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Forecasting methods in energy planning models

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A R T I C L E I N F O

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A B S T R A C T

Energy planning models (EPMs) play an indispensable role in policy formulation and energy sector development. The forecasting of energy demand and supply is at the heart of an EPM. Different forecasting methods, from statistical to machine learning have been applied in the past. The selection of a forecasting method is mostly based on data availability and the objectives of the tool and planning exercise. We present a systematic and critical review of forecasting methods used in 483 EPMs. The methods were analyzed for forecasting accuracy; applicability for temporal and spatial predictions; and relevance to planning and policy objectives. Fifty different forecasting methods were identified. Artificial neural network (ANN) is the most widely used method, which is applied in 40% of the reviewed EPMs. The other popular methods, in descending order, are: support vector machine (SVM), autoregressive integrated moving average (ARIMA), fuzzy logic (FL), linear regression (LR), genetic algorithm (GA), particle swarm optimization (PSO), grey prediction (GM) and autoregressive moving average (ARMA). Regarding accuracy, computational intelligence (CI) methods demonstrate better performance than that of the statistical ones, in particular for parameters with greater variability in the source data. Moreever, hybrid methods yield better accuracy than that of the stand-alone ones. Statistical methods are used for only short and medium range, while CI methods are preferable for all temporal forecasting ranges (short, medium and long). Based on objective, most EPMs focused on energy demand and load forecasting. In terms, geographical coverage, the highest number of EPMs were developed in China. However, collectively, more models were established for the developed countries than the developing ones. Findings would benefit researchers and professionals in gaining an appreciation of the forecasting methods and enable them to select appropriate method(s) to meet their needs.

1. Introduction

Increasing greenhouse gases (GHGs) emission contribute to global warming, resulting in amplified global temperature and associated vulnerabilities [1]. Mitigating the impacts of climate change requires the reduction or at the very least the stabilization of atmospheric CO_2 concentrations, which can be achieved by decreasing global carbon outflow from energy and land-use sectors, the two major GHG sources. Emissions from land-use have been nearly constant, while the emissions from fossil fuel based energy system climbed up by 29% between 2000 and 2008 [2]. If current GHG concentrations remain constant, the world will experience a few centuries of rising mean temperatures and sea levels [3–5]. Studies suggest that the current energy and transportation systems are likely to be responsible for significant CO_2 discharges over the next fifty years [6], which can increase the global mean temperature by approximately 1.1–1.4 °C between 2010 and 2060 [7]. Future initiatives on energy planning and development should, therefore, focus on decarbonizing the energy generation and demand sectors. Research indicates that CO_2 emissions are negatively associated with national expenditure on energy research; therefore, the transition away from carbonintensive energy generation for atmospheric CO_2 stabilization will require significant investments in innovative energy research and development [8].

EPMs are essential for assisting stakeholders in making informed decisions for future energy sector development – globally, regionally and nationally. The development of EPMs started in the 1960's [9], but the interest in them increased after the oil crisis in the 1970's that highlighted the effects of dependency on conventional fuel sources on global, regional and national economies, in particular, the role of exogenous political events on the oil market [10]. The crisis acted as a catalyst for the critical assessment of fuel resources, rational use and conservation of energy resources, and long-term energy planning for global, regional, national and sectoral utilization [11]. Also, the Rio Earth Summit in 1992 and the report of the Intergovernmental Panel on Climate Change (IPCC) in 1995 triggered further environmental studies on GHG emissions [12], while cautiously concluding that CO_2 emissions

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Table 1
Searched keywords and associated groups.

Model	Objective	Geographical extent	Time horizon
Energy Electricity Energy information Energy economic Energy supply and/or demand Emission reduction Energy planning	Forecasting Projection	Global Regional Country	Short Medium Long

had a noticeable impact on the environment [13]. Intensive discussions and debates followed, legislations were formulated, and GHG emission reduction targets were set; e.g., Kyoto Protocol in 1998. Although separate models for the evaluation, projection, and alleviation of environmental impacts were created, EPMs played a critical role in identifying system boundaries and underlying relationships between the socio-technical parameters of energy, economy and environment.

Different authors reviewed EPMs in previous years. Nguyen (2005) classified EPMs into six categories – energy information systems, macroeconomic, energy demand, energy supply, modular package and integrated models [9]. Pfenninger et al. categorized EPMs into four types – energy system optimization; energy system simulation; power system and electricity market and qualitative and mixed-method scenarios [14]. Most of the reviews focused on classifying the energy planning models as a whole, rather than investigating and categorizing the underlying forecasting methods. Suganthi investigated the models for forecasting energy demand [15], albeit only partially. Moreover, parameters for categorizing forecasting methods are not same as for EPMs. The choice of forecasting method can affect the accuracy and validity of results in an EPM.

