2 Mathematical formulation

The key observation is that prior to resolution time, the decision maker (and hence the model) does not know the eventual values of the random parameters, but still has to make decisions. On the contrary, after resolution, the decision maker knows with certainty the outcome of some event(s) and his decisions will be different depending of which outcome has occurred.

For the example of Fig. 5, in 2000 and 2005 there can be only one set of decisions, whereas in 2010 there will be two sets of decisions, contingent on which of the Mitigation outcomes (High or Low) has occurred, and in 2015, 2020, ..., 2035, there will be four sets of contingent decisions.

This remark leads directly to the following general multi-period, multi-stage stochastic program (2)–(4) below. The formulation described here is based on Dantzig (1963), also summarized in Kanudia and Loulou (1998), and uses the expected cost criterion. Note that this is a LP, but its size is larger than that of the deterministic TIMES model.

Minimize

$$Z = \sum_{t \in T} \sum_{w \in W(t)} C(t,w) \times X(t,w) \times p(t,w) \tag{2}$$

Subject to:

$$A(t,w) \times X(t,w) \geqslant b(t,w) \quad \forall t \in T, \;\; \forall w \in W(t), \tag{3}$$

$$\sum_{t \in T} D(t, g(t,w)) \times X(t, g(t,w)) \geqslant e(w) \quad \forall w \in W(T), \tag{4}$$

where

t	=	time period
T	=	set of time periods
w	=	state-of-the-world (sow) index
$W(t)$	=	set of sow indices for time period t; for Fig. 5, we have:
$W(1995)$	=	1; $W(2000)$ = 1; $W(2005)$ = 1; $W(2010)$ = (1,2); $W(2015)$ = (1,2,3,4); $W(2020)$ = (1,2,3,4); $W(2025)$ = (1,2,3,4); $W(2030)$ = (1,2,3,4); $W(2035)$ = (1,2,3,4);
$W(T)$	=	set of sow indices at the last stage (i.e. the set of *scenarios*). Set *W(T)* is homeomorphic to the set of paths from period 1 to last period T, in the event tree
$g(t,w)$	=	a unique mapping from $\{(t,w) \mid w \in W(T)\}$ to $W(t)$, according to the event tree. $g(t,w)$ is the sow at period t corresponding to sow w
$X(t,w)$	=	the column vector of decision variables in period t, under sow w
$C(t,w)$	=	the cost row vector under sow w
$p(t,w)$	=	event probabilities for each sow w
$A(t,w)$	=	the LP sub-matrix of single period constraints, in time period t, under sow w
$b(t,w)$	=	the right hand side column vector (single period constraints) in time period t, under sow w
$D(t,w)$	=	the LP sub-matrix of multi-period constraints under sow w
$e(w)$	=	the right hand side column vector (multi-period constraints) under sow w

5.3.3 An alternative optimization criteria: expected utility criterion with risk aversion

The preceding description of stochastic programming assumes that the policy maker accepts the expected cost as his optimizing criterion. This is equivalent to saying that he is risk neutral. In many situations, the assumption of risk neutrality is only an approximation of the true utility function of a decision maker. In

TIMES, there is an alternative objective function that simulates risk aversion. It takes the form of an expected utility criterion with linearized risk aversion.[12]

The approach is based on the classical E-V model (an abbreviation for Expected Value-Variance). In the E-V approach, it is assumed that the variance of the cost is an acceptable measure of the risk attached to a strategy in the presence of uncertainty. The variance of the cost of a given strategy k is defined as follows:

$$\mathrm{Var}(C_k) = \sum_w p_w \cdot (\mathrm{Cost}_{w|k} - \mathrm{EC}_k)^2,$$

where $\mathrm{Cost}_{w|k}$ is the cost when strategy k is followed and the wth state of the world prevails, and EC_k is the expected cost of strategy k defined[13] as usual by:

$$\mathrm{EC}_k = \sum_w p_w \cdot Cost_{w|k}.$$

In the E-V approach, the expected cost criterion is thus replaced by the following utility function to minimize:

$$U = \mathrm{EC} + \lambda \cdot \sqrt{\mathrm{Var}(C)},$$

where $\lambda > 0$ is a measure of the *risk aversion* of the decision maker. For λ=0, the usual expected cost criterion is obtained. Larger values of λ indicate increasing risk aversion. Note that the above formulation leads to a non-linear, non-convex model, with ensuing computational restrictions that would impose serious limitations on model size. The next subsection presents a linearized version of this criterion.

