Energy models: Methods and characteristics

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Abstract
Given the importance of models in complicated problem solving, an inappropriate energy model can lead to inaccurate decisions and poor policy prescriptions. This paper aims at developing a decision support tool with which the selection of appropriate model characteristics can be facilitated for developing countries. Hence, it provides a comparative overview of different ways of energy models characterization and extracts the underlying relationships amongst them. Moreover, evolution of dynamic characteristics of energy models for developing countries is identified according to the previous studies on the developed and developing countries. To do this, it reviews the related literature and follows a systematic comparative approach to achieve its purposes. These findings are helpful in cases where model developers themselves are looking for appropriate characteristics in terms of certain purpose or situation.

Keywords: energy models; energy models characterization; developing countries

1. Introduction

Over the past three decades, energy planning and management (EPM) has played an essential role in long-term social, environmental, and economic policy making of countries. Energy systems as an integral part of socio-economic systems of societies have several cross-disciplinary interactions with economy, society, and environment. To name a few, (1) the energy-economy interactions consist of changes over time in price elasticity of demand and also impacts of macroeconomic activity on energy demand; (2) the energy-society interactions are the impacts of energy cost on labour productivity, capital formation, energy consumption and therefore, economic growth and enhancing welfare and equality in the long term; (3) the energy-environment interactions include the impacts of energy policy on environmental phenomena such as climate change, resources stocks, ecosystem and human health. Therefore, the major difficulty of the EPM not only lies in its multi scales aspects (temporal and geographical), but also in the necessity to take into account the economic, technical, environmental and social criteria. Modelling of complex problems can lead to better decisions by providing decision makers with more information about the possible consequences of their choices. Hence, energy models as valuable tools for dealing with complicated problems can help decision makers to overcome this difficulty. Energy models are useful mathematical tools based on the system approach and the best model should be determined based on the problem that decision makers endeavour to solve.

Recently, the total number of developed energy models has grown tremendously and they vary considerably in characteristics and features. Hence, the key question is that 'which model(s) and characteristics are most suited for a certain purpose and situation?' Also 'what are the underlying relationships amongst these characteristics?' Given the diversity of the possible characterization approaches, this study aims at developing a comparative picture of them which can provide insight not only in the differences and similarities between them but also in the underlying relationships amongst them. Moreover, the evolution of dynamic characteristics of energy models for developing countries is identified according to the previous studies on the developed and developing countries. To do this, it reviews the related literature and follows a systematic comparative approach to achieve its purposes.

In this paper, we will first give an introduction to the different energy model categorization approaches as section 2 and then indicate their relationships via a schematic diagram. Trends in dynamic characteristics of energy model for developing countries are also extracted from the related literature in section 3.

2. Approaches of characterizing energy models

The energy models existing in the literature can be categorized via different ways; however, these categorizations are related to each other. In the following, we will discuss each of these ways in more details.

Model type

Descriptive or prognostic models depict or describe how things actually work or might work, and answer the question, 'What is this?' In comparison, normative models are prescriptive and suggest what should be done (how things ought to work) according to an assumption or standard. The first approach belongs to the concept of planning as reaction and the second approach involves goal attainment and assumes autonomous planning or planning as an action. Descriptive models comprise different methods of econometrics or simulation, while normative models lie within the scope of optimization.

Purpose

Energy models are usually designed to address specific questions and hence, are only suitable for the purpose they were developed. For our categorization, we will make a distinction between three purposes i.e., Prediction/Forecasting, Exploring, and Back-casting purpose as follows (Beek, 1999):

1. Prediction/forecasting

Basically, forecasting focuses on extrapolation of trends found in historical data. A prior condition for this method is that the critical underlying parameters remain constant. Therefore, this method can be applied for analysing relatively medium to long term impacts of actions. In fact, forecasting is about what things will look like in the future and the method used for forecasting depends on the situation. Prediction uses past observations to extrapolate future short-term observations. Long-term forecasting is usually made by econometrics methods and short-term prediction uses extrapolation methods (Armstrong, 2001).

2. Exploring:

Scenario analysis is utilized for exploring the future. In this method, a limited number of developed scenarios are compared with a Business As Usual (BAU) reference scenario. In developing scenarios, some assumptions like economic growth and technological progress, which are not relied on the parameters extracted from the past behaviour, are made.

