Energy models for demand forecasting—A review

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A R T I C L E   I N F O

A B S T R A C T

Energy is vital for sustainable development of any nation – be it social, economic or environment. In the past decade energy consumption has increased exponentially globally. Energy management is crucial for the future economic prosperity and environmental security. Energy is linked to industrial production, agricultural output, health, access to water, population, education, quality of life, etc. Energy demand management is required for proper allocation of the available resources. During the last decade several new techniques are being used for energy demand management to accurately predict the future energy needs. In this paper an attempt is made to review the various energy demand forecasting models. Traditional methods such as time series, regression, econometric, ARIMA as well as soft computing techniques such as fuzzy logic, genetic algorithm, and neural networks are being extensively used for demand side management. Support vector regression, ant colony and particle swarm optimization are new techniques being adopted for energy demand forecasting. Bottom up models such as MARKAL and LEAP are also being used at the national and regional level for energy demand management.

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1. Introduction

The twentieth century witnessed a transition from coal based to petroleum based resources. With the advent of industrialization and globalization, the demand for energy has increased exponentially. Fossil fuels in the form of coal, oil and natural gas comprise 80% of the world's energy use. It is predicted that if the current global energy consumption pattern continues, the world energy consumption will increase by over 50% before 2030 [1]. In this scenario, protection of the environment becomes very vital for sustainable living. Relevant factors of the environment include food, water, energy, natural resources, etc. Among these, energy is the most important factor.

Energy is essential for the functioning of all activities be it a developed or developing nation. It is estimated that industrial energy use in developing countries is around 45–50% of the total commercial energy consumption. Yet at the same time, large scale production and consumption of energy causes degradation of the environment. Also commercial energy resources are also non renewable in nature. This has led policy makers and industrialists to identify efficient means of energy utilization and also look at alternate sources of energy. In this backdrop, utilization of renewable energy is slowly gaining momentum across the globe.

Energy demand management is becoming an important issue since the future world is dependent on today's decision. Managing the energy resources in an optimal manner has become imperative among energy planners and policy makers. It is becoming mandatory that the commercial and renewable sources of energy be understood in its totality – quality, availability and environmental effects. In recent times, with climatic conditions going for drastic reversals, the attention has shifted to the utilization of renewable energy sources. The renewable energy sources have been established to be sustainable, nature friendly, non-polluting and renewable. An integrated energy management approach is essential for the sustainable development of any country.

2. Energy demand management

Energy demand management involves effective utilization of the energy resources, reliability in supply, efficient management of energy resources, energy conservation, combined heat and power systems, renewable energy systems, integrated energy systems, independent power delivery systems, etc. Demand management has to consider a series of options be it technical, organisation and behavioural solutions so as to decrease the energy consumption and demand. Cost effective options, commercially viable alternatives and environmental friendly solutions need to be explored. Demand management consists of planning, implementing, and monitoring activities of energy utilization that are designed to encourage consumers to modify their level and pattern of energy usage.

Demand side management has changed focus during the nineties with the several changes happening across the globe – technological advancements, communication breakthroughs, improvements in manufacturing processes resulting in better quality at lower costs. The emphasis of demand side management had shifted from residential load management to commercial and industrial demand management. Demand side management promotes energy efficiency for sustainable development.

Energy demand is found to be closely linked to energy price, GDP, population to name a few. Energy demand management should help in achieving self sufficiency and cost effectiveness to provide for a sustainable economic development. Energy demand management should thus help in

- planning for the future requirement, identifying conservation measures
- identification and prioritization of energy resources, optimized energy utilization, strategies for energy efficiency improvements
- framing policy decisions
- identification of strategies for reduced emission
- Energy models are developed using macro economic variables to forecast the energy demand. This helps in planning and drafting policies for energy management on the demand side.

3. Energy models

Energy models are developed for sustainable progress of any nation. Energy demand models can be classified in several ways such as static versus dynamic, univariate versus multivariate, techniques ranging from times series to hybrid models. Reviews of research done during the eighties and nineties are presented by Bohi [2], Bohi and Zimmerman [3] and David Wood Memorial Issue [4]. Chang et al. [5] reviews the production and consumption of both the traditional and the renewable energy in China over the past three decades. A review of energy management software tools are analysed to study the features of the tools in integrating renewable energy into various energy systems [6]. A review on the various optimization methods has been carried out by Baņos et al. [7] for optimum utilization of renewable energy sources.

Chen and Kung [8] have presented on how the forecasting accuracy can be improved by integrating qualitative and quantitative forecasting approaches. Energy demand is forecast using qualitative approaches such as survey whenever there is a dearth of information or when the end users perception, awareness and acceptance are required. The energy consumption pattern of households in different urban development forms is examined for Bandung City, Indonesia. A survey is conducted to determine the energy consumption patterns [9]. Liu et al. have used a survey to determine the household energy consumption pattern for a county in Tibet [10].

Energy forecasting models are developed specific to a nation or utility depending on the economic and market conditions prevailing. Baines and Bodger have adopted market forecasting approach for energy demand analysis. Energy accessibility and energy substitution are dealt with [11].

The Integrated Energy Planning Model (IEPM) is a technical and economic forecasting model. It is based on a detailed breakdown of energy consumption and energy transformation sectors. In this paper detailed analysis is presented for industrial sector. The main objective of the model is to balance energy supply with energy demand. The model considers variables such as: GDP growth rate and GDP structure, population growth rate, urbanization rate, number of households and industrial product share. The model presents various scenarios [12]. Unido's energy model consists of three sequential phases (i) analysis at aggregate level of current and future national energy matrices (ii) analysis of perspectives for decreasing energy intensity (iii) analysis of perspectives for increasing the supply and cost efficiency of sustainable (renewable) energy sources. The model is examined for China's energy situation [13].

Conditional demand analysis (CDA) is used to model the residential end-use energy consumption in Canada. The results are compared with neural network and engineering based models. The comparison of the predictions reveals that CDA is capable of accurately predicting the energy consumption [14].

The Integrated Energy System (IES) developed at Honeywell Prague Laboratory integrates all forms of cooling, heating, power generation, combined heat and power and cogeneration technologies. The system consists of a forecasting and optimization

mechanism. The forecasting module estimates the demand and the optimization module optimizes the load among the various production units [15].

A model is developed for Japan that simulates nationwide energy consumption of the residential sector by considering the diversity of household and building types. The model is used to develop scenarios and project the energy requirement in the residential sector [16]. Hu et al. present an Economy–Energy–Electricity–Environment (E4) framework [17]. It examines the strategy for low carbon and also presents China's economy growth, energy–electricity demand, renewable power generation and energy conservation and emissions mitigation until 2030.

Energy models are developed for sourcewise analysis – for oil, gas, electricity. Natural Resources Canada (NRCan) has used Oil and Gas Supply Model (OGSM) to predict the oil and natural gas supply and demand for Canada. The various parameters considered in the model include investment ratio, oil ratio, cost of oil reserves, oil prices, oil supply/production [18]. A technical and economic planning model (MIPE – Integrated Energy Planning Model) is used to estimate natural gas demand in three scenarios – low growth, high growth, sustainable development in four applications areas – industrial, electric power generation, domestic distribution, domestic distribution and vehicular fleet conversions [19]. A system dynamics model is used to forecast the growth of natural gas consumption. It is found that natural gas will become an important substitution for coal [20].

Electricity demand models are developed to study short term, medium term and long term load forecasting as well as for electricity demand country wide. A belief network model is used for forecasting the demand and required generating capacity of electricity. A dynamic simulation algorithm is applied to the belief network to take into account the feedback effects of decision [21]. Long term electric energy demand is determined using dynamic simulation theory by Jia et al. [22]. Social, economical and environmental factors are found to affect the electricity consumption. This results in seasonal, monthly, daily and hourly variations in electricity consumption pattern. Macro economic decision making is applied for electricity requirement forecast. By clustering the primary data and removing the periodic variance the complicated pattern is decomposed. Simple models are then applied and the electricity requirement is forecast [23].

Decision drivers for electricity demand and supply are identified for China. The framework consists of technological and socio-economic drivers, including those affecting electricity demand namely economic growth, structure, energy efficiency, urbanization, and change in per capita income and electricity supply namely deregulation, initiatives to promote natural gas, nuclear and renewable energy, air pollution regulations, price developments for coal and natural gas, and changes in generation technology [24]. The primary energy requirement is forecast for three scenarios – business as usual, conservative and optimistic by quantifying the above parameters [25].

Coarse modelling is used to develop a three stage electric energy load forecasting model to predict the yearly, weekly, hourly electric energy demand [26]. The model involves a stage wise prediction process (nested) involving analytical models. The manner by which hybrid renewable energy systems (HRES) can be commercially utilized for power generation in remote locations is examined by Deshmukh and Deshmukh [27]. Several HRES configurations such as PV–battery, PV–diesel, wind–battery, wind–diesel, PV–wind–battery, and PV–wind–diesel–battery are analysed and found to be commercially viable.

The review of energy demand forecasting models presented in this paper is categorized under broad headings as follows:

   i. Time series models
  ii. Regression models
 iii. Econometric models
 iv. Decomposition models
  v. Cointegration models
 vi. ARIMA models
 vii. Artificial systems – Experts systems and ANN models
viii. Grey prediction models
 ix. Input–output models
  x. Fuzzy logic/Genetic algorithm models
 xi. Integrated models – autoregressive, Support vector regression, Particle swarm optimization models
 xii. Bottom up models – MARKAL/TIMES/LEAP

3.1. Time series models

Time series models are the most simplest of models which uses time series trend analysis for extrapolating the future energy requirement. Bargur and Mandel have examined the energy consumption and economic growth using trend analysis for Israel [28]. Gonzales et al. have forecast energy production and consumption in Asturias-Northern Spain [29]. A semi statistical cyclic pattern analysis is used for forecasting the primary energy demand for Turkey. The results are found to be similar to Winter's exponential smoothing technique [30]. Hunt et al. investigated the energy demand in sectoral basis for the UK using time series approach [31]. Three time series models, namely, Grey-Markov model, Grey-Model with rolling mechanism, and singular spectrum analysis (SSA) are used to forecast the consumption of conventional energy in India. Grey-Markov model has been employed to forecast crude-petroleum consumption while Grey-Model with rolling mechanism to forecast coal, electricity (in utilities) consumption and SSA to predict natural gas consumption [32].

Sourcewise analysis is also carried out to determine the future demand. The consumption of oil and price is forecast under three scenarios: Parabolic, linear and chaotic behaviour [33]. Aras and Aras [34] used the first-order autoregressive time-series model to predict the natural gas requirement for Eskisehir.

Load forecasting of electric energy demand has been examined by several researchers. In short term forecasting ranging from an hour to over a week, temperature, humidity along with past consumption is considered for demand projection [35–38]. Medium-term forecasts are usually for a week to a year. Researchers who worked on medium term load forecast include Abdel-Aal and Al-Garni [39], Barakat [40] and Wills and Tram [41] have worked on long term forecast.

The potential of using simple logistic curves for forecasting electricity requirement sectorwise is analysed for New Zealand [42]. Electricity demand for India is predicted using time series models [43]. A time-series-based decision support system that integrates data management, model base management, simulation, graphic display, and statistical analysis to provide near-optimal forecasting models for electricity peak load forecasting in UAE is developed. The model base includes a variety of time-series techniques, such as exponential smoothing, Box–Jenkins (BJ), and dynamic regression [44].

Gonzalez-Romera et al. [45] used trend extraction method to examine the electric energy consumption for Spain. In the field of interval time-series (ITS) forecasting, different techniques have been developed. Arroyo et al. [46] have developed three exponential smoothing methods for ITS forecasting.

Himanshu and Lester [47] have used time series analysis for predicting electricity demand in Sri Lanka. Electrical power requirement for Jordon is predicted using models that account for trend, monthly, seasonal and cyclic dynamics [48]. Amarawickrama and Hunt [49] have presented a time series analysis of electricity

demand in Sri Lanka. Various time series estimation methods were used to analyse using past electricity consumption. They have used income and price elasticities to predict the future electricity consumption in Sri Lanka.

Technology diffusion models such as Bass, Gompertz, Logistic, Pearl are used for projecting the energy demand for irrigation water pumping in India. The renewable energy distribution sourcewise in the total energy scenario is determined based on the four models [50]. Pearl or logistic function is used to forecast the future wind energy patterns in India and in five states of India [51].

3.2. Regression models

Energy forecasts are very important in the framing of energy of environment policies. Regression models have been used to forecast the coal, oil, gas, electricity requirement [52,53]. O'Neill and Desai [54] analyse the accuracy in the projections of US energy consumption presented by Energy Information Administration (EIA). GDP and energy intensity (EI) are used in the projection of energy requirement. It is found that the GDP projections are consistently too high while EI projections are consistently too low. This tends to underestimate the future energy consumption. Linear and nonlinear effect of energy consumption on economic growth for Taiwan is examined by Lee and Chang [55]. It is found that a threshold regression provides a better empirical model than the standard linear model.

Regression models are also used for electric load forecasting – short term electric load forecasting [56–59] and long term electric load forecasting [60].

Jannuzzi and Schipper [61] have examined the of electrical energy consumption for the residential sector in Brazil. It was found that the increase in electricity demand was faster than the income. Dynamic relationship between electricity consumption and weather, price, and consumer income are examined by Harris and Lon-Mu [62] using 30 years data series from south east USA. Electricity demand based on the intensity of consumption is developed [63,64] to predict the future requirement.

The influence of economic variables on the annual electricity consumption in N. Cyprus is examined [65]. Using multiple regression analyses, the relationship between energy consumption, the number of customers, the price of electricity and the number of tourists is determined. A linear regression model was used [66] to predict the electricity consumption for Turkey based on the population and percapita consumption rates. Tunc et al. [67] used the regression analysis to predict Turkey's electric energy consumption.

Bessec and Fouquau [68] have examined the non linear relationship between electricity demand and temperature in the European Union. A panel threshold regression with exponential and logistic functions is considered for the data collected from 15 European countries. An empirical model based on multivariate regression is developed [69] to predict the electricity requirement of Jordon's industrial sector. Industrial production outputs and capacity utilization were found to be two most important variables that affect electrical power demand. The residential and commercial sector electricity consumption pattern in Hong Kong was examined [70]. Principal component analysis of five major climatic variables—drybulb temperature, wet-bulb temperature, global solar radiation, clearness index and wind speed—was conducted. It was found that sector-wide electricity consumption correlated with the corresponding two principal components determined using multiple regression technique.

A non parametric regression model [71] is used to assess the wind energy forecasts. The conditional price distribution is found to be non Gaussian. The forecasting models for electricity spot prices for which parameters are estimated by a least squares technique will not have Gaussian residuals.

3.3. Econometric models

Econometric models correlate the energy demand with other macro-economic variables. Samouilidis and Mitropoulos [72] have studied energy and economic growth in industrialized countries. Econometric models are developed to forecast energy consumption as a function of GNP, energy price, technology, population for India [73–75]. Ramaprasad Sengupta [76] and Rao and Parikh [77] have established that such models are effective in forecasting energy patterns in developing countries.

Arsenault et al. [78] have predicted the total energy demand as a function of previous year's energy demand, price of energy, real income and heating day for the province of Quebec. Ordinary least square technique (OLS) is used and prediction is made sectorwise – residential, commercial, industrial and street lighting. Yearly data has been used for demand side projection. Energy forecast is influenced by weather conditions data.