5.3.4 Utility function with linearized risk aversion

To avoid non-linearities, it is possible to replace the semi-variance by the Upper-absolute-deviation, defined by:

$$\mathrm{UpAbsDev}\ \ (\mathrm{Cost}_k) = \sum_w p_w \cdot \left\{\mathrm{Cost}_{w|k} - \mathrm{EC}_k\right\}^+,$$

where the function $y = \{x\}^+$ is defined by the following two *linear* constraints: $y \geq x$, and $y \geq 0$, and the utility is now written via the following *linear* expression:

$$U = \mathrm{EC} + \lambda \cdot \mathrm{UpsAbsDev}(C).$$

12 Another criterion of interest is the Minimax Regret criterion (Loulou and Kanudia 1999), but it is not yet implemented in TIMES.

13 Strategy k could more accurately be denoted $k(w)$ since it depends on the sow.

This is the expected utility formulation implemented into the TIMES model generator.

6 The climate module of TIMES

The Climate Module starts from global emissions as generated by the TIMES global model, and proceeds to compute successively:

- the changes in CO_2 concentrations in three reservoirs,
- the total change (over pre-industrial times) in atmospheric radiative forcing from anthropogenic causes, and
- the temperature changes (over pre-industrial times) in two reservoirs.

The Climate Equations used to perform these calculations are adapted from Nordhaus and Boyer (1999), The choice of the Nordhaus and Boyer's climate equations is motivated by the simplicity of their approach and by the fact that their climate module is well-documented and acceptably accurate (Drouet et al. 2006; Nordhaus and Boyer 1999). In our implementation, the non linear forcing equation has been replaced by a linear approximation whose values closely approach the exact ones as long as the useful range is carefully selected. This approximation was motivated by the modeling of temperature limits, not possible with a non linear forcing equation.

Rigorously, the concentration and forcing equations used in the climate module are applicable only to the carbon cycle, and a different treatment of other greenhouse gases —methane, N_2O, ozone, aerosols, etc. could be done using specific models of their own life cycles. However, following a commonly accepted approach, it is possible to use the CO_2 equations to calculate the impact of other gases on climate using their Global Warming Potentials (GWP) recommended by the IPCC Third Assessment Report (2001). Therefore, in what follows, the term CO_2 used in the climate equations should really be thought of as CO_2-equivalent.

We now describe the mathematical equations used at each of the three steps of the climate module.

6.1.1 Concentrations (accumulation of CO_2)

CO_2-eq accumulation is represented as the linear three-reservoir model below: the atmosphere, the quickly mixing upper ocean + biosphere, and the deep ocean. CO_2 flows in both directions between adjacent reservoirs. The three-reservoir model is represented by the following three equations when the step of the recursion is equal to 1 year:

$$M_{\mathrm{atm}}(y) = E(y-1) + (1-\varphi_{\mathrm{atm-up}})M_{\mathrm{atm}}(y-1) + \varphi_{\mathrm{up-atm}}M_{\mathrm{up}}(y-1) \quad (5)$$

$$M_{\mathrm{up}}(y) = (1-\varphi_{\mathrm{up-atm}}-\varphi_{\mathrm{up-lo}})M_{\mathrm{up}}(y-1) + \varphi_{\mathrm{atm-up}}M_{\mathrm{atm}}(y-1) + \varphi_{\mathrm{lo-up}}M_{\mathrm{lo}}(y-1) \quad (6)$$

$$M_{\mathrm{lo}}(y) = (1-\varphi_{\mathrm{lo-up}})M_{\mathrm{lo}}(y-1) + \varphi_{\mathrm{up-lo}}M_{\mathrm{up}}(y-1) \quad (7)$$

with

- $M_{atm}(y), M_{up}(y), M_{lo}(y)$: masses of CO_2 in atmosphere, in a quickly mixing reservoir representing the upper level of the ocean and the biosphere, and in deep oceans (GtC), respectively, at period t (GtC)
- $E(y-1)$ = CO_2 eq emissions in previous year (GtC)
- φ_{ij}, transport rate from reservoir i to reservoir $j(i, j = \text{atm, up, lo})$ from year $y-1$ to y