3. Back casting:

This approach is used to determine the conditions of a desired future and to define steps to attain a desired vision of the future. This is an alternative to traditional forecast which relies on what is known today and the future is viewed as a continuum of past or present. Back-casting is a planning methodology under uncertain circumstances that is particularly helpful when problems are complex, and there is a need for major change and in cases in which it is risky to view the future just in the mirror of the past (Holmberg, 2000).

Modelling paradigm

The difference between top-down and bottom-up models is related to the technological and sectoral aggregation. A broader economy is investigated by use of top-down models in order to examine effects between different sectors and they do not consider details of energy production technologies. Smooth production functions are used to represent energy sectors in an integrated way. In such models, substitution is determined by elasticity. On the other hand, technologies are represented in detail in bottom-up models, but they miss to take into account economy-wide interactions such as price distortions (Bohringer, 1998).

Grubb *et al.* (1993) stated that the top-down approach addresses the 'descriptive' economic paradigm, while the bottom-up approach is associated with– but not exclusively restricted to– the 'normative' engineering paradigm. In the economic paradigm, technology is considered as a set of processes by which inputs such as capital, labour, and energy can be transferred into useful outputs and the 'best' or most optimal techniques are defined by efficient markets. However, in the engineering paradigm, the developed model is independent of observed market behaviour. In other words, the economic paradigm is based on market behaviour and aggregated data, while the engineering paradigm tends to ignore existing market constraints and uses disaggregated data. For example, in the top-down approach the key question is 'By how much does a given energy price movement change energy demand or energy-related carbon emission?' In contrast, in bottom-up the question is 'How can a given emission reduction task be accomplished at minimum costs?'(e.g., see Frei *et al.* 2003).

While the traditional top-down approach follows an aggregated view and believes in the influence of price and markets, the bottom-up models focus on the technical characteristics of the energy sector. Hybrid models try to bridge the gap between top-down and bottom-up by including elements of both approaches. They attempt to combine the benefits of both top-down and bottom-up modelling schemes using each modelling vision where appropriate and a modular structure to integrate the disparate systems. The hybrid models undertake to consider economic effects on model outcomes through taking into consideration the market behaviour. Market behaviour is a result of interactions among the economy sector, supply side and demand side entities.

The underlying methodology

In the following part, an overview of commonly used methodologies in developing energy models will be presented.

1. Econometrics: Econometric methodology focuses on statistical methods to extrapolate past market behaviour into the future. They use aggregated data measured in the past to predict the short- or medium-term future in terms of labour, capital, or other inputs. They are frequently used to analyse energy-economy interactions. The experience of the expert using this method is a key element for achieving reliable results. Another shortcoming of this model is that it needs a large amount of data from the past and aggregated data is required to reduce the fluctuations over time. Furthermore, the stability of economic behaviour is a prerequisite for using this method.
2. Macro-economics: The macro-economic methodologies are methodologies that consider the entire economy of a society and the interaction between sectors. The economy-energy interaction is analysed by input-output tables. These tables describe transactions between different sectors of the economy that is viewed as a whole in this method. Therefore, energy is just a small sector between all sectors considered in the macroeconomic model and cannot concentrate on energy technologies, specifically in details. This approach is common in energy demand analysis when taken from a neo-Keynesian perspective (i.e., output is demand determined).
3. Economic equilibrium: In economic equilibrium methodology, the energy sector is considered as part of the overall economy and it focuses on interrelations between the energy sector and the rest of the economy sectors. Economic equilibrium models are sometimes also referred to as resource allocation models. Very long term growth paths are simulated by this method, but the underlying path towards the new equilibrium is not clear enough. The treatment of equilibrium in a single market is considered as partial equilibrium in which the price plays a key role in equilibrating demand and supply. General equilibrium indicates conditions allowing simultaneous equilibrium in all markets in the economy. In this extension a coherent theory of the price system and the coordination of economic activity have to be considered.
4. Optimization: An optimization problem consists in finding a good choice out of a set of alternatives by minimizing or maximizing one or some real functions. Input values are selected from an allowed set and must satisfy some constraints. Energy optimization models are used to optimize energy investment decisions endogenously and the outcome represents the best solution for input variables while meeting the given constraints. This method is a branch of applied mathematics and requires a relatively high level mathematical knowledge and that the included processes must be analytically defined. Optimization models often use Linear Programming (LP), Non-linear Programming (NLP), and Mixed Integer Linear Programming (MILP) techniques.
5. Simulation: According to the World Energy Conference (1999), simulation energy models are descriptive models based on a logical representation of an energy system, and they are used to present a simplified operation of this system. Simulation models are usually used as an alternative, when it is impossible, hard or really costly to do experiments with the real system (Rosseti *et al.,* 2009).
6. Back-casting: The back-casting methodology is used to construct visions of desired futures based on experts' ideas in the fields and subsequently by looking at which changes are required or needed to be carried out to accomplish such futures.
7. Multi-criteria: The multi-criteria methodology can be used for including various criteria such as economic efficiency and cost reduction. It can include quantitative as well as qualitative data in the analysis. This approach is not yet widely applied in energy models.
8. Hybrid: The hybrid methodology consists of two or more aforementioned methodology.