Energy supply and demand for the Asia-Pacific region is analysed [79]. The demand is forecast for three scenarios – high, low, base case considering variations in economic performance, prices and fuel substitution at the national and regional level. Four factors are considered for each country – econometric factors (GDP, foreign trade) with oil prices, domestic oil prices, substitution. A bottom up country by country approach is followed. Oil, natural gas, coal and electricity requirements are projected. The effect of price elasticities, income elasticities and technical efficiency on residential energy demand is studied for OECD countries using econometric energy models [80]. The energy requirement and CO_2 emission for Greece is forecast using econometric models. Demand equations are derived for each sector of economic activity traded, non-traded, public and agricultural sector and for each type of energy – oil, electricity and solid fuels. The energy system is integrated so that all interactions between energy, prices and production factors are considered [81].

Sharma et al. [82] analysed the requirement of three major forms of commercial energy in the state of Kerala (viz electricity, petroleum products and coal). Sectorwise/productwise econometric demand models are generated using regression method. ZhiDong [83] has conducted an econometric study for China linking energy, economy and the environment. A three equation model [84] is used for energy modelling and forecasting energy demand in UK and Germany. An economic model considers the price of electricity, oil, gas, coal, total energy demand and technological progress. The statistical model has the economic model embedded in its equation along with the error correction term. The results from the two models are then processes for structural change and stability.

Energy consumption in industrial, transportation, residential and commercial is determined for China using the consumption of fuel in a sector taking the case of a well off society [85]. Sectoral energy related parameters are identified to determine the final energy consumption in the sector. Econometric modelling is used for energy forecasting. Rural, social and economic data is collected for six provinces in China [86]. A sectoral energy demand analysis and a forecasting model are developed. Variables such as GDP, per capita income, agricultural production output, industrial production output, capital investment are used.

A modified form of econometric model EDM (Energy Demand Model) is used by Gori and Takanen [87] to forecast the Italian energy consumption. The possible substitution of various energy resources is investigated. In addition, the long term electricity consumption pattern in Italy is examined using cointegration and stationary time series models. The primary energy demand in Japan is determined by exploring the relationship between energy

demand, GNP and real energy price [88]. The resulting econometric model is used to determine long run price elasticity and income elasticity. The model is utilized to forecast the energy consumption and CO_2 emission.

Raghuvanshi et al. [89] determine the characteristics of the drivers of energy development for India. The primary energy consumption is decomposed as a product of three variables, population, per capita GDP and energy intensity of GDP. Similarly the CO_2 emissions are decomposed as the product of the primary energy consumption and the carbon intensity of primary supply. Ramanathan [90] has used data envelopment analysis to analyse the patterns of efficiency in terms of world energy consumption, Gross Domestic Product (GDP) growth and CO_2 emissions. The impacts of the changes in energy prices due to deregulation of prices is examined [91] on aggregate energy intensity and coal/oil/electricity intensity is studied. Price elasticities by energy type are determined.

The levels and types of demands for energy services in 2040 for Australia are determined by projecting the levels of economic activity [92]. Demand for 2040 is estimated by examining how energy intensity has been changing in each sector in recent years and this is used to project the future energy requirement. The changes in energy price elasticity and elasticities of substitution are examined [93] between energy and non-energy (capital and labour) sectors in China. It is found that accelerated market oriented reforms lead to energy efficiency improvements because the energy price elasticity declines, and elasticities of substitution and cross price elasticities between energy, capital and labour rise. An econometric model is developed to predict China's energy demand [94]. The energy requirement is forecast and an energy balance is presented for 2020 for China.

Bhattacharyya and Timilsina [95] have stated that basically two types of approaches namely econometric and end-use accounting are normally used in energy demand models. Lescaroux [96] presents a regional and sectoral model of global final energy demand. The main end-use sectors of consumption (industrial, commercial and public services, residential and road transportation), per capita demand is expressed as an S shaped function of per capita income. The effect of variables like energy prices, temperatures and technological trends are also examined. The model is applied on a panel of 101 countries. China's energy intensity is decomposed [97] to find the driving force that is increasing the energy intensity. A two stage approach with factor cost function and fuel share equations is used to determine the elasticities of substitution and price elasticities for interfactor substitution and interfuel substitution.

Econometric models are developed to forecast energy demand sourcewise – coal, oil, electricity and sectorwise – industrial, transport, residential for Korea [98] and for Nepal [99].

The IEA and DOE projections are used to determine the coal demand of China [100]. The paper indicates that even with conservative assumptions about Chinese GDP and income elasticity of electric demand, the coal demand in China will be high and consequently the CO_2 emission.

A modified logit function model is used for extrapolating crude oil and natural gas demands for France [101]. Population and GDP/capita are considered in forecasting the demand. A similar model is developed for Denmark [102].

Elkhafif [103] presents an iterative econometric technique for energy forecast which corrects the abnormal weather conditions data. The model is applied for sectoral natural gas sales data for the province of Ontario, Canada. The study reveals that residential and commercial natural gas data require more weather correction than the data for the industrial sector. Eltony [104] has used econometric models to examine the natural gas demand in Kuwait.

Econometric models are developed for the various petroleum products and natural gas for India [105]. Variables such as GDP/capita, population, price are considered to forecast the demand.

Logistic curve function is used predict the oil demand by considering consumption per capita against GDP per capita [106]. The IEA projections to 2030 for the OECD countries show no reduction in oil demand on a per capita basis. Historical data for China is projected using least squares technique. The results indicate that IEA's oil forecast has been underestimated. Transport energy demand is forecast for China using Partial Least Square Error (PSLE) method based on gross domestic product (GDP), urbanization rate, passenger turnover and freight turnover [107]. Econometric model is used to model five most important crude oil products demand in Spain [108]. The elasticity of demand is determined. It is found that the main factor driving demand is real income with prices having little impact on energy consumption.

Econometric models are used for electricity demand analysis. Liu et al. [109] have used econometric model to forecast electricity consumption and has compared the results with a neural network model. Logistic function is used to predict the electricity demand in Greece [110]. The correlation of gross domestic product, investments and relative electric price on demand is also examined.

Regression and correlation analyses are carried out for Hong Kong [111] to investigate the relationships between residential electricity consumption, economic variables and climatic factors. The seasonal and the yearly electricity use in the residential sector are forecast using the household income, household size, electricity price and cooling degree days. The econometric relationship between electricity consumption and income, price of electricity and diesel (used in for captive power generation to meet the shortages), and reliability of power supply from utilities in sectors namely residential, commercial, agriculture, small and medium industries, and large industries are examined for India [112].

Cobb–Douglas function is used for electricity demand projection for China with parameters – GDP, electricity price and autonomous energy efficiency [113]. The income and price elasticities are determined. An engineering and econometric model is used to predict the household electricity requirement for Norway [114]. The electricity consumption in New Zealand is forecast using economic and demographic variables [115]. Models are developed using multiple linear regression analysis with electricity consumption as a function of gross domestic product, average price of electricity and population. The model is validated by comparing the forecasts with those obtained using Logistic model.

In the context of climate change the future electricity demand is determined for Greece [116]. The electricity demand is determined using regression equation which considers population, GDP, energy intensity, monthly seasonality of electricity demand, monthly heating and cooling degree days. It is found that economic development has a strong effect on the future electricity demand. The electricity requirement in Italy is forecast using linear regression models [117]. The elasticities of GDP, price, GDP per capita for short run and long run and for domestic and non domestic electricity consumption are determined.

Two empirical models are developed based on multivariate linear regression analysis to identify the main drivers behind changes in electricity and fuel consumptions in the household sector in Jordan [118]. The results indicate that fuel unit price, income level, and population are the most important variables that affect demand on electrical power, while population is the most important variable in the case of fuel consumption. The relationship between electricity consumption and gross domestic product is examined for Malaysia using bivariate and multivariate models [119]. It is found that electricity consumption, real GDP and price share a long-run relationship.

The electricity consumption of China is forecast by categorizing the industry as primary, secondary and tertiary [120]. The annual electricity consumption is determined as a function of gross domestic product of primary industry, gross domestic product of secondary industry, gross domestic product of tertiary industry, consumption of rural household, consumption of urban household and consumption of government using partial least square method. Zachariadis [121] forecasts the electricity consumption of Cyprus using econometric analysis of energy use as a function of macro economic variables, prices and weather conditions. The research determines the future electricity demand in Europe using log-linear econometric model [122]. It also highlights how the electricity change impacts the climate, electricity costs including carbon costs.

3.4. Decomposition models

A list of 51 studies related to industrial energy decomposition are reviewed by Ang [123]. Two common approaches to decomposition are the energy consumption (EC) and the energy intensity (EI) approaches. In the energy consumption approach, the basic specified effects are associated with the change in aggregate production level, structural change in production, and changes in sectoral energy intensities, while in the energy intensity approach only the last two effects are considered. Relevant application issues, such as method selection, periodwise versus time-series decomposition, significance of levels of sector disaggregation, and result interpretation are reviewed in the paper. The decomposition of industrial energy consumption in Singapore at two levels of sector disaggregation is studied by Ang [124]. The impact of structural change and changes in sectoral energy efficiencies is examined for Singapore and Taiwan [125] by decomposing the industrial energy consumption. The decomposition is used to energy prediction.

A decomposition model is used for predicting aggregate energy demand in 15 European Union countries [126]. The model is decomposed into components to study the effect of sectoral energy intensity, structure change and GDP. The energy consumption and economic growth relationship is determined by examining how much of the variance in national income growth can be explained by the growth of different sources of energy consumption and employment in Turkey [127]. A generalized forecast error variance decomposition technique is used to determine the information content of the growth rate of energy consumption in Turkey.

The paper [128] applies an aggregate production function to examine the relationship among energy consumption, capital stock, and real income (real GDP per capita) in G-7 countries. Granger causality test, the generalized impulse response approach, and variance decompositions in a multivariate setting to determine the extent and the magnitude of the relationship among variables.

Decomposition models are also applied sourcewise – for oil, electricity. The studies carried out for oil, electricity are reviewed. Factor Decomposition method and System Dynamics (SD) modelling is used to predict the pattern of future oil consumption per capita (OCPC) [129]. Three factors were used for decomposition, i.e. economic activity, technological progress, and structure of energy consumption.

Short term load forecasting for Iran electricity market is done using singular spectral analysis (SSA) [130]. SSA decomposes a time series into trend and oscillation components. Simulation results show that the method gives better results.

Energy consumption pattern is analysed using fractional integration method. Gil-Alana et al. [131] have analysed the energy consumption by the US electric power by various energy sources using fractional integration. Research is carried out to test for long memory in disaggregated petroleum consumption in the United States using univariate and multivariate Lagrange Multiplier (LM) tests for fractional integration [132].

3.5. Unit root test and cointegration models

An econometric model of fossil fuel demand is determined for eight OECD countries, relating coal, oil and gas demands to GDP and prices [133]. In addition a model of endogenous technical progress has been estimated, aiming to include both price induced innovation in energy and structural change in the economy as long-term determinants of energy consumption. Cointegration and error correction model is applied to examine their relationships. Cointegration models were used with multivariate models to examine the influence of gross domestic product (GDP), income, degree-days, population, and energy price on energy demand in various countries by Dincer and Dost [134].

Johansen's multivariate cointegration tests preceded by various unit root or non-stationarity tests are used to test for cointegration between total energy consumption and real income of six Asian economies: India, Pakistan, Malaysia, Singapore, Indonesia and the Philippines [135]. A dynamic vector error-correction model is used to analyse the direction of Granger-causation and within-sample Granger-exogeneity or endogeneity of each of the variables. The relative strength of the causality is determined using the dynamic variance decomposition technique.

The disaggregated behaviour of UK energy crisis is examined [136]. The short and long run determinants of fuel demand, economic activity and real prices are examined. Cointegration analysis has been used to determine the longrun relationships; the residuals which are considered adjustments to the long run, has been fitted into an error correction model to determine short run elasticities. The researchers state that the real oil price is a major determinant of real national income and energy consumption for Korea [137]. It is also found that the combined effects of real money and real government expenditure on real income and energy consumption are also substantial for Korea.

Vector error-correction model estimation is used to examine the relationship between energy consumption and economic growth for Greece [138]. The vector specification includes energy consumption, real GDP and price developments – the latter taken to represent a measure of economic efficiency. The results indicate that there is a long-run relationship between the three variables, supporting the endogeneity of energy consumption and real output. The demand for the different types of energy consumption for Mexico is presented [139]. The Johansen procedure and the likelihood ratio tests are used to find the relationship between the types of energy and income. It is found that in Mexico the demand for energy is driven by income and relative prices. The stability between energy consumption and GDP for Taiwan is examined [140]. Aggregate and disaggregate data of energy consumption, including coal, oil, gas, and electricity, is used. Unit root tests and the cointegration tests allowing for structural breaks are performed on the data.

Al-Irian [141] examines the causality relationship between gross domestic product (GDP) and energy consumption in the six countries of the Gulf Cooperation Council (GCC). Panel cointegration and causality techniques are used to find the direction of energy – GDP causality in the GCC. Panel unit root testing procedure with multiple structural breaks is used to re-investigate the stationarity of energy consumption per capita across regions of the world [142]. The cointegration between energy consumption and GDP are analysed for Turkey [143]. The short term variation is predicted using a vector error correction model (ECM). The causality between variables is determined using the Granger causality model.

The energy imports in China is increasing at an enormous pace because of extensive energy consumption. China's energy import demand is predicted using cointegraiton and vector error correction (VEC) model techniques [144]. The paper examines the dynamic causal relationships between energy consumption,

emissions and output for France using cointegration and vector error-correction modelling techniques [145]. The relationship between energy consumption and economic growth is examined for China using cointegration and VEC approach at both aggregated and disaggregated level [146]. The relationship between energy consumption structure, economic structure and energy intensity in China is examined [147]. Cointegration, causality tests and VEC model have been applied to the energy data for China.

The energy consumption in China is forecast as a function of population growth, economic growth and urbanization level. Autoregressive distributed lag (ARDL) cointegration approach is used to find the long run relationship between urbanization process and energy consumption [148]. Unrestricted error correction model (UECM) is applied. The specification of the Granger causality test will be a vector autoregression (VAR) in first difference form. Factor decomposition model is used to find the changes in total energy consumption (direct and indirect) through its own key elements.

An empirical model of renewable energy consumption for the G7 countries is developed [149]. Panel cointegration estimates show that in the long term, increases in real GDP per capita and CO_2 per capita are found to be major drivers behind per capita renewable energy consumption. The intertemporal causal relationship between energy consumption and economic growth in Tanzania is examined [150]. The auto regressive distributed lag (ARDL) is used for the two types of energy consumption data, namely total energy consumption per capita and electricity consumption per capita. Causality tests are also conducted to find the causal flow.

The causal relationship between energy consumption and economic growth in three sub-Saharan African countries is examined [151]. Using the ARDL-bounds testing procedure, the causality between energy consumption and economic growth are determined. The unit root null hypothesis is performed on the energy consumption data for Australian states and territory [152]. The causal relationship between carbon dioxide emissions, energy consumption, and real output within a panel vector error correction model for eleven countries of the Commonwealth of Independent states is examined [153]. The impact of growth, energy and financial development on the environment in China is analysed using Autoregressive Distributed Lag (ARDL) cointegration approach [154]. The long run equilibrium relationship between financial development and environmental pollution is examined.