6.1.2 Radiative forcing

The relationship between GHG accumulations and increased radiative forcing, $\Delta F(t)$, is derived from empirical measurements and climate models.

$$\Delta F(t) = \gamma \times \frac{\ln\left(M_{atm}(t)/M_0\right)}{\ln 2} + O(t), \tag{8}$$

where

- M_0 is the pre-industrial (Ca. 1750) reference atmospheric concentration of $CO_2 = 596.4$ GtC
- γ is the radiative forcing sensitivity to atmospheric CO_2 concentration doubling = 3.71 W/m^2, value based on the IPCC Third Assessment Report by Working Group I (2001)
- O(t) is the increase in total radiative forcing at period t relative to pre-industrial level due to anthropogenic GHG's not accounted for in the computation of CO_2 emissions. Units = W/m^2. In Nordhaus and Boyer (1999), only emissions of CO_2 were explicitly modeled, and therefore O(t) accounted for all other GHG's. In TIMES, N_2O and CH_4 are fully accounted for, but others are not (e.g., CFC's, aerosols, ozone). Therefore, our values for O(t) will differ from those in Nordhaus and Boyer. It is the modeler's responsibility to include in the calculation of O(t) only those gases not included in the CO_2-equivalent emissions.

The parameterization of the forcing equation is not controversial. The γ value might change, based on improved scientific knowledge. Therefore, users are free to experiment with other values of the γ parameter.

In TIMES, the logarithmic forcing function (8) is replaced by the linear approximation shown in Eq. (9), in order to preserve the linearity of the TIMES equations. With the linearized forcing, the forcing and temperature equations are regular TIMES equations, allowing a user to put bounds on these quantities.

The linear approximation is obtained as follows:

- First, an interval of interest for M must be selected by the user. The interval should be large enough to accommodate the anticipated values of the concentrations, but not so wide as to make the approximation inaccurate. We denote the interval as (M_1, M_2).

- Next, the linear forcing equation is taken as the half sum of two linear expressions, which respectively underestimate and overestimate the exact forcing value. The underestimate consists of the chord of the logarithmic curve, whereas the overestimate consists of the tangent to the logarithmic curve that is parallel to the chord.

The general formulas for the two estimates are as follows:
Underestimate: $F_1(M) = \gamma \cdot \ln(\text{slope}/\ln 2) + \text{slope} \cdot (M/M_0 - \text{slope}/\ln 2)$,
Overestimate: $F_2(M) = \gamma \cdot \ln(M_1/M_0)/\ln 2 + \text{slope} \cdot (M - M_1)/M_0$,

$$\text{Final approximation :} \qquad F_3(M) = \frac{F_1(M) + F_2(M)}{2}, \tag{9}$$

where slope $= \gamma \cdot \frac{\ln(M_2/M_1)/\ln 2}{(M_2 - M_1)/M0}$

6.1.3 Temperature increase

In the TIMES Climate Module as in many other integrated models, climate change is represented by the global mean surface temperature. The idea behind the two-reservoir model is that a higher radiative forcing warms the atmospheric layer, which then quickly warms the upper ocean. In this model, the atmosphere and upper ocean form a single layer, which slowly warms the second layer consisting of the deep ocean.