Resolution technique

At the level of concrete models, a further distinction can be made considering the resolution tools utilized in the models. Linear Programming (LP), is widely used for modelling energy supply (e.g., capacity expansion planning) because of its simplicity in solution.

Mixed Integer Linear Programming (MILP) models the problems in which some variables are discrete. This technique has been widely used in MES (Multi-Energy Systems) planning problems, where various energy carriers with different units in terms of size and type are considered.

When there are nonlinear relations in either constraints or objective functions, the problem is modelled as a Non-Linear Problem (NLP). Often, endogenizing the model variables such as technological learning leads to convert a linear model into a nonlinear one. The multi-criteria models are used when there is more than one criterion, usually conflicting ones, as the objective functions to be optimized.

Dynamic Programming (DP) divides the problem into sub problems to be able to solve them more easily. In addition, in most recent studies fuzzy programming (FP) or stochastic and/or interval programming (SP) methods have been applied to deal with uncertainties. Energy demand, price market, and learning rate of technologies are common parameters assumed uncertain in the energy system modelling (Salas, 2013).

Techniques such as Artificial Neural Networks (ANN), Autoregressive, Adaptive Neural Fuzzy Inference Systems (ANFIS), and Markov chain techniques are extensively used for forecasting/prediction purposes (Ettoumi *et al.*, 2003).

Geographical coverage

Energy models may analyse different levels of geographical and spatial areas. This level will effectively influence the structure of the model. The world economy is investigated in global energy models as a whole at a large scale. These models are designed to replicate how the world energy markets function. They are practical tools that generate region by region projections for different scenarios. In the regional models international areas like Latin America, South-East Asia and Europe are taken into consideration. National models study all major sectors inside one country endogenously, while the world energy parameters are considered exogenously in the model. The local level is related to the models encompassing regions inside a country.

According to the available literature, the comprehensiveness of models relying on the global or national level often (not always) requires aggregated data and uses economic (top-down) approach. In this regard, the models focusing on regional or local level often (not always) disregard macro-economic effects on energy system applying an engineering (bottom-up) approach.

Sectoral coverage

The economy can be divided into certain sectors. Based on this division, models can be classified, into sub-sectoral, sectoral, and economy wide models. Sub-sectoral models provide only information in just one particular sector and do not take into account the macro-economic linkages of that sector with the rest of the economy. The other sectors of the economy are simplified in these models. Sub-sectoral models addressing specific short-term concerns e.g., dispatch scheduling of a set of power generating units in a utility, fall into the first category. On the other hand, sectoral models investigate more than one sector of the economy and the interaction between the studied sectors. Sub-sectoral or sectoral models having one year to few years of planning horizon can be classified as medium-term and long-term models with implications at national or global level.

The time horizon

The time frame defined in energy models are usually categorized as short term (day, month, till 5 years), medium term (from 5 to 15 years), and long term (beyond 15 years) (Grubb et al., 1993). The structure of the models differs in different time horizons. Technological changes, paradigm shifts, long-range scenario analysis and multi-stage modelling are an innate part of the long term energy models. While in daily or monthly analysis of one energy sector, these issues are of less importance.