The impact of trade on energy consumption in a sample of 8 Middle Eastern countries using the panel cointegration data estimation techniques is examined [155]. Granger causality tests are conducted to determine the causality dynamics existing among the variables. The long-run relationship between energy consumption and real GDP including energy prices for 25 OECD countries is investigated [156]. The cointegration model indicates that international developments dominate the long-run relationship between energy consumption and real GDP. Energy consumption is found to be price-inelastic. Causality tests indicate the presence of a bi-directional causal relationship between energy consumption and economic growth. The causal relationship analysis between Gross Domestic Product, Energy Intensity and CO_2 emissions in Greece using Johansen cointegration tests and Granger causality tests based on a multivariate Vector Error Correction Modelling is studied [157].

Cointegration and error correction analyses have been extensively adopted in the study of energy demand sourcewise. Stock Watson dynamic (DOLS) and error correction modelling approaches have been used for estimating the demand for coal in China [158]. Cointegration and error correction method is used to find the short run and long run price and income elasticities. Long-run structural relationships of coal demand with price and income variables for the four major coal consuming sectors in India are

analysed using cointegration model [159]. The models have been estimated using cointegrating VAR framework, which allows for endogeneity of regressors. The paper estimates the demand for gasoline in Kuwait using a cointegration and error correction model (ECM) [160]. Gasoline demand is inelastic with respect to price in the short and long run, while it is elastic in the long run. Gasoline demand is inelastic with respect to income in the short run. The relationship between gasoline demand, national income and price of gasoline is empirically examined using cointegration and error correction techniques for India [161].

The short run and long run effects between oil consumption and economic growth in China is explored [162]. Cointegration tests suggest that these two variables tend to move together in the long run. Granger causality test indicates oil consumption could be a useful factor to forecast changes in the economy both in the short and in the long run. The results indicate economic growth can be used as a predictive factor to predict oil consumption in the long run.

The future demand for petroleum products in India is studied [163]. Cointegration and error correction modelling approach is used. The long term demand elasticity for petroleum products is also determined. The demand for imported crude oil in South Africa is studied as a function of real income and the price of crude oil [164]. Johansen cointegration multivariate analysis is performed to find the long run relationship with income and price. The short-run dynamics are estimated by specifying a general error correction model.

Gallo et al. [165] Q15 uses unit root tests with two endogenous breaks to analyse the characteristics of oil prices, production, and consumption for several countries. By taking into account structural breaks, the relationship between oil consumption and oil prices is examined. Causality tests are also performed to determine the direction of any possible relationship between oil price and oil consumption and production for Organisation for Economic Co-operation and Development (OECD) countries.

Cointegration models are used to study the relationship between electricity demand and economic variables for Kuwait [166]. Co-integration techniques are used in the analysis of short and long-run effects of economic variables on energy use for US residential electricity demand [167]. An error correction model is also applied on the data. Ranjan and Jain [168] have studied the cointegrating relationship for electrical energy consumption in Delhi. Econometric models are used to investigate the determinants of electrical energy consumption in post-war Lebanon [169]. The impact of the Gross Domestic Product, total imports and degree days on electricity consumption is examined. Cointegration analysis is performed. Error correction models are applied. Statistical performance measures such as mean square error, mean average deviation and mean average percentage error are determined to validate the models.

The relationship between electricity consumption, employment and real income is examined using a cointegration and causality framework for Australia [170]. It is found that electricity consumption, employment and real income are cointegrated. Using cointegration analysis and autoregressive integrated moving average (ARIMA) modelling, the electricity demand is forecast for Turkey [171]. The projections are compared with government based projections and analysed.

Electricity consumption and its interaction with income, prices and the weather in the residential and the services sectors in Cyprus have been examined [172]. The analysis was done using time series techniques such as unit root tests with and without a structural break in levels, cointegration tests, Vector Error Correction models, Granger causality tests and impulse response functions. Cointegration analysis is carried out between electricity consumption and GDP for China [173]. Granger causality and Hodrick–Prescott

(HP) filter are applied to analyse the data for its directionality and decomposition.

Electricity consumption in G7 countries is determined using the panel unit root and panel cointegration techniques [174]. The model presents the long-run and short-run income and price elasticities for residential demand for electricity in G7 countries. The model is used to curtail residential electricity demand and to curtail carbon emissions in the long run. The cointegration analysis is also performed for 30 OECD countries by Narayan and Prased [175].

The causal relationship between electricity consumption and economic growth for Lebanon is examined using cointegration and Granger causality models [176]. Empirical results of the study confirm the absence of a long-term equilibrium relationship between electricity consumption and economic growth in Lebanon. Odhiambo [177] has examined the causal relationship between electricity consumption and economic growth in South Africa. The employment rate as an intermittent variable in the bivariate model between electricity consumption and economic growth is formulated. This results in simple trivariate causality framework.

Inglesi [178] examined the disaggregated behaviour of UK energy crisis. The short and long run determinants of fuel demand, economic activity and real prices are examined. Cointegration analysis has been used to determine the longrun relationships; the residuals which are considered adjustments to the long run, has been fitted into an error correction model to determine short run elasticities. Lai et al. [179] have investigated the causal relationship between electricity consumption and economic growth in a gaming and tourism centre in China. The gross domestic product is co-integrated with quarterly electricity consumption. Vector error correction (VEC) models indicated a lack of short-run relationships but showed that there was a long-run equilibrium relationship between electricity consumption and gross domestic product.

The increase in economic growth and energy demand has led to increased utilization of renewable energy especially in developing countries. Two empirical models for renewable energy consumption and income for a panel of emerging economies are presented [180]. Panel cointegration estimates indicate increases in real per capita income have a positive and statistically significant impact on per capita renewable energy consumption.

3.6. ARIMA models

ARIMA models have been extensively used in energy demand forecasting. A decision support system for forecasting fossil fuel production is developed using regression, ARIMA and SARIMA method for Turkey [181,182]. The method integrates each model by using certain decision parameters related to goodness-of-fit and confidence interval, behaviour of the curve, and reserves. Different forecasting models are proposed for different fossil fuel types. The prediction is made sourcewise – oil, natural gas, hard coal, lignite, wood, hydropower, petrocoke, plantain remains, geothermal heat, solar, asphaltite, geothermal electricity, primary energy.

Erdogdu [183] has estimated short and long-run price and income elasticities of sectoral natural gas demand in Turkey. The future electric energy demand is forecast using ARIMA. Short term electric load is forecast using ARIMA transfer function model [184].

A hybrid model with AR(1) and a finite impulse response filter is used for forecasting Lebanon's electricity demand [185]. The model is compared with autoregressive and ARIMA models and it is found that the hybrid model gave higher accuracy. Conejo et al. [186] have used ARIMA to forecast electric price while Pappas et al. [187] have used ARIMA to study the electricity demand load.

Sumer et al. [188] have used three models namely ARIMA, seasonal ARIMA and regression model to predict the electricity demand and have concluded that regression model with seasonal latent variable gave better result. Tourism-induced electricity consumption is studied for Balearics Islands, Spain [189]. ARMAX and GARCH models are applied to examine the daily electricity demand and the effect of tourism.

3.7. Expert systems and ANN models

In the past, expert systems and neural networks were being used extensively for electricity load forecasting. In recent times, it is also being used for long term energy demand projections considering macro economic variables. Neural network is used to model the energy consumption of appliances, lighting, and space-cooling in Canadian residential sector [190]. The energy consumption for Turkey is predicted using artificial neural-network (ANN) technique [191]. Two models are used: population, gross generation, installed capacity and years are used in the input layer of the network for Model 1 and other energy sources are used in input layer of network for Model 2.

Researchers have argued that green energy can be considered as a catalyst for energy security, sustainable development, and social, technological, industrial and economic development. The paper analyses the world green energy consumption through artificial neural networks (ANN). The world primary energy consumption including fossil fuels such as coal, oil and natural gas is also considered [192]. Sectoral energy consumption in Turkey is determined using ANN [193]. The model is then used for greenhouse gas prediction and mitigation.

Sözen and Arcaklioglu [194] have used three different models to train the ANN. In Model 1, energy indicators such as installed capacity, generation, energy import and energy export, in Model 2, GNP was used and in the Model 3, GDP was used as the input in ANN. The output of the network is net energy consumption (NEC). It is found that the ANN approach presents greater accuracy when economic indicators namely GNP, GDP are used for prediction. The energy demand for South Korea is estimated using a feed forward multilayer perception, error back propagation algorithm [195]. The model considered gross domestic product, population, import and export. The results are compared with the multiple linear and exponential regression energy demand models.

Pao [196] examines the following linear models: the exponential smoothing model (Winters), the exponential form of the generalized autoregressive conditional heteroscedasticity (EGARCH) and seasonal EGARCH (SEGARCH) models, the combined Winters with volatility EGARCH model (WARCH) and ANN non linear model. Based on the above models, two hybrid non linear models SEGARCH – ANN and WARCH – ANN are developed to predict Taiwan's consumption of electricity and petroleum. The models are validated using root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The results indicate the hybrid models give better accuracy and among the hybrid models WARCH-ANN is the better model.

The extent to which an economy relies upon imports in order to meet its energy needs is defined as Energy dependency (ED). Turkey's energy dependency is determined using ANN based on basic energy indicators and sectoral energy consumption [197]. Two models have been used. In Model 1, main energy indicators such as total production of primary energy per capita, total gross electricity generation per capita and final energy consumption per capita were used in the input layer of the ANN while sectoral energy consumption per capita was used in Model 2. A global optimization method called "Modal Trimming Method" is used to identify the values of model parameters [198]. In addition, the trend and periodic change are removed from time series data on energy demand. The converted data is used as the main input to a neural network. Furthermore, predicted values of air temperature and relative humidity are considered as additional inputs to the neural network, and their effect on the prediction of energy demand is investigated.

The Greek long-term energy consumption is predicted using ANN multilayer perception model. The input variables chosen are yearly ambient temperature, installed power capacity, yearly per resident electricity, consumption, gross domestic product [199]. Energy consumption in Turkey is modelled based on socio-economic and demographic variables (gross domestic product-GDP, population, import and export amounts, and employment) using artificial neural network (ANN) and regression analyses. The models are validated using relative errors and RMSE [200].

Neural Networks is used to predict the oil and natural gas consumption. Gorucu and Gumrah [201] have used ANN to predict the gas requirement for Ankara. GNP, population and vehicle kilometre are used as input parameters in training neural network model for predicting the transport energy demand for Turkey [202]. The best network architecture is selected using the training and validation data set. The final network is tested using the test data. The transport energy consumption in Thailand is determined using the national gross domestic product, population and the numbers of registered vehicles as independent variables [203]. Log-linear regression models and feed-forward neural network models are used in the study.

Neural Network models have been extensively used for short term load forecasting for electricity [23,204–238]. Several researchers have worked on NN models for medium term load forecasting [239–245] and also long term load forecasting [246]. Xia et al. [247] have used NN to forecast short, medium and long term load forecasting.

Wavelets are also used for short term load forecasting [248–250]. Benaoudaa et al. [251] have used wavelet based nonlinear multiscale decomposition model for electricity load forecasting. Adaptive wavelet neural network model is used for forecasting short term electric load with feed forward neurons [252].

ANN is used to forecast regional peak load planning for Taiwan [253]. The daily electric load profile is forecast using a combined approach of unsupervised and supervised neural network [254]. Kohanen's self organising map is used during the unsupervised stage. The neural network is trained using climate data along with historical load data to find the influence of climate variability. The model is validated to give good accurate results for short term load forecasting problem. The power distribution load is forecast using neural network for short term and medium term load in Nigde, Turkey [255].

Researchers have also used neural network to forecast electricity price. Gareta et al. have used a neural network model is used to forecast short term hourly electricity price [256] while Amjady [257] has used a neuro fuzzy approach to forecast electricity price.

Pao [258] has forecast the electricity requirement for Taiwan using nonlinear ANN and linear models – multiple log-linear regression (LNREG), response surface regression (RSREG), and regression with ARMA errors model (ARMAX) models. Four economic factors namely the national income (NI), population (POP), gross of domestic production (GDP), and consumer price index (CPI) are used to study its influence on the electricity consumption. Maia et al. [259] have used auto regressive moving average models (ARMA) with neural network and Maia et al. [260] present models for interval valued time series forecasting based on AR, ARIMA and Artificial Neural Networks.

Hamzacebi [261] used ANN to estimate the net electricity consumption of Turkey on sectoral basis while Sozen et al. [262] have used ANN to forecast sectoral energy consumption and greenhouse gas emission and discussed on consequent mitigation policies for Turkey. Gonzalez-Romera et al. [263] used neural network approach to forecast the trend and monthly fluctuation of electric energy demand. The monthly electric demand for Spain is analysed and a hybrid forecasting model is proposed [264]. The periodic behaviour is forecast using Fourier series function and the trend is forecast using a neural network.

Azadeh et al. [265] have used ANN for forecasting the annual electricity consumption in high energy consuming industries in Iran. The ANN approach is based on a multilayer perception model. The accuracy of the ANN results over regression models are validated using ANOVA. Midterm load forecasting of power systems is performed using a preforecast model (NN) and a hybrid model (neural network and evolutionary algorithm) [266].

The electricity consumption in the Asian gaming and tourism centre – Macao SAR, People's Republic of China is determined using multiple regression, artificial neural network (ANN) and wavelet ANN [267]. Five factors, namely temperature, population, the number of tourists, hotel room occupancy and days per month, are used to characterize Macao's monthly electricity consumption. The models are compared for their accuracy using mean squared error (MSE), the mean squared percentage error (MSPE) and the mean absolute percentage error (MAPE). It is found wavelet ANN is best among the models to forecast the electricity consumption.

Regression analysis, decision tree and neural networks are modelled using SAS Enterprise Miner for the prediction of electricity energy consumption in Hong Kong [268]. The decision tree and neural network models appear to be viable alternatives to the stepwise regression model in understanding energy consumption patterns and predicting energy consumption levels. The monthly electric power demand per hour is forecast in Spain for two years using two approaches – vector autoregressive (VAR) models and internal multi layer perception model (iMLP) [269]. The authors have concluded that for electric power demand forecasting for Spain iMLP has given better accuracy.

Meteorological and geographical data is fitted into an ANN model to determine the solar-energy potential in Turkey [270]. Scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) learning algorithms and a logistic sigmoid transfer function have been used in the network.

3.8. Grey prediction

Grey prediction gained popularity in the past decade because of its simplicity and ability to characterize unknown system by using a few data points. Energy demand forecasting can be regarded as grey system problem, because a few factors such as GDP, income, population are known to influence the energy demand but how exactly they affect the energy demand is not clear. Grey forecasting consists several forecasting models of which GM(1,1) is commonly used for forecasting. Grey relation analysis was used to predict the motor vehicular energy consumption in Taiwan [271]. The relative influence of the fuel price, the gross domestic product, the number of motor vehicles and the vehicle kilometres of travel (VKT) per energy increase are evaluated.

Energy consumption in China is forecast using grey prediction model which incorporates genetic algorithm [272]. A grey based cost efficiency model is used for optimal forecasting of power generation cost of renewable energy technologies [273]. The model quantifies the influences of cost reduction in power generation. Grey prediction model (GM) to predict and explore the dynamic relationships between pollutant emissions, energy consumption, and the output for Brazil [274]. In the long-run equilibrium emissions appear to be both energy consumption and output inelastic, but energy is a more important determinant of emissions than output. The causality results indicate that there is a bidirectional strong causality running between income, energy consumption and emissions. The GM model is compared with ARIMA model for validation.

The trend in the number of motor vehicle, vehicular energy consumption and the resulting CO_2 emission in Taiwan is studied using the grey prediction model [275].

Grey prediction model is used for electricity demand forecasting [276,277]. A taguchi method was used to optimize the parameter settings for the grey based electricity demand predictor [278]. The system when used in conjunction with a PC based electricity demand control system was expected to reduce the usage of electricity. A grey prediction model with trignometric residual modification is used for forecasting electricity demand in China [279]. The authors state that the model has improved the prediction accuracy to a large extent.