Previous studies on forecasting methods of EPMs either divided the topic into its areas of application or the broad categories of underlying techniques. Application areas are always evolving – through the integration of new domains and concepts, as well as by expanding the breadth and depth of a modeled domain. The difficulty arises when previously categorized application areas are not flexible enough to accommodate a new area. For example, behavioral energy conservation is an important environmental psychology aspect of climate and energy debate; and widely considered for the modeling of energy use in buildings and transportation, as well as for national energy demand forecasting and policy making.[1] On the other hand, dividing forecasting methods based on the underlying techniques has similar issues. For example, Weron classified forecasting methods into two broad categories – statistical approaches and artificial intelligence (AI) based techniques [16]. The developments in computing over the past decades have enabled the use of compute-intensive methods for improved accuracy and reduced computation time, thereby enhancing their applicability. AI techniques are now widely used to tune up parameters in statistical models. Moreover, some soft computing or computational intelligence[2] techniques routinely use advanced statistical concepts. Therefore, categorizing the forecasting methods as either statistical or artificial intelligence not only gives an inaccurate account but also hinders the informed comprehension of the strengths and weaknesses of different approaches. The hybridization of methods to suit application areas is characterized by data incompleteness and uncertainty; temporal and spatial variability; and domain features – all of which mandates a new classification scheme.

Existing reviews thus lack a comprehensive coverage regarding scope, accuracy, and applicability. The objective of this review is, therefore, to analyze the methods utilized in different EPMs to investigate their accuracy, objective, temporal and spatial extents with a view to identifying the factors behind the choice of forecasting methods. Findings of this study would benefit researchers in gaining an appreciation of the methods, as well as enable them to select appropriate forecasting methods for future research.

2. Methodology

A state-of-the-art systematic review was undertaken on published electronic resources for the study of underlying forecasting methods in EPMs. A preliminary study was conducted to gather an overview of the topics related to forecasting methods in energy planning. The identified main topics were: energy demand and/or supply model and/or forecasting; energy planning models; emission reduction models; time series analysis; and forecasting. These topics were used to identify relevant keywords, listed in Table 1. Keywords were then utilized to search electronic databases: Google Scholar, ScienceDirect, Scopus, Ei Compendex and Web of Science, for relevant publications on forecasting methods of EPMs.

An advanced search was conducted within the databases by categorizing keywords into four-word groups and by combining them using the Boolean operator 'AND.' The search was conducted in two stages. Firstly, the model, objective and geographical extent keywords were used. Secondly, the model, objectives, methods, and analysis measures were applied. The initial search results at each stage were refined by applying the following inclusion criteria:

- Objective: Energy forecasting
- Language: English
- Sources: Publications from journals related to energy and core forecasting and planning of energy; fossil fuel; renewable energy; carbon emissions.

Abstracts of the selected publications were scrutinized. Articles were chosen for review if the substance was within the scope of the study. A further search was conducted on the recognized authors who had contributed noticeably in related fields. 600 publications were found from the search. The criteria for retention were:

- Studies covering energy demand and/or supply forecasting
- Studies with significant contribution in forecasting of GHG emissions
- Studies on forecasting methods for energy planning
- Key review articles from established authors/institutions in the area of energy forecasting and planning models

Finally, 483 publications and reviews on energy forecasting and planning were retained for analysis and interpretation.

3. Classification

Forecasting involves the predictions of the future based on the analysis of trends of present and past data, comprising three major components: input variables (past and present data), forecasting/estimation methods (analysis of trends) and output variables (future predictions), as shown in Fig. 1. Based on the number of techniques used for trend analysis, the investigated methods can be broadly classified

[1] Examples of the use of behavioral aspects of public energy conservation in policy making can be found in Japan's Third National Communication under the United Nations Framework Convention on Climate Change (UNFCC) (http://unfccc.int/resource/docs/natc/japnc3.pdf) and Energy Outlook of Vietnam through 2025 (http://open_jicareport.jica.go.jp/pdf/11899796_02.pdf).

[2] It can be argued that the so called AI methods used in forecasting are in fact, more specifically, computational intelligence (CI) techniques, also known as soft computing in AI. For further information on how computational intelligence branched out from general AI, initially to distinguish neural networks from hard AI but later to incorporate fuzzy systems and evolutionary computation, the reader is referred to the history of IEEE Computational Intelligence Society (CIS) at http://ethw.org/IEEE_Computational_Intelligence_Society_History.