Data type

Aggregated and disaggregated data are two extremes for required data of energy models. Top-down models use aggregated data for short term predicting purposes, while bottom-up models use disaggregated data for exploring purposes. Most of models usually need quantitative data. But in some circumstances that little quantitative data is available or the available quantitative data is unreliable, the models should be able to deal with qualitative data. Furthermore, it may happen that considering stochastic or fuzzy data, instead of deterministic data, will lead the model to better and more robust results.

Endogenization degree

A model with high endogenization degree is one that its parameters are incorporated within the model equation so as to minimize the number of exogenous parameters. The analytical approach is in a close relationship with the level of endogenization. A high level of endogenization is considered in top-down models while in bottom-up engineering energy models, many parameters are reflected exogenously. It is very common that population growth, economic growth or even energy demand is carried out exogenously in bottom-up energy models.

Addressed side

Energy models are usually designed to deal with demand side issues such as demand forecasting, or supply side (e.g., capacity expansion plans) or both of them so called energy system models. Forecasting energy demand can be performed in just one sector like electricity, natural gas, heat, or in all different types of energy as a whole. In these models, both forms of final or useful demand may be predicted and is usually regarded as a function of income, population, price, etc. In the supply side, the demand is usually put into the model exogenously so as to investigate conditions needed to reach equilibrium between demand and supply. Technological aspects are concerned in more detail and financial aspects of each technology are used for evaluation of different scenarios.

Figure 1 relates the different ways of energy model characterization to each other while they vary along a spectrum. However, a few exceptions can be founded in the literature. This figure provides guidelines to facilitate efficient selection of the model characteristics based on the available models in the literature.

As it can be seen in Figure 1, almost all of the models addressing demand side are descriptive with a top-down modelling paradigm. The purpose of these models is often (not always) a prediction with aggregate data while underlying methodologies for data processing are econometrics or macro-economics. Given the widely applications of AR and ANN techniques in these models, the endogenization degree of these models are high. In contrast with these models, the models addressing supply side are often normative with a bottom-up modelling paradigm. The general purpose of these models is often (not always) exploring and they rely on disaggregated data rather than aggregated data. Long-term considered time horizon and hence, low a endogenization degree are the main characteristics of these models.

For instance; Dilavar and Hunt (2011) applied a structural time series analysis to forecast industrial electricity demand of Turkey in 2020, by focusing on the relationship between electricity consumption of industries, value added of industries, and the price of electricity. The annual data over the period 1960 to 2008 is used to develop the industrial electricity demand function. This descriptive demand side model uses aggregated data of annual industrial electricity consumption from the International Energy Agency, IEA, and industrial value added from the World Bank in the econometric estimation model. No technological details are considered in this national sectoral model. Also, a long term model for natural gas and electricity expansion planning developed by Unsihuay-Vila *et al.* (2010), named Gas Electricity Planning Model (GEP). They used a mixed integer linear programming model for this energy supply planning model. The objective of the model is to minimize investment and operational cost of new facilities by selecting the optimum ones for power generation. Different technologies, with their related costs and constraints are taken into account. Disaggregated data with specific details for different supply technologies is required to be able to deal with this bottom-up model. This is a normative model, since an optimization is performed for the optimum selection of NG and electricity expansion facilities in order to meet the future growth of energy demand.

3. Trends in energy models characteristics

A first step in developing an appropriate model is to make decision about its characteristics (which were previously introduced) according to the defined problem. Some of these characteristics are static, i.e. they do not change over time, such as 'Model type' or 'Purpose' and the rest are dynamic and will change over time such as 'Analytical approach'. Therefore, to select dynamic characteristics of a model, it is necessary to consider their evolutions in the future. Understanding the evolution of a dynamic characteristic help identifying the requirements set of characteristics and features of a model in order to be in accordance with its future needs. This section undertakes to extract the evolution of dynamic characteristics, i.e. analytical approach, problem formulation, problem environment, sus-