Grey prediction with rolling mechanism (GPRM) approach is used to predict the total and industrial electricity consumption in Turkey [280]. The results are compared with the energy prediction studies obtained using Model of Analysis of the Energy Demand (MAED). GPRM is found to have better prediction accuracy. Two models are developed. GDP and price elasticities are initially used to estimate nonresidential short run electricity for Romania [281]. A Holt–Winters exponential smoothing method and a trigonometric grey model with rolling mechanism (TGMRM) is then used for nonresidential electricity prediction. The results of the two models are then compared.

Grey prediction analysis is also used for prediction of renewable energy sources. Grey relative analysis and prediction is carried out for biofuels consumption on rural household in China [282].

3.9. Input–output models

An input–output model is used to assess how social and economic changes will affect energy requirements and energy intensity in China [283]. Six scenarios were developed by introducing major impact factors, such as technological advancement, population, income, and urbanization, in the input–output model to project China's energy requirements. Liang et al. [284] divided China into eight economic regions. A multi-regional input–output model for energy requirements and CO_2 emissions in China was established. Scenario and sensitivity analysis for each economic region is performed. The indirect energy consumption in the households of China is evaluated using an input–output model [285]. The indirect energy consumption of both rural and urban households is determined. Using the economic data, the input–output model is used to evaluate how the alternative energy policies impact production prices, consumption prices, and real income of rural and urban households through the mechanism of indirect energy consumption.

A growth model is integrated with an input–output model to analyse the impacts of economic growth on the energy consumption in Brazil [286]. Renewable and nonrenewable energy are considered. He et al. [287] have forecast the energy demand using the input–output table for Liaoning province in China. Scenarios are developed for three cases. Energy intensity and energy efficiency are considered in demand projection.

An input–output table of electricity demand (IOTED) is developed for China based on the input–output table of national economy (IOTNE) [288]. The electricity demand in various sectors is determined using the IOTED. Electricity demand multiplier (EDM) is used to identify dominant sectors that has a high electricity demand. Alcántara et al. [289] have developed an input–output table to study the electricity consumption pattern in Spain. The table helps in effective utilization of electricity by increasing energy efficiency.

3.10. Genetic algorithm/fuzzy logic/neuro fuzzy

3.10.1. Genetic algorithm

In recent years soft computing techniques are being in energy demand forecasting. Ceylan and Ozturk [290] have used genetic algorithm to estimate the energy demand for Turkey using economic indicators namely gross national product (GNP), population and import and export amounts. They established that the genetic algorithm (GA) model gave better accuracy as compared to the government's model. Genetic algorithm demand estimation models (GA-DEM) are developed to determine the future requirement of coal, oil and natural gas in Turkey based on population, gross national product, import and export [291].

Haldenbilen and Ceylan [292] have used genetic algorithm to estimate the transport energy demand in Turkey. Ozturk et al. [293] used the Genetic Algorithm EXergy consumption model (GAPEX) for predicting the petroleum exergy demand. Transport energy in Turkey is determined using meta-heuristic harmony search algorithm – HArmony Search Transport Energy Demand Estimation (HASTEDE) considering population, gross domestic product and vehicle kilometres as input [294]. Linear, exponential and quadratic models are used in the HASTEDE methodology. Optimum values are determined using sensitivity analysis (SA). A logistic based method is used to forecast the natural gas consumption for residential and commercial sectors in Iran [295]. Two methods are used to estimate the logistic parameters – one using nonlinear programming (NLP) and the second using genetic algorithm (GA).

Modern computational techniques using genetic algorithms are being adapted for load forecasting [296]. Tzafestas and Tzafestas [297] have used computational intelligence techniques for short term electric load forecasting. Ozturk et al. [298] used GA for forecasting the electricity energy demand of Turkey. The electricity consumption is determined based on gross national product, population, import and export data. Two different non-linear estimation models are developed using GA. The models are validated using actual data.

Azadeh and Tarverdian [299] present an integrated algorithm for forecasting monthly electrical energy consumption based on genetic algorithm (GA), computer simulation and design of experiments using stochastic procedures. Time-series model is developed as a benchmark for developing the GA and simulation models. ANOVA is used to validate the results. Considering electricity consumption, GNP, primary energy consumption, installed capacity, population, a neural network is designed which is improved upon using Genetic algorithm for the prediction of hydroelectric power in Turkey [300].

3.10.2. Fuzzy logic

Fuzzy logic is used for short term electric load forecasting [301–305]. Pai [306] has used hybrid ellipsoidal fuzzy systems while Ying and Pan [307] have used adaptive network based fuzzy inference system to forecast regional electricity loads.

The short term gross annual electricity demand for Turkey is forecast using fuzzy logic methodology [308]. GDP based purchasing power parity was the only parameter used in the model. The model is validated by comparing the forecasts with regression based forecasts and MENR projections (MAED).

Short term electric load forecasting has been predicted using neuro fuzzy system [309,310]. Padmakumari et al. [311] have forecast long term distribution demand using neuro fuzzy computations.

3.11. Integrated models – Bayesian vector autoregression, support vector regression, particle swarm optimization models

Some of the latest techniques such as Bayesian vector autoregression, support vector regression, ant colony, particle swarm optimization models are being used in energy demand analysis. A review of a few studies related to energy demand analysis is presented.

3.11.1. Bayesian vector autoregression (BVAR) model

Bayesian vector auto regressive model is used to predict energy requirement for China [312]. The primary energy requirement of coal, oil, gas, hydro is projected till 2010. A Bayesian Vector Autoregression (BVAR) model and Granger-causality are applied to study growth in energy demand and the relationship between energy consumption to real gross domestic product per capita in selected few Caribbean countries [313]. The increased growth in energy consumption indicate the need for long-term commitments to undertake a series of economic, market, and research and development measures to advance the adoption and deployment of new energy technologies. Bayesian neural network approach is used for short term electric load forecasting [314,315].

3.11.2. Support vector regression

Fan et al. [316] and Hong [317] have used support vector model electricity load. Electricity consumption is derived as a function of socio-economic indicators such as population, gross national product, imports and exports [318]. SVR (support vector regression) was created for each of the input variables to predict the electricity consumption for Turkey. RMSE was used to find the best e-SVR model for each variable. Moving average and e-SVR (support vector regression) are used to forecast the short term electricity demand. ANOVA is used to validate the accuracy of forecast obtained by comparing its results with ARIMA model [319].

3.11.3. Ant Colony Optimization (ACO)

The energy demand in Turkey is determined using Ant Colony Optimization (ACO) [320] with independent variables such as gross domestic product (GDP), population, and import and export amounts. Toksari [321] again used ACO technique for forecasting Turkey's electricity energy demand.

3.11.4. Particle swarm optimization (PSO)

Particle swarm optimization (PSO) based energy demand forecasting (PSOEDF) is used to forecast the energy demand of Turkey [322]. Gross domestic product (GDP), population, import and export are used as energy indicators of energy demand. The results are validated by comparing with the ant colony optimization (ACO) technique performed for energy demand estimation. El-Telbany and El-Karmi [323] have used PSO for short term forecasting of Jordon's electricity demand.

A particle swarm optimization method is used for annual peak load forecasting in electrical power systems [324]. Actual recorded data from Kuwaiti and Egyptian networks are used. The model is validated using least error squares estimation technique.

3.11.4.1. Hybrid models.

The review states that SVR with genetic algorithm and SVR with simulated annealing are superior to other competitive forecasting models. However genetic algorithm (GA) and simulated annealing (SA) algorithm loses the previous knowledge of the problem once the population (GA) or the temperature changes (SA). Chaotic particle swarm optimization algorithm is used in the SVR for electric load forecasting model. The results indicate that the above model gives better accuracy than GA or SA algorithm [325].

A new combined model for electric load forecasting based on the seasonal ARIMA forecasting model, the seasonal exponential smoothing model and the weighted support vector machines is used for electric load forecasting [326]. The model is found to effectively map the seasonality and nonlinearity normally present in the electric load data. The adaptive particle swarm optimization is used to optimize the weight coefficients in the combined forecasting model.

The paper presents an SVR-based electric load forecasting model that applied chaotic ant swarm optimization (CAS) technique, to improve the forecasting performance [327]. The CAS combines with the chaotic behaviour of single ant and self-organisation behaviour of ant colony. The empirical results indicate that the SVR model with CAS (SVRCAS) performs better as compared to SVRCPSO (SVR with chaotic PSO), SVRCGA (SVR with chaotic GA), regression model or ANN model.

3.12. Bottom up models – MARKAL/TIMES/LEAP

3.12.1. MARKAL

The MARKAL (acronym for MARKet ALlocation) is a bottom-up, dynamic technique which was originally developed as a least cost linear programming model by the Energy Technology Systems Analysis Program (ETSAP) of the International Energy Agency. The equations for the initial MARKAL model are given by Fishbone and Abilock [328]. Numerous improvements have been made in the model for in depth analysis [329–331].

The MARKAL model depicts both the energy supply and demand sides of the energy system. It is an analytical tool that can be adapted to model different energy systems at the national, state and regional level. MARKAL model is used to study the impact of policy changes. Carbon mitigation strategies can also explored using the model. Scenarios are developed using the 'what if' framework [332,333]. As of 2005, Loulou et al. [334] have documented that MARKAL and TIMES models have been used in more than 80 institutions in 50 countries for various purposes including economic analysis of climate policies.

The MARKAL model is used for Shanghai to develop scenarios during various policy conditions. The study analyses how the air pollutant emission can be reduced using the MARKAL model when different policy decisions are taken and also the benefits that accrue by mitigating the increase of CO_2 emissions is also explored [335–341].

Analysis for 2003, 2007 and the regulatory impact assessment of the Climate Change Bill were undertaken using the UK MARKAL and MARKAL – Macro (M-M) energy–economic models by Strachan et al. [342]. To achieve 60% CO_2 reduction, a range of scenarios focusing on energy supply, technology pathways and macro-economic cost implications are presented. MARKAL model is used to model the UK residential energy sector with an objective of reaching a target of a 60% reduction in carbon dioxide (CO_2) emissions by 2050 [343].

MARKAL model is applied to allocate various energy sources across sectors in India for Business As Usual (BAU) scenario [344]. The paper analyses the sectoral energy consumption pattern and emissions of CO_2 and local air pollutants in the Kathmandu Valley, Nepal using MARKAL model [345]. The paper also presents various scenarios for emission reduction.

The drivers for increased utilization of natural gas is identified using the economic optimization model MARKAL [346]. The drivers are identified to be government mandates of emissions standards, reform of the Chinese financial structure, the price and supply of natural gas, and the rate of penetration of advanced power generation systems.

3.12.2. TIMES G5 model (the integrated MARKAL–EFOM system)

Long term energy demand and CO_2 emission for China is forecast using TIMES G5 model. Sourcewise and sectorwise energy demand are determined using the key indicators such as population, GDP, person-km, GDP per capita, heating per capita, cooking per capita, heating per GDP, cooling per GDP [347].

3.12.3. LEAP

The Long-range Energy Alternatives Planning system (LEAP) model was developed by the Stockholm Environment Institute at Boston (SEI-B). It is a bottom-up-type accounting framework which

is used for forecasting. The LEAP Model also has been developed to model the energy needs at the national, state and regional level Lazarus et al. [348].

Energy demand and supply are calculated for different Mexican end-use sectors based on the data from the national energy balance [349]. The transformation programme simulates the energy demand in terms of electricity generation and distribution, natural gas, oil and coke production, etc. Based on the energy requirements calculated in the demand analysis programme the primary energy supplies in transformation programme are matched with the energy demand.

In 1997, SEI-Boston along with five leading international research and training institutes – EDRC (South Africa), ENDA (West Africa), ETC (Europe), FAO-RWEDP (Asia), IDEE (Latin America) – joined to create a new suite of tools for integrated energy-environment analysis. This was funded by the Netherlands Ministry of Foreign Affairs (DGIS). The LEAP 2000 was designed to cater to the needs of energy planners and policy makers. The model can be used to study the effect of introducing strategies, greenhouse gas mitigation assessments for sustainable energy development. LEAP 2000 is a scenario-based energy-environment modelling tool. Its scenarios are based on a comprehensive accounting of how energy is consumed, converted and produced in a given region or economy under a range of alternative assumptions including population, economic development, technology, price, etc.

LEAP model has been used for energy systems planning at country level – US Country Studies program (USCS) [350], Mexico [351], China [352], Taiwan [353], Rawalpindi and Islamabad [354].

LEAP has also been used for sector-level analysis: in electricity generation [355], in electricity generation for China [356], transportation [357,358], household [359], in household sector in Delhi [360]. Other studies about bioenergy scenarios have been reported for Vietnam [361], Korea [362] and biofuels for Mexico [363].

Kadian et al. have used LEAP system for modelling the total energy consumption and associated emissions from the household sector of Delhi, India [360]. Energy consumption under different sets of policy and technology options is analysed. The LEAP model is applied for long term forecast of Taiwan's energy supply and demand, the greenhouse gas emission. Scenarios are developed for various case situations [353]. The LEAP model was used to estimate total energy demand and the vehicular emissions in Rawalpindi and Islamabad [354]. LEAP system software is used to study the potential effects of electric trolley bus system in Kathmandu Valley [364]. The fuel consumption and greenhouse gas emissions are projected till 2025.

LEAP model is used to predict the electricity requirement for China [356]. Three scenarios are developed and CO_2 emission level is determined. To combat the CO_2 emission which is expected to triple or quadruple various structural adjustments in the electricity sector is suggested such as demand side management, circulating fluidized bed combustion. Islas et al. [363] have used the LEAP model for Mexico to find the feasibility of using biofuels in the transportation and electricity generation sector. Their impact on the Mexican energy system is analysed. Future scenarios based on moderate and high use are developed. It also evaluates the efficient use of biofuels in the residential sector, particularly in the rural sub-sector.

4. Conclusion

Energy demand forecasting models for commercial and renewable energy have been reviewed. It is found that every nation is interested in detailed energy planning for its sustained development. Energy intensity is being determined to find the relative energy utilization by a nation. The econometric models indicate

that GNP, energy price, gross output, population are being linked to energy demand. Technological development, energy efficiency are also linked to the energy demand in econometric models. Decomposition models highlight the strength of the macro variables with energy demand with reference to a certain nation. Cointegration models and causality tests indicate the direction of the causal variables with reference with energy demand. It is found that ARIMA models are linked with neural networks and other soft computing techniques to improve the accuracy of energy demand forecasting. Grey prediction is yet another technique being tried successfully for energy demand analysis. Genetic algorithms, fuzzy logic, SVR, AGO, PSO are emerging techniques in forecasting commercial and renewable energy sources. It is found that the models link energy, economy and environment for planning the future energy utilization in a sustainable manner. It is expected that such models will help energy planners to accurately plan for the future and utilize the sustainable and renewable energy resources to a larger extent. The models will facilitate policy makers and administrators to take decisions for a greener tomorrow. The review indicates that macro economic energy modelling is vital for every nation. Sophisticated modelling techniques such as grey prediction, genetic algorithms, fuzzy logic, SVR, AGO, PSO can be used by researchers for macro energy economic planning for accurate energy demand prediction.