$$\begin{aligned} \Delta T_{\text{up}}(y) = {} & \Delta T_{\text{up}}(y-1) \\ & + \sigma_1\{F(y) - \lambda \Delta T_{\text{up}}(y-1) - \sigma_2[\Delta T_{\text{up}}(y-1) - \Delta T_{\text{low}}(y-1)]\} \end{aligned} \tag{10}$$

$$\Delta T_{\text{low}}(y) = \Delta T_{\text{low}}(y-1) + \sigma_3[\Delta T_{\text{up}}(y-1) - \Delta T_{\text{low}}(y-1)] \tag{11}$$

with

- ΔT_{up} = globally averaged surface temperature increase above pre-industrial level,
- ΔT_{low} = deep-ocean temperature increase above pre-industrial level,
- σ_1 = 1−year speed of adjustment parameter for atmospheric temperature (also known as the lag parameter),
- σ_2 = coefficient of heat loss from atmosphere to deep oceans,
- σ_3 = 1−year coefficient of heat gain by deep oceans,
- λ = feedback parameter (climatic retroaction). It is customary to write λ *as* $\lambda = \gamma/C_s, C_s$ being the climate sensitivity parameter, defined as the change in equilibrium atmospheric temperature induced by a doubling of CO_2 concentration.

Remark In contrast with most other parameters, the value of C_s is highly uncertain, with a possible range of values from 1 to 10°C. This parameter is therefore a prime candidate for sensitivity analysis, or for treatment by probabilistic methods.

7 Conclusion and recent applications of TIAM

The TIMES model and its ETSAP-TIAM incarnations are the result of a multi-year multi-partner effort, resulting in a set of tools for the analysis of long term energy and emission issues based on technoeconomics. The tools include the TIMES model equations, a large technological multiregional database for TIAM, and the VEDA shells. The suite of tools has been used for several global and local analyses over the recent past. The following list concerns only the applications at the multiregional or global level. Many other country specific applications were also made in several countries (Finland, Belgium, South Africa, etc.).

- The first global TIMES model was constructed in 2004 for the European Fusion Development Agreement (EFDA) project based at the Max Planck Institute of Munich University, with the help of the Canadian Team and supervised by Giancarlo Tosato. This was also the first time a very long TIMES horizon (100 years) was selected. The purpose of this project was to study the role of nuclear power (including Fusion) in the long term.
- The ETSAP-TIAM model has been used within the Energy Modelling Forum (EMF-22) to assess long term climate stabilization strategies in the presence of economic and climatic uncertainties. This project is sponsored by ETSAP and accomplished by the Canadian team. It led to a paper by Labriet et al. (2006), in which four possible climate sensitivities and two economic development rates are modeled with full resolution of uncertainties in 2040; the stochastic analysis allows the identification of robust early mitigation options constituting an optimal hedging strategy.
- Another recent application of TIAM is reported in Vaillancourt et al. (2006), which analyzes the role of nuclear energy in long-term climate scenarios under various sets of assumptions on technological parameters and nuclear energy policies
- The IER team recently conducted a full review of the TIAM supply side leading to several improvements of the database. The results were presented (Remme et al. 2006) and reported in an internal report available on request.
- A prospective study of transportation technologies was also conducted and presented at the Entretiens du Centre Jacques Cartier (Labriet 2006)

Three new applications of TIAM are in progress. Future applications of TIAM will include:

- The simulation of transition policies for the 2010–2040 period, such as global or regional/sectoral cap-and-trade policies or gradual increase of efficiency standards (work undertaken within the framework of the EMF).
- A newly started project "Simulation de stratégies de négociation post-Kyoto dans un régime climatique international fragmenté", sponsored by the French Ministry of Ecology and Sustainable Development (GICC Programme: Gestion et impacts du changement climatique) in which the TIAM

will be linked to the GEMINI-E3 general equilibrium model to investigate the impact of oil pricing policies on climate mitigation

- The new TOCSIN project (Technology-Oriented Cooperation and Strategies in India and China: Reinforcing the EU dialogue with Developing Countries on Climate Change Mitigation), sponsored by the European Commission (Sixth Framework Program), which will analyze the role of large developing countries in the long term abatement of greenhouse gases, with particular focus on technology diffusion.

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