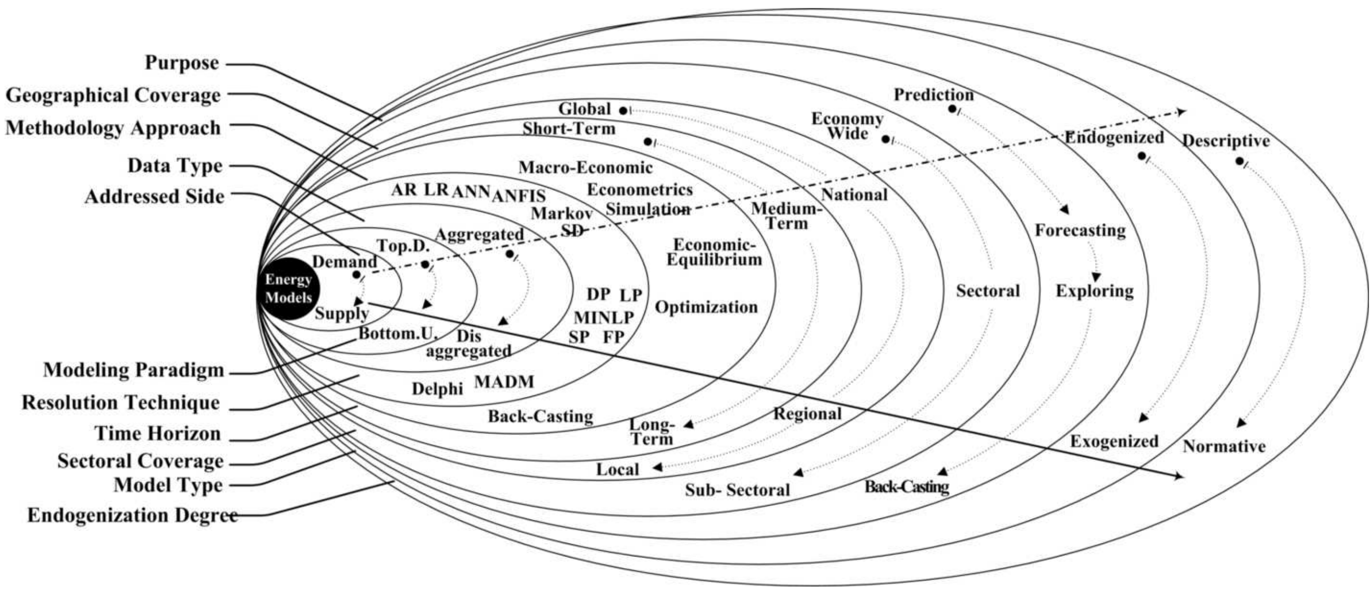

Figure 1: Schematic diagram of relations between different ways of energy model characterization

tainable criteria, and solution techniques for developing countries according to the previous studies on the developed and developing countries. To do this, it introduces different states for each key characteristic, and addresses them by mentioning the first related paper as well as an example (as a representative of other studies). It should be noted that this section aims at determining the evolution of dynamic characteristics of energy models for developing countries, rather than reviewing all relevant studies of the energy model literature.

Analytical approach

Top-down and bottom up approaches are two extreme modelling paradigms. Several authors linked bottom-up energy models to top-down ones in order to simulate the macro-level economy and micro-level technology details of the energy systems. The available integrated models can be generally categorized as: (1) the models which try to endogenize the market price using game theory and real option concepts in the bottom-up models (Botterud and Korpås, 2007; Pereira and Saraiva, 2011); (2) the models which employ System Dynamics or Computable General Equilibrium (CGE) techniques to incorporate price dynamics of demand and supply into the bottom-up models (Frei *et al.,* 2003; Andreas Schafer *et al.*, 2006; Wei *et al.*, 2006; Pereira and Saraiva, 2011); and (3) the integrated multi-agent based models that consider not only inter-temporal price dynamics of supply and demand but also demand side interactions in the model (Hodge *et al.*, 2008; Jiang Chang and Shu-Yun Jia, 2009; Logenthiran *et al.*, 2011; Ma and Nakamori, 2009).

Generally, there are two main solution approaches used in these studies. In the first approach, a combination of LP and an econometric demand equation is used to determine equilibrium price and quantities of fuels. This approach demonstrates perfect foresight and is proved to be non-realistic and unsuitable for the resulting year by year analysis. The second approach namely; a modular approach is developed in order to compute equilibrium price and quantities by iterative interactions between various modules