References

[1] CSIRO & The Natural Edge Project. Energy transformed: sustainable energy solutions for climate change mitigation; 2007. p. 6.
[2] Bohi DR. Analzing demand behavior: a study of energy elasticities, resources for the future. Baltimore: Johns Hopkins University Press; 1981.
[3] Bohi DR, Zimmerman MB. An update on econometric studies of energy demand behavior. Annual Review of Energy 1984;9:105–54.
[4] David Wood Memorial Issue. The Energy Journal 1993.
[5] Chang J, Leung DYC, Wu CZ, Yuan ZH. A review on the energy production, consumption, and prospect of renewable energy in China. Renewable and Sustainable Energy Reviews 2003;7(5):453–68.
[6] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Applied Energy 2010;87(4):1059–82.
[7] Baños R, Manzano-Agugliaro F, Montoya FG, Gil C, Alcayde A, Gómez J. Optimization methods applied to renewable and sustainable energy: a review. Renewable and Sustainable Energy Reviews 2011;15(4):1753–66.
[8] Chen K, Kung SH. Synthesis of qualitative and quantitative approaches to long-range forecasting. Technological Forecasting and Social Change 1984;26(3):255–66.
[9] Permana AS, Perera R, Kumar S. Understanding energy consumption pattern of households in different urban development forms: a comparative study in Bandung City, Indonesia. Energy Policy 2008;36(11):4287–97.
[10] Liu G, Lucas M, Shen L. Rural household energy consumption and its impacts on eco-environment in Tibet: taking Taktse county as an example. Renewable and Sustainable Energy Reviews 2008;12(7):1890–908.
[11] Baines JT, Bodger PS. Further issues in forecasting primary energy consumption. Technological Forecasting and Social Change 1984;26(3):267–80.
[12] Tolmasquim MT, Cohen C, Szklo AS. CO_2 emissions in the Brazilian industrial sector according to the integrated energy planning model (IEPM). Energy Policy 2001;29:641–51.
[13] Miranda-da-Cruz SM. A model approach for analysing trends in energy supply and demand at country level: case study of industrial development in China. Energy Economics 2007;29(4):913–33.
[14] Aydinalp-Koksal M, Ugursal VI. Comparison of neural network, conditional demand analysis, and engineering approaches for modeling end-use energy consumption in the residential sector. Applied Energy 2008;85(4):271–96.
[15] Marík K, Schindler Z, Stluka P. Decision support tools for advanced energy management. Energy 2008;33(6):858–73.
[16] Shimoda Y, Yamaguchi Y, Okamura T, Taniguchi A, Yamaguchi Y. Prediction of greenhouse gas reduction potential in Japanese residential sector by residential energy end-use model. Applied Energy 2010;87:1944–52.
[17] Hu Z, Yuan J, Hu Z. Study on China's low carbon development in an economy–energy–electricity–environment framework. Energy Policy 2011;39:2596–605.
[18] Persaud AJ, Kumar U. An eclectic approach in energy forecasting: a case of Natural Resources Canada's (NRCan's) oil and gas outlook. Energy Policy 2001;29(4):303–13.
[19] Fernandes E, Fonseca MVA, Alonso PSR. Natural gas in Brazil's energy matrix: demand for 1995–2010 and usage factors. Energy Policy 2005;33(3):365–86.
[20] Li J, Dong X, Shangguan J, Hook M. Forecasting the growth of China's natural gas consumption. Energy 2011;36:1380–5.

[21] Lehtila A, Silvennoinen P, Vira J. A belief network model for forecasting within the electricity sector. Technological Forecasting and Social Change 1990;38(2):135–50.

[22] Jia NX, Yokoyama R, Zhou YC, Gao ZY. A flexible long-term load forecasting approach based on new dynamic simulation theory – GSIM. Electrical Power and Energy Systems 2001;23:549–56.

[23] Yao SJ, Song YH, Zhang LZ, Cheng XY. Wavelet transform and neural networks for short-term electrical load forecasting. Energy Conversion and Management 2000;41(18):1975–88.

[24] Steenhof PA, Fulton W. Factors affecting electricity generation in China: current situation and prospects. Technological Forecasting and Social Change 2007;74(5):663–81.

[25] Steenhof PA, Fulton W. Scenario development in China's electricity sector. Technological Forecasting and Social Change 2007;74(6):779–97.

[26] Filik ÜB, Gerek ÖN, Kurban M. A novel modeling approach for hourly forecasting of long-term electric energy demand. Energy Conversion and Management 2010;52:199–211.

[27] Deshmukh MK, Deshmukh SS. Modeling of hybrid renewable energy systems. Renewable and Sustainable Energy Reviews 2008;12(1):235–49.

[28] Bargur J, Mandel A. Energy consumption and economic growth in Israel: trend analysis (1960–1979). In: Proceedings of the third international conference on energy use management. 1981.

[29] Gonzales CS, Xiberta BJ, Llaneza CH. Forecasting of energy production and consumption in Asturias (Northern Spain). Energy 1999;24:183–98.

[30] Ediger V, Tathdil H. Forecasting the primary energy demand in Turkey and analysis of cyclic patterns. Energy Conversion and Management 2002;43(4):473–87.

[31] Hunt JG, Judge G, Ninomiya Y. Underlying trends and seasonality in UK energy demand: a sectoral analysis. Energy Economics 2003;25:93–118.

[32] Kumar U, Jain VK. Time series models (Grey-Markov. Grey Model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India. Energy 2010;35(4):1709–16.

[33] Gori F, Ludovisi D, Cerritelli PF. Forecast of oil price and consumption in the short term under three scenarios: parabolic, linear and chaotic behaviour. Energy 2007;32:1291–6.

[34] Aras H, Aras N. Forecasting residential natural gas demand. Energy Sources 2004;26(5):463–72.

[35] Hagan MT, Behr SM. The time series approach to short term load forecasting. IEEE Transactions on Power Systems 1987;PWRS-2:785–91.

[36] Fan JY, McDonald JD. A real-time implementation of short-term load forecasting for distribution power systems. IEEE Transactions on Power Systems 1994;9:988–94.

[37] Amjady N. Short-term hourly load forecasting using time series modeling with peak load estimation capability. IEEE Transactions on Power Systems 2001;16:798–805.

[38] Nogales FJ, Contreras J, Conejo AJ, Espinola R. Forecasting next-day electricity prices by time series models. IEEE Transactions on Power Systems 2002;17:342–8.

[39] Abdel-Aal RE, Al-Garni AZ. Forecasting monthly electric energy consumption in Eastern Saudi Arabia using univariate time-series analysis. Energy 1997;22(11):1059–69.

[40] Barakat EH. Modeling of nonstationary time-series data. Part II. Dynamic periodic trends. Electrical Power and Energy Systems 2001;23:63–8.

[41] Wills HL, Tram HN. Load forecasting for transmission planning. IEEE Transactions on Power Systems 1984;103:561–8.

[42] Bodger PS. Logistic and energy substitution models for electricity forecasting: a comparison using New Zealand consumption data. Technological Forecasting and Social Change 1987;31(1):27–48.

[43] Tripathy SC. Demand forecasting in a power system. Energy Conversion and Management 1997;38(14):1475–81.

[44] Badri MA, Al-Mutawa A, Davis D, Davis D. EDSSF: a decision support system (DSS) for electricity peak-load forecasting. Energy 1997;22(6):579–89.

[45] Gonzalez-Romera E, Jaramillo-Maron MA, Carmona-Fernandez D. Monthly electric energy demand forecasting based on trend extraction. IEEE Transactions on Power Systems 2006;21(4):1946–53.

[46] Arroyo J, Munoz San Roque A, Mate C, Sarabia A. Exponential smoothing methods for interval time series. In: ESTSP 07: first European symposium on time series prediction (TSP). Proceedings of symposium. 2007. p. 231–40.

[47] Himanshu AA, Lester CH. Electricity demand for Sri Lanka: a time series analysis. Energy 2008;33:724–39.

[48] Al-Shobaki S, Mohsen M. Modeling and forecasting of electrical power demands for capacity planning. Energy Conversion and Management 2008;49(11):3367–75.

[49] Amarawickrama HA, Hunt LC. Electricity demand for Sri Lanka: a time series analysis. Energy 2008;33(5):724–39.

[50] Purohit P, Kandpal TC. Renewable energy technologies for irrigation water pumping in India: projected levels of dissemination, energy delivery and investment requirements using available diffusion models. Renewable and Sustainable Energy Reviews 2005;9(6):592–607.

[51] Mabel MC, Fernandez E. Growth and future trends of wind energy in India. Renewable and Sustainable Energy Reviews 2008;12:1745–57.

[52] Farahbalhsh H, Ugursal VI, Fung AS. A residential enduse energy consumption model for Canada. Energy Research 1998;22:1133–43.

[53] Sharma DP, Chandramohanan Nair PS, Balasubramanian R. Residential demand for electrical energy in the state of Kerala: an econometric analysis with medium range projections. In: Proceedings of the IEEE power engineering society winter meeting. 2000.

[54] O'Neill BC, Desai M. Accuracy of past projections of US energy consumption. Energy Policy 2005;33(8):979–93.

[55] Lee CC, Chang CP. The impact of energy consumption on economic growth: evidence from linear and nonlinear models in Taiwan. Energy 2007;32(12):2282–94.

[56] Mohgram I, Rahman S. Analysis and evaluation of five short-term load forecasting techniques. IEEE Transactions on Power Systems 1989;4:1484–91.

[57] Papalexopoulos D, Hesterberg TC. A regression based approach to short-term load forecasting. IEEE Transactions on Power Systems 1990;5:1535–50.

[58] Haida T, Muto S. Regression based peak load forecasting using a transformation technique. IEEE Transactions on Power Systems 1994;9:1788–94.

[59] Charytoniuk W, Chen MS, Van Olinda P. Nonparametric regression based short term load forecasting. IEEE Transactions on Power Systems 1998;13:725–30.

[60] Al-Hamadi HM, Soliman SA. Long-term/mid-term electric load forecasting based on short-term correlation and annual growth. Electrical Power and Energy Systems 2005;74(3):353–61.

[61] Jannuzzi G, Schipper L. The structure of electricity demand in the Brazilian household sector. Energy Policy 1991;19(9):879–91.

[62] Harris JL, Lon-Mu L. Dynamic structural analysis and forecasting of residential electricity consumption. Forecasting 1993;9:437–55.

[63] Furtado AT, Suslick SB. Forecasting of petroleum consumption in Brazil using the intensity of energy technique. Energy Policy 1993;21(9):958–68.

[64] Harry CM. Trends in Dutch energy intensities for the period 1969–1988. Energy 1998;23(10):815–22.

[65] Egelioglu F, Mohamad AA, Guven H. Economic variables and electricity consumption in Northern Cyprus. Energy 2001;26(4):355–62.

[66] Yumurtaci Z, Asmaz E. Electric energy demand of Turkey for the year 2050. Energy Sources 2004;26(12):1157–64.

[67] Tunc M, Camdali U, Parmaksizoglu C. Comparison of Turkey's electrical energy consumption and production with some European countries and optimization of future electrical power supply investments in Turkey. Energy Policy 2006;34(1):50–9.

[68] Bessec M, Fouquau J. The non-linear link between electricity consumption and temperature in Europe: a threshold panel approach. Energy Economics 2008;30(5):2705–21.

[69] Al-Ghandoor A, Al-Hinti I, Jaber JO, Sawalha SA. Electricity consumption and associated GHG emissions of the Jordanian industrial sector: empirical analysis and future projection. Energy Policy 2008;36(1):258–67.

[70] Lam JC, Tang HL, Li DHW. Seasonal variations in residential and commercial sector electricity consumption in Hong Kong. Energy 2008;33(3):513–23.

[71] Jónsson T, Pinson P, Madsen H. On the market impact of wind energy forecasts. Energy Economics 2010;32(2):313–20.

[72] Samouilidis JE, Mitropoulos CS. Energy and economic growth in industrialized countries. Energy Economics 1984:191–201.

[73] Suganthi L, Jagadeesan TR. A modified model for prediction of India's future energy requirement. Energy and Environment 1992;3(4):371–86.

[74] Suganthi L, Williams A. Renewable energy in India – a modelling study for 2020–2021. Energy Policy 2000;28:1095–109.

[75] Iniyan S, Suganthi L, Samuel AA. Energy models for commercial energy prediction and substitution of renewable energy sources. Energy Policy 2006;34:2640–53.

[76] Ramaprasad Sengupta. Energy modelling for India: towards a policy for commercial energy. New Delhi: Study Report of Planning Commission, Government of India; 1993.

[77] Rao RD, Parikh J. Forecast and analysis of demand for petroleum products in India. Energy Policy 1996;24(6):583–92.

[78] Arsenault E, Bernard JT, Carr CW, Genest-Laplante E. A total energy demand model of Québec, Forecasting properties. Energy Economics 1995;17(2):163–71.

[79] Intarapravich D, Johnson CJ, Li B, Long S, Pezeshki S, Prawiraatmadja W, et al. Asia-Pacific energy supply and demand to 2010. Energy 1996;21(11):1017–39.

[80] Haas R, Schipper L. Residential energy demand in OECD-countries and the role of irreversible efficiency improvements. Energy Economics 1998;20(4):421–42.

[81] Christodoulakis NM, Kalyvitis SC, Lalas DP, Pesmajoglou S. Forecasting energy consumption and energy related CO_2 emissions in Greece: an evaluation of the consequences of the Community Support Framework II and natural gas penetration. Energy Economics 2000;22:395–422.

[82] Sharma DP, Chandramohanan Nair PS, Balasubramanian R. Demand for commercial energy in the state of Kerala, India: an econometric analysis with medium-range projections. Energy Policy 2002;30(9):781–91.

[83] ZhiDong L. An econometric study on China's economy, energy and environment to the year 2030. Energy Policy 2003;31:1137–50.

[84] McAvinchey ID, Yannopoulos A. Stationarity, structural change and specification in a demand system: the case of energy. Energy Economics 2003;25(1):65–92.

[85] Lu W, Ma Y. Image of energy consumption of well off society in China. Energy Conversion and Management 2004;45:1357–67.

[86] Yang M, Yu X. China's rural electricity market—a quantitative analysis. Energy 2004;29(7):961–77.

[87] Gori F, Takanen C. Forecast of energy consumption of industry and household and services in Italy. Heat Technology 2004;22(2):115–21.

[88] Hunt LC, Ninomiya Y. Primary energy demand in Japan: an empirical analysis of long-term trends and future CO_2 emissions. Energy Policy 2005;33(11):1409–24.

[89] Raghuvanshi SP, Chandra A, Raghav AK. Carbon dioxide emissions from coal based power generation in India. Energy Conversion and Management 2006;47:427–41.

[90] Ramanathan R. A multi-factor efficiency perspective to the relationships among world GDP, energy consumption and carbon dioxide emissions. Technological Forecasting and Social Change 2006;73:483–94.

[91] Hang L, Tu M. The impacts of energy prices on energy intensity: evidence from China. Energy Policy 2007;35(5):2978–88.

[92] Saddler H, Diesendorf M, Denniss R. Clean energy scenarios for Australia. Energy Policy 2007;35:1245–56.

[93] Fan Y, Liao H, Wei YM. Can market oriented economic reforms contribute to energy efficiency improvement? Evidence from China. Energy Policy 2007;35(4):2287–95.

[94] Adams FG, Shachmurove Y. Modeling and forecasting energy consumption in China: implications for Chinese energy demand and imports in 2020. Energy Economics 2008;30(3):1263–78.

[95] Bhattacharyya SC, Timilsina GR. Modelling energy demand of developing countries: are the specific features adequately captured? Energy Policy 2010;38(4):1979–90.

[96] Lescaroux F. Dynamics of final sectoral energy demand and aggregate energy intensity. Energy Policy 2011;39:66–82.

[97] Wang R, Liu W, Xiao L, Liu J, Kao W. Path towards achieving of China's 2020 carbon emission reduction target—a discussion of low-carbon energy policies at province level. Energy Policy 2011;39:2740–7.

[98] Kim SH, Kim TH, Kim Y, Na IG. Korean energy demand in the new millennium: outlook and policy implications, 2000–2005. Energy Policy 2001;29(11):899–910.

[99] Pokharel S. An econometric analysis of energy consumption in Nepal. Energy Policy 2007;35(1):350–61.

[100] Shealy M, Dorian JP. Growing Chinese coal use: dramatic resource and environmental implications. Energy Policy 2010;38(5):2116–22.

[101] Mackay RM, Probert SD. Crude oil and natural gas supplies and demands up to the year 2010 for France. Applied Energy 1995;50(3):185–208.

[102] Mackay RM, Probert SD. Crude oil and natural gas supplies and demands for Denmark. Applied Energy 1995;50(3):209–32.

[103] Elkhafif MAT. An iterative approach for weather-correcting energy consumption data. Energy Economics 1996;18(3):221–30.

[104] Eltony MN. Demand for natural gas in Kuwait: an empirical analysis using two econometric models. Energy Research 1996;20(11):957–63.

[105] Parikh J, Purohit P, Maitra P. Demand projections of petroleum products and natural gas in India. Energy 2007;32(10):1825–37.

[106] Nel WP, Cooper CJ. A critical review of IEA's oil demand forecast for China. Energy Policy 2008;36(3):1096–106.

[107] Zhang M, Mu H, Li G, Ning Y. Forecasting the transport energy demand based on PLSR method in China. Energy 2009;34(9):1396–400.

[108] Pedregal DJ, Dejuán O, Gómez N, Tobarra MA. Modelling demand for crude oil products in Spain. Energy Policy 2009;37(11):4417–27.

[109] Liu XQ, Ang BW, Goh TN. Forecasting of electricity consumption: a comparison between an econometric model and a neural network model. In: IEEE international joint conference on neural networks, vol. 2. 1991. p. 1254–9.

[110] Skiadas CH, Papayannakis LL, Mourelatos AG. An attempt to improve the forecasting ability of growth functions: the Greek electric system. Technological Forecasting and Social Change 1993;44(4):391–404.

[111] Lam JC. Climatic and economic influences on residential electricity consumption. Energy Conversion and Management 1998;39(7):623–9.

[112] Bose RK, Shukla M. Elasticities of electricity demand in India. Energy Policy 1999;27(3):137–46.

[113] von Hirschhausen C, Andres M. Long-term electricity demand in China—from quantitative to qualitative growth? Energy Policy 2000;28(4):231–41.

[114] Larsen BM, Nesbakken R. Household electricity end-use consumption: results from econometric and engineering models. Energy Economics 2004;26(2):179–200.

[115] Mohamed Z, Bodger P. Forecasting electricity consumption in New Zealand using economic and demographic variables. Energy 2005;30(10):1833–43.

[116] Mirasgedis S, Sarafidis Y, Georgopoulou E, Kotroni V, Lagouvardos K, Lalas DP. Modeling framework for estimating impacts of climate change on electricity demand at regional level: case of Greece. Energy Conversion and Management 2007;48(5):1737–50.

[117] Bianco V, Manca O, Nardini S. Electricity consumption forecasting in Italy using linear regression models. Energy 2009;34(9):1413–21.

[118] Al-Ghandoor A, Jaber JO, Al-Hinti I, Mansour IM. Residential past and future energy consumption: potential savings and environmental impact. Renewable and Sustainable Energy Reviews 2009;13(6–7):1262–74.

[119] Chandran VGR, Sharma S, Madhavan K. Electricity consumption-growth nexus: the case of Malaysia. Energy Policy 2010;38(1):606–12.

[120] Meng M, Niu D. Annual electricity consumption analysis and forecasting of China based on few observations methods. Energy Conversion and Management 2011;52:953–7.

[121] Zachariadis T. Forecast of electricity consumption in Cyprus up to the year 2030: the potential impact of climate change. Energy Policy 2010;38(2):744–50.

[122] Pilli-Sihvola K, Aatola P, Ollikainen M, Tuomenvirta H. Climate change and electricity consumption—witnessing increasing or decreasing use and costs? Energy Policy 2010;38(5):2409–19.

[123] Ang BW. Decomposition methodology in industrial energy demand analysis. Energy 1995;20(11):1081–95.

[124] Ang BW. Multilevel decomposition of industrial energy consumption. Energy Economics 1995;17(1):39–51.

[125] Ang BW, Lee PW. Decomposition of industrial energy consumption: the energy coefficient approach. Energy Economics 1996;18(1–2):129–43.

[126] Sun JW. Energy demand in the fifteen European Union countries by 2010: a forecasting model based on the decomposition approach. Energy 2001;26(6):549–60.

[127] Sari R, Soytas U. Disaggregate energy consumption, employment and income in Turkey. Energy Economics 2004;26(3):335–44.

[128] Lee CC, Chien MS. Dynamic modelling of energy consumption, capital stock, and real income in G-7 countries. Energy Economics 2010;32(3):564–81.

[129] Tao Z. Scenarios of China's oil consumption per capita (OCPC) using a hybrid Factor Decomposition-System Dynamics (SD) simulation. Energy 2010;35(1):168–80.

[130] Afshar K, Bigdeli N. Data analysis and short term load forecasting in Iran electricity market using singular spectral analysis (SSA). Energy; doi:10.1016/j.energy.2011.02.003, in press.

[131] Gil-Alana LA, Payne JE, Loomis D. Does energy consumption by the US electric power sector exhibit long memory behaviour? Energy Policy 2010;38:7512–8.

[132] Lean HH, Smyth R. Long memory in US disaggregated petroleum consumption: evidence from univariate and multivariate LM tests for fractional integration. Energy Policy 2009;37(8):3205–11.

[133] Smith C, Hall S, Mabey N. Econometric modelling of international carbon tax regimes. Energy Economics 1995;17(2):133–46.

[134] Dincer I, Dost S. Energy and GDP. Energy Research 1997;21(2):153–67.

[135] Masih AMM, Masih R. Energy consumption, real income and temporal causality: results from a multi-country study based on cointegration and error-correction modelling techniques. Energy Economics 1996;18(3):165–83.

[136] Fouquet R, Pearson David P, Robinson Paul C. The future of UK final user energy demand. Energy Policy 1997;25(2):231–40.

[137] Glasure YU. Energy and national income in Korea: further evidence on the role of omitted variables. Energy Economics 2002;24(4):355–65.

[138] Hondroyiannis G, Lolos S, Papapetrou E. Energy consumption and economic growth: assessing the evidence from Greece. Energy Economics 2002;24(4):319–36.

[139] Galindo LM. Short-and long-run demand for energy in Mexico: a cointegration approach. Energy Policy 2005;33(9):1179–85.

[140] Lee CC, Chang CP. Structural breaks, energy consumption, and economic growth revisited: evidence from Taiwan. Energy Economics 2005;27(6):857–72.

[141] Al-Irian MA. Energy—GDP relationship revisited: an example from GCC countries using panel causality. Energy Policy 2006;34:3342–50.

[142] Chen PF, Lee CC. Is energy consumption per capita broken stationary? New evidence from regional-based panels. Energy Policy 2007;35(6):3526–40.

[143] Lise W, Montfort KV. Energy consumption and GDP in Turkey: is there a cointegration relationship? Energy Economics 2007;29:1166–78.

[144] Zhao X, Wu Y. Determinants of China's energy imports: an empirical analysis. Energy Policy 2007;35(8):4235–46.

[145] Ang JB. CO_2 emissions, energy consumption, and output in France. Energy Policy 2007;35(10):4772–8.

[146] Yuan JH, Kang JG, Zhao CH, Hu ZG. Energy consumption and economic growth: evidence from China at both aggregated and disaggregated levels. Energy Economics 2008;30(6):3077–94.

[147] Feng T, Sun L, Zhang Y. The relationship between energy consumption structure, economic structure and energy intensity in China. Energy Policy 2009;37(12):5475–83.

[148] Liu Y. Exploring the relationship between urbanization and energy consumption in China using ARDL (autoregressive distributed lag) and FDM (factor decomposition model). Energy 2009;34(11):1846–54.

[149] Sadorsky P. Renewable energy consumption, CO_2 emissions and oil prices in the G7 countries. Energy Economics 2009;31(3):456–62.

[150] Odhiambo NM. Energy consumption and economic growth nexus in Tanzania: an ARDL bounds testing approach. Energy Policy 2009;37(2):617–22.

[151] Odhiambo NM. Energy consumption, prices and economic growth in three SSA countries: a comparative study. Energy Policy 2010;38(5):2463–9.

[152] Kumar Narayan P, Narayan S, Popp S. Energy consumption at the state level: the unit root null hypothesis from Australia. Applied Energy 2010;87(6):1953–62.

[153] Apergis N, Payne JE. The emissions, energy consumption, and growth nexus: evidence from the commonwealth of independent states. Energy Policy 2010;38(1):650–5.

[154] Jalil A, Feridun M. The impact of growth, energy and financial development on the environment in China: a cointegration analysis. Energy Economics 2011;33:284–91.

[155] Sadorsky P. Trade and energy consumption in the Middle East. Energy Economics; doi:10.1016/j.eneco.2010.12.012, in press.

[156] Belke A, Dobnik F, Dreger C. Energy consumption and economic growth: new insights into the cointegration relationship. Energy Economics; doi:10.1016/j.eneco.2011.02.005, in press.

[157] Hatzigeorgiou E, Polatidis H, Haralambopoulos D. CO$_2$ emissions, GDP and energy intensity: a multivariate cointegration and causality analysis for Greece, 1977–2007. Applied Energy 2011;88:1377–85.

[158] Masih R, Masih AMM. Stock-Watson dynamic OLS (DOLS) and error-correction modelling approaches to estimating long-and short-run elasticities in a demand function: new evidence and methodological implications from an application to the demand for coal in mainland China. Energy Economics 1996;18(4):315–34.

[159] Kulshreshtha M, Parikh JK. Modeling demand for coal in India: vector autoregressive models with cointegrated variables. Energy 2000;25(2):149–68.

[160] Eltony MN, Al-Mutairi NH. Demand for gasoline in Kuwait: an empirical analysis using cointegration techniques. Energy Economics 1995;17(3):249–53.

[161] Ramanathan R. Short-and long-run elasticities of gasoline demand in India: an empirical analysis using cointegration techniques. Energy Economics 1999;21(4):321–30.

[162] Zou G, Chau KW. Short-and long-run effects between oil consumption and economic growth in China. Energy Policy 2006;34(18):3644–55.

[163] Ghosh S. Future demand of petroleum products in India. Energy Policy 2006;34:2032–7.

[164] Ziramba E. Price and income elasticities of crude oil import demand in South Africa: a cointegration analysis. Energy Policy 2010;28:7844–9.

[165] Gallo A, Mason P, Shapiro S, Fabritius M. What is behind the increase in oil prices? Analyzing oil consumption and supply relationship with oil price. Energy 2010;35:4126–41.

[166] Eltony MN, Hosque A. A cointegrating relationship in the demand for energy: the case of electricity in Kuwait. Energy Development 1997;21(2):293–301.

[167] Silk JI, Joutz FL. Short and long-run elasticities in US residential electricity demand: a co-integration approach. Energy Economics 1997;19(4):493–513.

[168] Ranjan M, Jain VK. Modeling of electrical energy consumption in Delhi. Energy 1999;24:351–61.

[169] Nasr GE, Badr EA, Dibeh G. Econometric modeling of electricity consumption in post-war Lebanon. Energy Economics 2000;22:627–40.

[170] Narayan PK, Smyth R. Electricity consumption, employment and real income in Australia evidence from multivariate Granger causality tests. Energy Policy 2005;33(9):1109–16.

[171] Erdogdu E. Electricity demand analysis using cointegration and ARIMA modelling: a case study of Turkey. Energy Policy 2007;35(2):1129–46.

[172] Zachariadis T, Pashourtidou N. An empirical analysis of electricity consumption in Cyprus. Energy Economics 2007;29(2):183–98.

[173] Yuan J, Zhao C, Yu S, Hu Z. Electricity consumption and economic growth in China: cointegration and co-feature analysis. Energy Economics 2007;29:1179–91.

[174] Narayan PK, Smyth R, Prasad A. Electricity consumption in G7 countries: a panel cointegration analysis of residential demand elasticities. Energy Policy 2007;35(9):4485–94.

[175] Narayan PK, Prased A. Electricity consumption-real GDP causality nexus: evidence from a bootstrapped causality test for 30 OECD countries. Energy Policy 2008;36(2):910–8.

[176] Abosedra S, Dah A, Ghosh S. Electricity consumption and economic growth, the case of Lebanon. Applied Energy 2009;86:429–32.

[177] Odhiambo NM. Electricity consumption and economic growth in South Africa: a trivariate causality test. Energy Economics 2009;31(5):635–40.

[178] Inglesi R. Aggregate electricity demand in South Africa: conditional forecasts to 2030. Applied Energy 2010;87(1):197–204.

[179] Lai TM, To WM, Lo WC, Choy YS, Lam KH. The causal relationship between electricity consumption and economic growth in Gaming and Tourism Center: the case of Macao SAR, the People's Republic of China. Energy 2011;36:1134–42.

[180] Sadorsky P. Renewable energy consumption and income in emerging economies. Energy Policy 2009;37(10):4021–8.

[181] Ediger VS, Akar S, Ugurlu B. Forecasting production of fossil fuel sources in Turkey using a comparative regression and ARIMA model. Energy Policy 2006;34(18):3836–46.

[182] Ediger VS, Akar S. ARIMA forecasting of primary energy demand by fuel in Turkey. Energy Policy 2007;35:1701–8.

[183] Erdogdu E. Natural gas demand in Turkey. Applied Energy 2010;87:211–9.

[184] Cho MY, Hwang JC, Chen CS. Customer short-term load forecasting by using ARIMA transfer function model. In: Proceedings of the international conference on energy manage power delivery, vol. 1. 1995. p. 317–22.

[185] Saab S, Badr E, Nasr G. Univariate modeling and forecasting of energy consumption: the case of electricity in Lebanon. Energy 2001;26(1):1–14.

[186] Conejo AJ, Plazas MA, Espinola R, Molina AB. Day-ahead electricity price forecasting using the wavelet transform and ARIMA models. IEEE Transactions on Power Systems 2005;20:1035–42.

[187] Pappas SS, Ekonomou L, Karamousantas DC, Chatzarakis GE, Katsikas SK, Liatsis P. Electricity demand loads modeling using auto regressive moving average (ARMA) models. Energy 2008;33:1353–60.

[188] Sumer KK, Goktas O, Hepsag A. The application of seasonal latent variable in forecasting electricity demand as an alternative method. Energy Policy 2009;37:1317–22.

[189] Bakhat M, Rosselló J. Estimation of tourism-induced electricity consumption: the case study of Balearics Islands, Spain. Energy Economics 2011;33:437–44.

[190] Aydinalp M, Ismet Ugursal V, Fung AS. Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks. Applied Energy 2002;71(2):87–110.

[191] Sozen A, Arcaklioglu E, Ozkaymak M. Turkey's net energy consumption. Applied Energy 2005;81(2):209–21.

[192] Ermis K, Midilli A, Dincer I, Rosen MA. Artificial neural network analysis of world green energy use. Energy Policy 2007;35(4):1731–43.