Problem formulation

Energy systems as an integral part of socio-economic systems of societies have several cross-disciplinary interactions with the economy, society, and environment. Moreover, a set of interdependencies between its parameters and variables exists that all cause an uncertain problem environment for energy systems. Endogenizing uncertain parameters is an effective way to reduce the uncertainty of the problem environment. A parameter is endogenized into the model through developing it internally within the model equation. To name a few, endogenizing: the future demand (Cerisola *et al.,* 2009; Choi and Thomas, 2012; 'EIA – The National Energy Modeling System: An Overview 2003-Overview of NEMS,' 2011; Hodge *et al.*, 2008; Ko *et al.*, 2010; Murphy and Smeers, 2005); the energy market price (Pereira and Saraiva, 2011), the technological change (Duncan, 2012; Hedenus *et al.,* 2005; Ma and Nakamori, 2009; Messner, 1997; Tödtling, 2012); the discounted rate (Neuhoff, 2008); and the marginal cost (Olsina *et al.*, 2006; Pereira and Saraiva, 2011) are addressed in this manner.

Problem environment

According to the literature, both certain and uncertain environments have been assumed for EPM problems. The uncertain information in energy systems is usually classified into three types (i.e., possibility distributions, probability distributions, or single/dual discrete intervals). In order to address these uncertainties, three corresponding inexact programming techniques i.e., fuzzy programming (e.g., Li and Cheng (2007)), stochastic programming (e.g., Lin and Huang (2009)) and single/dual interval-parameter programming (e.g., Zhu et al. (2012)) have been widely applied for energy systems modelling.

These approaches mostly focused on particular type of uncertainty or certain hybrid uncertainties within energy systems. However, in many real-world problems, multiple uncertainties may coexist in energy planning and management systems, of which the systems complexities may not be adequately reflected through the current approaches. Moreover, system dynamics associated with multi-stage decision makings are frequently confronting decision makers, which also need to be integrated and addressed in the same modelling framework. Thus, it brings about the requirement that can directly incorporate system uncertainties expressed as fuzzy membership functions, probability density functions, discrete intervals and dual intervals within a multi-stage modelling framework. Fuzzy dual-interval multi-stage stochastic (FDMS) approach is an efficient one that could not only tackle uncertainties with single/dual interval values and possibility distributions existed in energy, economy and environment systems, but also conduct in-depth analysis of long-term stochastic planning problems within multi-layer scenario trees (e.g., Li et al, 2014).

Sustainable criteria

The most common definition of sustainable development is a development which meets the needs of the present without compromising the ability of future generations to meet their own needs. This definition first appeared in the World Commission on Environment and Development's report, Our

Common Future (World Commission on Environment and Development, 1987).

Nowadays, the assessment criteria (economic, environmental, and social) of sustainable development are becoming important because of the rapid increase in awareness of the importance of sustainability. The energy system (supply, transport and usage) is of the highest importance in the context of sustainable development. According to the literature, the energy systems are required to meet several important goals, including conformance with the environmental goals (e.g., Akisawa et al., 1999; Bala and Khan, 2003; Dong et al., 2013; 'LEAP: Long range Energy Alternatives Planning system – Stockholm Environment Institute,' 2011; Reich-Weiser et al., 2008); economical goals (e.g., Grubb et al., 1993; Gustafsson, 1993; Heinzelman *et al.*, 2000; Kanniappan and Ramachandran, 1998; Liu, 2007; Sadeghi and Mirshojaeian Hosseini, 2006; Sirikum and Techanitisawad, 2005); social (e.g., Correljé and van der Linde, 2006; Pereira and Saraiva, 2011; Sirikum and Techanitisawad, 2005); or integrated goals (e.g., Bazmi and Zahedi, 2011; Cai, 2010; Ren et al., 2010b; Thery and Zarate, 2009; van Vliet et al., 2012) of sustainable development.

Underlying solution techniques

Exact solution algorithms which are suitable for linear (e.g., MILP, LP) and nonlinear (NLP) problems encourage shortages rather than inexact algorithms when problems are complex, non-smooth or non-convex. Despite its name, optimization does not necessarily mean finding the optimum solution to a complex problem with non-smooth function, since it may be unfeasible due to the characteristics of the problem, which in many cases are included in the category of NP-hard problems. Optimization problems with no polynomial time algorithm need exponential computation time in the worst case to obtain the optimum, which leads to computation times that are too high for practical purposes.