[193] Sözen A, Gülseven Z, Arcaklioglu E. Forecasting based on sectoral energy consumption of GHGs in Turkey and mitigation policies. Energy Policy 2007;35(12):6491–505.

[194] Sözen A, Arcaklioglu E. Prediction of net energy consumption based on economic indicators (GNP and GDP) in Turkey. Energy Policy 2007;35(10):4981–92.

[195] Geem ZW, Roper WE. Energy demand estimation of South Korea using artificial neural network. Energy Policy 2009;37(10):4049–54.

[196] Pao HT. Forecasting energy consumption in Taiwan using hybrid nonlinear models. Energy 2009;34(10):1438–46.

[197] Sözen A. Future projection of the energy dependency of Turkey using artificial neural network. Energy Policy 2009;37(11):4827–33.

[198] Yokoyama R, Wakui T, Satake R. Prediction of energy demands using neural network with model identification by global optimization. Energy Conversion and Management 2009;50(2):319–27.

[199] Ekonomou L, Greek long-term energy consumption prediction using artificial neural networks. Energy 2010;35:512–7.

[200] Kankal M, AkpInar A, Komurcu MI, Ozsahin TS. Modeling and forecasting of Turkey's energy consumption using socio-economic and demographic variables. Applied Energy 2011;88:1927–39.

[201] Gorucu FB, Gumrah F. Evaluation of forecasting of gas consumption by statistical analysis. Energy Sources 2004;26:267–76.

[202] Murat YS, Ceylan H. Use of artificial neural networks for transport energy demand modeling. Energy Policy 2006;34(17):3165–72.

[203] Limanond T, Jomnonkwao S, Srikaew A. Projection of future transport energy demand of Thailand. Energy Policy 2011;39:2754–63.

[204] Rahman S, Bhatnagar R. An expert system based algorithm for short-term load forecasting. IEEE Transactions on Power Systems 1988;3(2):392–9.

[205] Ho KL, Hsu YY, Chen FF, Lee TE, Liang CC, Lai TS, et al. Short-term load forecasting of Taiwan power system using a knowledge based expert system. IEEE Transactions on Power Systems 1990;5:1214–21.

[206] Hsu YY, Yang CC. Design of artificial neural networks for short-term load forecasting. Part II: multilayer feedforward networks for peak load and valley load forecasting. IEE Proceedings-C 1991;138(5):414–8.

[207] Park DC, El-Sharkawi MA, Marks RJ, Atlas LE, Damborg MJ. Electric load forecasting using an artificial neural network. IEEE Transactions on Power Systems 1991;6:442–9.

[208] Peng TM, Hubele NF, Karadi GG. Advancement in the application of neural networks for short-term load forecasting. IEEE Transactions on Power 1992;7(1):250–7.

[209] Lee KY, Cha YT, Park JH. Short-term load forecasting using an artificial neural network. IEEE Transactions on Power Systems 1992;7(1):124–32.

[210] Ho KL, Hsu YY, Yang CC. Short-term load forecasting using a multilayer neural network with an adaptive learning algorithm. IEEE Transactions on Power Systems 1992;7(1):141–9.

[211] Chen ST, Yu DC, Moghaddamjo AR. Weather sensitive short-term load forecasting using nonfully connected artificial neural network. IEEE Transactions on Power Systems 1992;7(3):1098–105.

[212] Lu CN, Wu HT, Vemuri S. Neural network based short term load forecasting. IEEE Transactions on Power Systems 1993;8(1):336–42.

[213] Papalexopoulos AD, Hao S, Peng TM. An implementation of a neural network based load forecasting model for the EMS. IEEE Transactions on Power Systems 1994;9:1956–62.

[214] Sforna M, Proverbio F. A neural network operator oriented short-term and online load forecasting environment. Electric Power Systems Research 1995;33:139–44.

[215] Mohammed O, Park D, Merchant R, Dinh T, Tong C, Azeem Farah A. Practical experiences with an adaptive neural network short-term load forecasting system. IEEE Transactions on Power Systems 1995;10:254–65.

[216] Khotanzad A, Hwang RC, Abaye A, Maratukulam D. An adaptive modular artificial neural network hourly load forecaster and its implementation at electric utilities. IEEE Transactions on Power Systems 1995;10(3):1716–22.

[217] Khotanzad A, Davis MH, Abaye A, Maratukulam DJ. An artificial neural network hourly temperature forecaster with applications in load forecasting. IEEE Transactions on Power Systems 1996;11:870–6.

[218] Rahman S, Hazim O. Load forecasting for multiple sites: development of an expert system-based technique. Electric Power Systems Research 1996;39:161–9.

[219] Bakirtzis AG, Petridis V, Kiartzis SJ, Alexiadis MC, Maissis AH. A neural network short-term load forecasting model for the Greek power system. IEEE Transactions on Power Systems 1996;11:858–63.

[220] Hill T, O'Connor M, Remus W. Neural networks models for time series forecasts. Management Science 1996:1082–92.

[221] Chow TWS, Leung CT. Neural network based short-term load forecasting using weather compensation. IEEE Transactions on Power Systems 1996;11(4):1736–42.

[222] Vermaak J, Botha EC. Recurrent neural networks for short-term load forecasting. IEEE Transactions on Power Systems 1998;13(1):126–32.

[223] Hobbs BF, Helman U, Jitprapaikulsarn S, Konda S, Maratukulam D. Artificial neural networks for short-term energy forecasting: accuracy and economic value. Neurocomputing 1998;23:71–84.

[224] Khotanzad A, Rohani RA, Maratukulam D. Artificial neural network short-term load forecaster – generation three. IEEE Transactions on Neural Networks 1998;13:1413–22.

[225] Lin CT, Ji LW, Kao YK. A study on electric power load prediction in Taiwan. In: Proceedings of the 4th conference on grey theory and applications. 1999. p. 342–6.

[226] Gao R, Tsoulakas LH. Neural-wavelet methodology for load forecasting. Intelligent and Robotic Systems 2001;31:149–57.

[227] Mandal P, Senjyu T, Funabashi T. Neural networks approach to forecast several hour ahead electricity prices and loads in a deregulated market. Energy Conversion and Management 2003;47:2128–42.

[228] Tai N, Stenzel J, Wu H. Techniques of applying wavelet transform into combined model for short-term load forecasting. Electric Power Systems Research 2006;76:525–33.

[229] Kandil N, Wamkeue R, Saad M, Georges S. An efficient approach for short term load forecasting using artificial neural networks. Electrical Power and Energy Systems 2006;28:525–30.

[230] Topalli AK, Erkmen I, Topalli I. Intelligent short-term load forecasting in Turkey. Electrical Power and Energy Systems 2006;28:437–47.

[231] Santos PJ, Martins AG, Pires AJ. Designing the input vector to ANN-based models for short-term load forecast in electricity distribution systems. Electrical Power and Energy Systems 2007;29:338–47.

[232] Al-Shareef AJ, Mohamed EA, Al-Judaibi E. One hour ahead load forecasting using artificial neural network for the western area of Saudi Arabia. World Academy of Science, Engineering and Technology 2008;37:219–24.

[233] Amin-Naseri MR, Soroush AR. Combined use of unsupervised and supervised learning for daily peak load forecasting. Energy Conversion and Management 2008;49(6):1302–8.

[234] Vahidinasab V, Jadid S, Kazemi A. Day-ahead price forecasting in restructured power systems using artificial neural networks. Electric Power Systems Research 2008;78:1332–42.

[235] Xiao Z, Ye SJ, Zhong B, Sun CX. BP neural network with rough set for short term load forecasting. Expert Systems with Applications 2009;36:273–9.

[236] Kurban M, Filik UB. Next day load forecasting using artificial neural network models with autoregression and weighted frequency bin blocks. Innovative Computing, Information and Control 2009;5(4):889–98.

[237] Shayeghi H, Shayanfar HA, Azimi G. Intelligent neural network based STLF. Intelligent Systems and Technologies 2009;4(1):17–27.

[238] Siwek K, Osowski S, Szupiluk R. Ensemble neural network approach for accurate load forecasting in a power system. Applied Mathematics and Computer Science 2009;19(2):303–15.

[239] Islam SM, Al-Alawi SM, Ellithy KA. Forecasting monthly electric load and energy for a fast growing utility using an artificial neural network. Electric Power Systems Research 1995;34:1–9.

[240] Abdel-Aal RE, Al-Garni AZ, Al-Nassar YN. Modeling and forecasting monthly electric energy consumption in eastern Saudi Arabia using abductive networks. Energy 1997;22:911–21.

[241] Al-Shehri A. Artificial neural network for forecasting residential electrical energy. Energy Research 1999;23(8):649–61.

[242] Ghiassi M, Zimbra DK, Saidane H. Medium term system load forecasting with a dynamic artificial neural network model. Electric Power Systems Research 2006;76(5):302–16.

[243] Azadeh A, Ghaderi SF, Sohrabkhani S. Improving neural networks output with preprocessed data in electricity consumption forecasting. In: Proceedings of the 36th international conference on computers and industrial engineering. 2006. p. 20–3.

[244] Azadeh A, Ghaderi SF, Sohrabkhani S. Forecasting electrical consumption by neural network. In: Proceedings of the Energex 2006: the 11th international energy conference and exhibition. 2006. p. 12–5.

[245] Azadeh A, Ghaderi SF, Sohrabkhani S. Forecasting electrical consumption by integration of neural network, time series and ANOVA. Applied Mathematics and Computation 2007;186:1753–61.

[246] Carpinteiro OAS, Leme RC, de Souza ACZ, Pinheiro CAM, Moreira EM. Long-term load forecasting via a hierarchical neural model with time integrators. Electric Power Systems Research 2007;77:371–8.

[247] Xia C, Wang J, McMenemy K. Short, medium and long term load forecasting model and virtual load forecaster based on radial basis function neural networks. Electrical Power and Energy Systems 2010;32:743–50.

[248] Truong NV, Wang L, Wong PKC. Modeling and short-term forecasting of daily peak power demand in Victoria using two-dimensional wavelet based SDP models. Electrical Power and Energy Systems 2008;30:511–8.

[249] Chaturvedi DK, Premdayal SA, Chandiok A. Short-term load forecasting using soft computing techniques. Communications, Network and System Sciences 2010;3:273–9.

[250] Hang T, Nguyen HT, Nabney IT. Short-term electricity demand and gas price forecasts using wavelet transforms and adaptive models. Energy 2010;35:3674–85.

[251] Benaoudaa D, Murtaghb F, Starckc JL, Renaudd O. Wavelet-based nonlinear multiscale decomposition model for electricity load forecasting. Neurocomputing 2006;70(1–3):139–54.

[252] Pindoriya MM, Singh SN, Singh SK. Forecasting of short-term electric load using application of wavelets with feed-forward neural networks. Emerging Electric Power Systems 2010;11(1):1–24.

[253] Hsu CC, Chen CY. Regional load forecasting in Taiwan—applications of artificial neural networks. Energy Conversion and Management 2003;44(12):1941–9.

[254] Beccali M, Cellura M, Lo Brano V, Marvuglia A. Forecasting daily urban electric load profiles using artificial neural networks. Energy Conversion and Management 2004;45(18–19):2879–900.

[255] Yalcinoz T, Eminoglu U. Short term and medium term power distribution load forecasting by neural networks. Energy Conversion and Management 2005;46(9–10):1393–405.

[256] Gareta R, Romeo LM, Gil A. Forecasting of electricity prices with neural networks. Energy Conversion and Management 2006;47:1770–8.

[257] Amjady N. Day-ahead price forecasting of electricity markets by a new fuzzy neural network. IEEE Transactions on Power Systems 2006;21:887–96.

[258] Pao HT. Comparing linear and nonlinear forecasts for Taiwan's electricity consumption. Energy 2006;31(12):2129–41.

[259] Maia SAL, Carvalho F, Ludermir TB. Symbolic interval time series forecasting using a hybrid model. In: Symposium on neural networks. 2006.

[260] Maia SAL, Carvalho F, Ludermir TB. Forecasting models for interval valued time series. Neurocomputing 2008;71(16–18):3344–52.

[261] Hamzacebi C. Forecasting of Turkey's net electricity energy consumption on sectoral bases. Energy Policy 2007;35(3):2009–16.

[262] Sozen A, Gulseven Z, Arcaklioglu E. Forecasting based on sectoral energy consumption of GHGs in Turkey and mitigation policies. Energy Policy 2007;35(12):6491–505.

[263] Gonzalez-Romera E, Jaramillo-Maron MA, Carmona-Fernandez D. Forecasting of the electric energy demand trend and monthly fluctuation with neural network. Computers and Industrial Engineering 2007;52(3):336–43.

[264] González-Romera E, Jaramillo-Morán MA, Carmona-Fernández D. Monthly electric energy demand forecasting with neural networks and Fourier series. Energy Conversion and Management 2008;49(11):3135–42.

[265] Azadeh A, Ghaderi SF, Sohrabkhani S. Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors. Energy Conversion and Management 2008;49(8):2272–8.

[266] Amjady N, Keynia F. Mid-term load forecasting of power systems by a new prediction method. Energy Conversion and Management 2008;49(10):2678–87.

[267] Lai TM, To WM, Lo WC, Choy YS. Modeling of electricity consumption in the Asian gaming and tourism center—Macao SAR, People's Republic of China. Energy 2008;33(5):679–88.

[268] Tso GKF, Yau KKW. Predicting electricity energy consumption: a comparison of regression analysis, decision tree and neural networks. Energy 2007;32(9):1761–8.

[269] García-Ascanio C, Maté C. Electric power demand forecasting using interval time series: a comparison between VAR and iMLP. Energy Policy 2010;38(2):715–25.

[270] Sozen A, Arcakliolu E, Ozalp M, Kanit EG. Solar-energy potential in Turkey. Applied Energy 2005;80(4):367–81.

[271] Lu IJ, Lin SJ, Lewis C. Grey relation analysis of motor vehicular energy consumption in Taiwan. Energy Policy 2008;36:2556–61.

[272] Lee Y-S, Tong L-I. Forecasting energy consumption using a grey model improved by incorporating genetic programming. Energy Conversion and Management 2011;52:147–52.

[273] Lee S-C, Shih L-H. Forecasting of electricity costs based on an enhanced grey-based learning model: a case study of renewable energy in Taiwan. Technological Forecasting and Social Change 2011.

[274] Pao H-T, Tsai C-M. Modeling and forecasting the CO_2 emissions, energy consumption, and economic growth in Brazil. Energy 2011;36(May (5)):2450–8.

[275] Lu IJ, Lewis C, Lin SJ. The forecast of motor vehicle, energy demand and CO_2 emission from Taiwan's road transportation sector. Energy Policy 2009;37:2952–61.

[276] Hsu CC, Chen CY. Applications of improved grey prediction model for power demand forecasting. Energy Conversion and Management 2003;44:2241–9.

[277] Yao AWL, Chi SC, Chen JH. An improved grey-based approach for electricity demand forecasting. Electric Power Systems Research 2003;67:217–24.

[278] Yao AWL, Chi SC. Analysis and design of a Taguchi-Grey based electricity demand predictor for energy management systems. Energy Conversion and Management 2004;45(7–8):1205–17.

[279] Zhou P, Ang BW, Poh KL. A trigonometric grey prediction approach to forecasting electricity demand. Energy 2006;31(14):2839–47.

[280] Akay D, Atak M. Grey prediction with rolling mechanism for electricity demand forecasting of Turkey. Energy 2007;32(9):1670–5.

[281] Bianco V, Manca O, Nardini S, Minea AA. Analysis and forecasting of nonresidential electricity consumption in Romania. Applied Energy 2010;87(11):3584–90.