In recent years, due to issues such as hybridizing energy models, considering uncertainty in modelling, necessity of modelling with large geographical coverage and examining global changes such as global warming, the size and complexity of energy problems have increased and accurate algorithm have failed to solve this class of problem, given too huge convergence time and required computer memory. Consequently, in recent decades, many authors have proposed approximate methods, including heuristic approaches to solve NP-hard problems instead of using traditional solution methods, such as Mixed Integer programming (MIP) technique (Mirzaesmaeeli, 2007; Ren *et al.,* 2010a); Nonlinear Complementary programming (NCP) algorithms ('EIA – The National Energy Modeling System: An Overview 2003-Overview of NEMS,' 2011; Messner, 1997); quadratic programming (QP) techniques (Cai, 2010); and fuzzy-parameter linear programming techniques (Agrawal R.K. and Singh1 S.P., 2001; Li *et al.*, 2010; Sadeghi and Mirshojaeian Hosseini, 2006).

Heuristic methods as simple procedures provide satisfactory, but not necessarily optimal solutions to large instances of complex problems rapidly. Metaheuristics are generalizations of heuristics in the sense that they can be applied to a wide set of problems, needing few modifications to be addressed to a specific case. Based on our knowledge, heuristic methods have not been yet used for energy system planning, however, several studies have been adopted (meta)heuristic algorithms to generation expansion planning problem (Chung *et al.,* 2004; Pereira and Saraiva, 2011; Safari *et al.,* 2013; Sirikum and Techanitisawad, 2005; Subramanian *et al.,* 2006).

The detailed survey is summarized in terms of developing and developed countries as Table 1.

3.1. Synthesis results of literature

According to Table 1, we grasped the literature analytically and made a digest of the related literature chronologically and addressed the key issues. The important findings extracted from Table 1 are listed here:

- The developing countries often experience the lagging research concerns of developed countries. For instance, in the 2000s, the focus was based on merging two analytical modelling paradigms in developed countries, while this is postponed to the next decade for developing countries. In fact, promoting some changes in energy strategies of developed countries can be a strategy for future energy of developing countries.
- In the late 2000s, the efforts have been directed to merge top-down and bottom-up modelling paradigms so as to consider economic, social, and environmental impacts simultaneously. The uncertainty and risks of such extensions are large and the validity of behavioural assumptions, technological specifications and resource allocations becomes complex in developing economies. This has led to incorporation of uncertainty analysis into the system analysis on one hand, and new model development initiatives on the other hand in these countries.
- Recently, the researchers have approached the endogenized models in order to capture the economic and technological effects and especially, to take care of structural changes and competition in the emerging markets and the uncertain patterns of business environment in developing countries.
- Given the used solution techniques, the energy planning problems experience a rapid growth in

Table1: Trends in energy models characteristics in terms of developing and developed countries

Key issues		Timespan	1990-2000	2000-2005	2005-2013
Analytical approach	Top-down		■ e.g., Neubauer et al., 1997 ▲ e.g., Shresth, 1999	■ e.g., Sun, 2001 ▲ e.g., Volkan, 2003	▲ e.g., Shafiei et al., 2009 ■ e.g., Duran, 2007
	Hybrid			■ As pioneer, Messner and Schratten, 2000	▲As pioneer, Chen, 2005 ■ e.g., Andreas Schafer et al., 2006
	Bottom-up		▲ e.g., Luhanga et al., 1993	▲ e.g., Kumar, 2003 ■e.g.,Rosakis et al., 2001	▲ e.g., Ghaderi et al., 2006 ■ e.g., Liu, 2006
Problem formulation	Exogenous ↕ Endogenous		■ e.g., Halliwell & Sherif 1990; Pereira & Pinto, 1991 ■ e.g., Luhanga et al., 1993 ▲ As pioneer, Wu and Chen, 1990	▲ e.g., Frei et al., 2003 ■ e.g, Messner & Schrattenholzer, 2000; Rozakis et al., 2001	▲ e.g, Shafiei et al., 2009 ■ e.g, Andreas Schafer et al., 2006; Liu, 2006; Pereira & Saraiva, 2011
Problem environment	Certain		■ e.g, Ellis et al., 1995	–	–
	Uncertain	Stoch astic	■ e.g, Scott et al., 1999 ■ e.g, Messner et al., 1996	▲ e.g, Jain &Lungu, 2002	▲ e.g, Xie et al., 2010 ■ e.g, Liu, 2009 No Def. Li and Cheng, 2007
		Fuzzy	–	▲As Pioneer, Agrawal R.K. & Singh1 S.P., 2001	▲ e.g, Sadeghi et al., 2008 ▲ e.g, Lin, 2008; ▲Kaya and Kahraman, 2011; ▲Jebari and Iniyan, 2007; ▲ e.g, Xie et al. 2010; ▲ e.g, Saboohi et al., 2006
		Vague		–	■ e.g, Pereira & Saraiva, 2011
Sustainable criteria	Economic		■ e.g, Henning, 1997; ▲e.g, Kanniappan & Ramach, 1998		▲ e.g, Sadeghi and Mirshojaei & Hosseini, 2006
	Environmental		■ e.g, Akisawa et al., 1999; Ang & Zhang, 2000	■ e.g, Kumar A. et al., 2003	▲e.g, Liu, 2006; e.g, Mirzaesmaeeli, 2007; Cai, 2010 ▲ e.g, Lin, 2008 ▲ e.g, Ghaderi et al., 2006
	Social		-		
	Integrated		■ e.g, Akisawa et al., 1999	▲ e.g, Bala and Khan, 2003	–
Underlying solution techniques	Traditional		■ e.g, Ang, 1995; ■ e.g, Ramanathan & Ganesh, 1995 ■ e.g, Malik et al., 1994	▲ e.g, Beccali et al. 2003 ■ e.g, Sirikum & Techanitisawad, 2005	■ e.g, Andreas Schafer et al., 2006; Pereira & Saraiva, 2011 ▲ e.g, Ghaderi et al., 2006; Sadeghi & MirshojaeianHosseini, 2008 ■ e.g, Pham et al., 2011
	Heuristic				■ e.g, Subramanian et al., 2006; Pereira & Saraiva, 2011

Legend ■ Developed countries; ▲ Developing countries

magnitude and also computational difficulties associated with non-convex and non-smooth objective functions.
- In recent years, multi dimension integrated criteria has attracted much interest rather than single dimension criteria such as cost or profit.

Although there is a huge variation amongst developing countries in terms of socio-economic structure, a few features are found in common in the energy sector of many developing countries. These characteristics include: (1) reliance on traditional energies, (2) the existence of large informal sectors which are sometimes as large as the formal sector, (3) prevalence of inequity and poverty, (4) structural changes of the economy and accompanying transition from traditional to modern lifestyles, (5) inefficient energy sector characterized by supply shortages and poor performance of energy utilities, and (6) existence of multiple social and economic barriers to capital flow and slow technology diffusion make developing countries' energy systems significantly different from that of developed countries.

Top-down models use a price-driver which play a limited role in developing countries and cannot capture informal sector or traditional energies adequately. These models also have difficulties in capturing the technological diversity, besides, they require high skill levels. Bottom-up models have a good description of technological features of the energy sector with high-level skill needs. Moreover, the problems of subsidies and shortages are also not adequately captured as the demand in these models. Hence, hybrid models appear to be more appropriate for developing country contexts because of their flexibility and limited skill requirement.

It can be concluded that most of the standard (computer based) models are perhaps not suitable for developing countries applications considering their underlying assumptions. As most of the standard models are designed and developed in the developed world, they fail to capture the specific needs of the developing countries because they are incapable of reflecting the specific features of energy models of developing countries.

4. Conclusions

Up to now, many characterizations have been made for energy models, whereas the relationship among them is under question. In this study, we gave an introduction to the different ways of energy model categorization approaches (e.g., modelling paradigm, endogenization degree, model type, and addressed side) and the relationships behind these approaches were indicated schematically. The designed diagram as a decision support tool facilitates efficient selection of the model characteristics based on the examined models in the literature. But some characteristics are dynamic and will change over time such as analytical approach. Therefore, in order to select the dynamic properties for a model, it is necessary to consider their evolution in the future. The evolution of dynamic energy model characteristics for the developing countries were extracted from the related literature digests.

The findings of this paper confirms the fact that it is required to incorporate the specific features of developing countries in energy system modelling and to consider the informal sector and traditional energy use in the analysis of these systems.

This study suggests identifying the evolution of dynamic energy model characteristics for developing countries in terms of geographic coverage (global, national, regional, local) as future research.

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