[282] Mu HL, Kondoua Y, Tonookab Y, Satoa Y, Zhou WS, Ning YD, et al. Grey relative analysis and future prediction on rural household biofuels consumption in China. Fuel Processing Technology 2004;85:1231–48.

[283] Wei YM, Liang QM, Fan Y, Okada N, Tsai HT. A scenario analysis of energy requirements and energy intensity for China's rapidly developing society in the year 2020. Technological Forecasting and Social Change 2006;73(4):405–21.

[284] Liang QM, Fan Y, Wei YM. Multi-regional input–output model for regional energy requirements and CO_2 emissions in China. Energy Policy 2007;35:1685–700.

[285] Liu HT, Guo JE, Qian D, Xi YM. Comprehensive evaluation of household indirect energy consumption and impacts of alternative energy policies in China by input–output analysis. Energy Policy 2009;37(8):3194–204.

[286] Arbex M, Perobelli FS. Solow meets Leontief: economic growth and energy consumption. Energy Economics 2010;32(1):43–53.

[287] He YX, Zhang SL, Zhao YS, Wang YJ, Li FR. Energy-saving decomposition and power consumption forecast: the case of Liaoning province in China. Energy Conversion and Management 2011;52:340–8.

[288] Mu T, Xia Q, Kang C. Input–output table of electricity demand and its application. Energy 2010;35(1):326–31.

[289] Alcántara V, Del Rio P, Hernández F. Structural analysis of electricity consumption by productive sectors. The Spanish case. Energy 2010;35(5):2088–98.

[290] Ceylan H, Ozturk HK. Estimating energy demand of Turkey based on economic indicators using genetic algorithm approach. Energy Conversion and Management 2004;45(15–16):2525–37.

[291] Canyurt OE, Ozturk HK. Application of genetic algorithm (GA) technique on demand estimation of fossil fuels in Turkey. Energy Policy 2008;36(7):2562–9.

[292] Haldenbilen S, Ceylan H. Genetic algorithm approach to estimate transport energy demand in Turkey. Energy Policy 2005;33:89–98.

[293] Ozturk HK, Ceylan H, Hepbasli A, Utlu Z. Estimating petroleum exergy production and consumption using vehicle ownership and GDP based on genetic algorithm approach. Renewable and Sustainable Energy Reviews 2004;8(3):289–302.

[294] Ceylan H, Ceylan H, Haldenbilen S, Baskan O. Transport energy modeling with meta-heuristic harmony search algorithm, an application to Turkey. Energy Policy 2008;36(7):2527–35.

[295] Forouzanfar M, Doustmohammadi A, Menhaj MB, Hasanzadeh S. Modeling and estimation of the natural gas consumption for residential and commercial sectors in Iran. Applied Energy 2010;87(1):268–74.

[296] Chaturvedi DK, Mishra RK, Agarwal A. Load forecasting using genetic algorithms. Institution of Engineers (India) 1995;76:161–5.

[297] Tzafestas S, Tzafestas E. Computational intelligence techniques for short-term electric load forecasting. Intelligent and Robotic Systems 2001;31:7–68.

[298] Ozturk HK, Ceylan H, Canyurt OE, Hepbasli A. Electricity estimation using genetic algorithm approach: a case study of Turkey. Energy 2005;30(7):1003–12.

[299] Azadeh A, Tarverdian S. Integration of genetic algorithm, computer simulation and design of experiments for forecasting electrical energy consumption. Energy Policy 2007;35(10):5229–41.

[300] Cinar D, Kayakutlu G, Daim T. Development of future energy scenarios with intelligent algorithms: case of hydro in Turkey. Energy 2010;35(4):1724–9.

[301] Kiartzis SJ, Bakirtzis AG. A fuzzy expert system for peak load forecasting: application to the Greek power system. In: Proceedings of the 10th Mediterranean electro technical conference, vol. 3. 2000. p. 1097–100.

[302] Miranda V, Monteiro C. Fuzzy inference in spatial load forecasting. In: Proceedings of IEEE power engineering society winter meeting, vol. 2. 2000. p. 1063–8.

[303] Song KB, Baek YS, Hong DH, Jang G. Short-term load forecasting for the holidays using fuzzy linear regression method. IEEE Transactions on Power Systems 2005;20:96–101.

[304] Mamlook R, Badran O, Abdulhadi E. A fuzzy inference model for short-term load forecasting. Energy Policy 2009;37:1239–48.

[305] Jain A, Srinivas E, Rauta R. Short term load forecasting using fuzzy adaptive inference and similarity. In: Proceedings of the World Congress on nature and biologically inspired computing Coimbatore. 2009. p. 1743–8.

[306] Pai PF. Hybrid ellipsoidal fuzzy systems in forecasting regional electricity loads. Energy Conversion and Management 2006;47(15–16):2283–9.

[307] Ying LC, Pan MC. Using adaptive network based fuzzy inference system to forecast regional electricity loads. Energy Conversion and Management 2008;49(2):205–11.

[308] Kucukali S, Baris K. Turkey's short-term gross annual electricity demand forecast by fuzzy logic approach. Energy Policy 2010;38:2438–45.

[309] Bakirtzis AG, Theocharis JB, Kiartzis SJ, Satsois KJ. Short term load forecasting using fuzzy neural networks. IEEE Transactions on Power Systems 1995;10(3):1518–24.

[310] Srinivasan D, Chang DS, Liew AC. Demand forecasting using fuzzy neural computation, with special emphasis on weekend and public holiday forecasting. IEEE Transactions on Power Systems 1995;10(4):1897–903.

[311] Padmakumari K, Mohandas KP, Thiruvengadam S. Long term distribution demand forecasting using neuro fuzzy computations. Electrical Power and Energy Systems 1999;21:315–22.

[312] Crompton P, Wu Y. Energy consumption in China: past trends and future directions. Energy Economics 2005;27(1):195–208.

[313] Francis BM, Moseley L, Iyare SO. Energy consumption and projected growth in selected Caribbean countries. Energy Economics 2007;29(6):1224–32.

[314] Saini LM. Peak load forecasting using Bayesian regularization, resilient and adaptive backpropagation learning based artificial neural networks. Electrical Power and Energy Systems 2008;78(7):1302–10.

[315] Lauret P, Fock E, Randrianarivony RN, Manicom-Ramsamy JF. Bayesian neural network approach to short term load forecasting. Energy Conversion and Management 2008;49(5):1156–66.

[316] Fan S, Chen LN, Lee WJ. Machine learning based switching model for electricity load forecasting. Energy Conversion and Management 2008;49(6):1331–44.

[317] Hong WC. Electric load forecasting by support vector model. Applied Mathematical Modelling 2009;33:2444–54.

[318] Kavaklioglu K, Ceylan H, Ozturk HK, Canyurt OE. Modeling and prediction of Turkey's electricity consumption using Artificial Neural Networks. Energy Conversion and Management 2009;50(11):2719–27.

[319] Wang J, Zhu W, Zhang W, Sun D. A trend fixed on firstly and seasonal adjustment model combined with the [epsilon]-SVR for short-term forecasting of electricity demand. Energy Policy 2009;37(11):4901–9.

[320] Toksari MD. Ant colony optimization approach to estimate energy demand of Turkey. Energy Policy 2007;35(8):3984–90.

[321] Toksari MD. Estimating the net electricity energy generation and demand using the ant colony optimization approach: case of Turkey. Energy Policy 2009;37(3):1181–7.

[322] Ünler A. Improvement of energy demand forecasts using swarm intelligence: the case of Turkey with projections to 2025. Energy Policy 2008;36(6):1937–44.

[323] El-Telbany M, El-Karmi F. Short-term forecasting of Jordanian electricity demand using particle swarm optimization. Electrical Power and Energy Systems 2008;78(3):425–33.

[324] AlRashidi MR, EL-Naggar KM. Long term electric load forecasting based on particle swarm optimization. Applied Energy 2010;87:320–6.

[325] Hong WC. Chaotic particle swarm optimization algorithm in a support vector regression electric load forecasting model. Energy Conversion and Management 2009;50(1):105–17.

[326] Wang J, Zhu S, Zhang W, Lu H. Combined modeling for electric load forecasting with adaptive particle swarm optimization. Energy 2010;35(4):1671–8.

[327] Hong WC. Application of chaotic ants warm optimization in electric load forecasting. Energy Policy 2010;38:5830–9.

[328] Fishbone LG, Abilock H. MARKAL, a linear-programming model for energy systems analysis: technical description of the BNL version. Energy Research 1981;5:353–75.

[329] Kanudia A, Loulou R. Advanced bottom-up modelling for national and regional energy planning in response to climate change. Environment and Pollution 1999;12:191–216.

[330] Kanudia A, Labriet M, Loulou R, Vaillancourt K, Waaub JP. The world-MARKAL model and its application to cost-effectiveness, permit sharing and cost benefit analyses. In: Loulou R, Waaub JP, Zaccour G, editors. Energy and environment. US: Springer; 2005. p. 111–48.

[331] Loulou R, Goldstein G, Noble K. Documentation for the MARKAL family of models; 2004. Available from www.etsap.org.

[332] Smekens K. Response from a MARKAL technology model to the EMF scenario assumptions. Energy Economics 2004;26:655–74.

[333] IEA. Energy technology perspectives 2008: scenarios and strategies to 2050. Paris: International Energy Agency; 2008.

[334] Loulou R, Remme U, Lehtila A, Goldstein G. Documentation for the TIMES model, Part II. Energy technology systems analysis programme (ETSAP); 2005, http://www.etsap.org/documentation.asp.

[335] Smekens K. Using MARKAL as an analytic tool for pollution control and energy policy options: the Shanghai and 3-Cities' cases. Paper presented at the 4th Sino-Korea-US Energy and Environmental Modeling Workshop, Beijing, May 23–25; 2001.

[336] Gielen D, Chen C. The CO_2 emission reduction benefits of Chinese energy policies and environmental policies: a case study for Shanghai, period 1995–2020. Ecological Economics 2001;39:257–70.

[337] Chen C, Green C, Wu C. Application of MARKAL model to energy switch and pollutant emission in Shanghai. Shanghai Environmental Sciences 2002;21:515–9 [in Chinese].

[338] Chen C, Du J. Reduction of emission from energy system under implementing atmospheric pollutant emission control. Energy Research and Information 2002;18:10–6 [in Chinese].

[339] Chen C, Chen B, Green C, Wu C. Benefits of expanded use of natural gas for pollutant reduction and health improvements in Shanghai. Sinosphere 2002;5:58–64.

[340] Kan H, Chen B, Chen C, Fu Q, Chen M. An evaluation of public health impact of ambient air pollution under various energy scenarios in Shanghai, China. Atmospheric Environment 2004;38:95–102.

[341] Changhong C, Bingyan W, Qingyan F, Green C, Streets DG. Reductions in emissions of local air pollutants and co-benefits of Chinese energy policy: a Shanghai case study. Energy Policy 2006;34(4):754–62.

[342] Strachan N, Kannan R, Pye S. Final report on DTI-DEFRA scenarios and sensitivities using the UK MARKAL and MARKAL-macro energy system models, UKERC research report; 2007. Available at http://ukerc.ac.uk/ResearchProgrammes/EnergySystemsand Modelling/ESM.aspx.

[343] Kannan R, Strachan N. Modelling the UK residential energy sector under long-term decarbonisation scenarios: comparison between energy systems and sectoral modelling approaches. Applied Energy 2009;86:416–28.

[344] Mallah S, Bansal NK. Allocation of energy resources for power generation in India: business as usual and energy efficiency. Energy Policy 2010;38(2):1059–66.

[345] Shrestha RM, Rajbhandari S. Energy and environmental implications of carbon emission reduction targets: case of Kathmandu Valley, Nepal. Energy Policy 2010;38(9):4818–27.

[346] Jiang B, Wenying C, Yuefeng Y, Lemin Z, Victor D. The future of natural gas consumption in Beijing, Guangdong and Shanghai: an assessment utilizing MARKAL. Energy Policy 2008;36:3286–99.

[347] Rout UK, Voβ A, Singh A, Fahl U, Blesl M, Gallachóir BPO. Energy and emissions forecast of China over a long-time horizon. Energy 2011;36:1–11.

[348] Lazarus M, Heaps C, Raskin P. Long range energy alternatives planning system (LEAP). Reference manual. Boston, MA: Boston Stockholm Environment Institute (SEI); 1995.

[349] SENER, Secretarıa de Energıa (Secretariat of Energy). National Energy Balance 1996 (Balance Nacional de Energıa). Mexico City; 1997 [in Spanish].

[350] Sathaye J, Dixon R, Rosenzweig C. Climate change country studies. Applied Energy 1997;56(3/4):225–35.

[351] Manzini F, Islas J, Martınez M. Reduction of greenhouse gases using renewable energies in Mexico 2025. Hydrogen Energy 2000;26(2):145–9.

[352] Guo B, Wang Y, Zhang A. China's energy future: LEAP tool application in China. Vancouver, British Columbia, Canada: East Asia Energy Futures (EAEF), Asia Energy Security Project Energy Paths Analysis, Methods Training Workshop; 2003. See also: http://www.nautilus.org/archives/energy/eaef/EAEFdatasets/CHINA_ENERGY_FUTURE.pdfs.

[353] Huang Y, Bor YJ, Peng CY. The long-term forecast of Taiwan's energy supply and demand: LEAP model application. Energy Policy; in press.

[354] Shabbir R, Ahmad SS. Monitoring urban transport air pollution and energy demand in Rawalpindi and Islamabad using leap model. Energy 2010;35(5):2323–32.

[355] Islas J, Manzini F, Martınez M. Renewable energies in the electricity generation for reduction of greenhouse gases in Mexico 2025. Ambio 2002;31(1):35–9.

[356] Cai W, Wang C, Wang K, Zhang Y, Chen J. Scenario analysis on CO_2 emissions reduction potential in China's electricity sector. Energy Policy 2007;35(12):6445–56.

[357] Manzini F. Inserting renewable fuels and technologies for transport in Mexico City Metropolitan Area. Hydrogen Energy 2006;31:327–35.

[358] Pradhan S, Bahadur B, Bhusan V. Mitigation potential of greenhouse gas emission and implications on fuel consumption due to clean energy vehicles as public passenger transport in Kathmandu Valley of Nepal: a case study of trolley buses in ring road. Energy 2006;31(12):1748–60.

[359] Davoudpour H, Sadegh-Ahadi M. The potential for greenhouse gases mitigation in household sector of Iran: cases of price reform/efficiency improvement and scenario for 2000–2010. Energy Policy 2006;34(1):40–9.

[360] Kadian R, Dahiya RP, Garg HP. Energy-related emissions and mitigation opportunities from the household sector in Delhi. Energy Policy 2007;35(12):6195–211.

[361] Kumar A, Bhattacharya SC, Pham HL. Greenhouse gas mitigation potential of biomass energy technologies in Vietnam using the long range energy alternative planning system model. Energy 2003;28(7):627–54.

[362] Shin HC, Park JW, Kim HS, Shin EI. Environmental and economic assessment of landfill gas electricity generation in Korea using LEAP model. Energy Policy 2005;33:1261–70.

[363] Islas J, Manzini F, Masera O. A prospective study of bioenergy use in Mexico. Energy 2007;32(12):2306–20.

[364] Pradhan S, Ale BB, Amatya VB. Mitigation potential of greenhouse gas emission and implications on fuel consumption due to clean energy vehicles as public passenger transport in Kathmandu Valley of Nepal: a case study of trolley buses in ring road. Energy 2006;31:1748–60.