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Long-term electrical energy consumption forecasting for developing and developed economies based on different optimized models and historical data types

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A B S T R A C T

The objectives of this study are (a) development of optimized regression and ANN (artificial neural network) models for EEC (electrical energy consumption) forecasting based on several optimization methodologies, (b) examination of the effects of different historical data types on accuracy of EEC forecasting, and (c) long-term EEC forecasting for Iran and the U.S. as developing and developed economies, respectively. For long-term EEC forecasting for 2010–2030, the two types of historical data used in this study include, (i) EEC and (ii) socio-economic indicators, namely, gross domestic product, energy imports, energy exports, and population, for 1967–2009 period. For both types of economies, the results demonstrate that using historical data of socio-economic indicators leads to more accurate EEC forecasting than those of EEC, when IPSO (improved particle swarm optimization) is used for optimal design of ANN for EEC forecasting. It is found that for developing and developed economies, forecasted EEC trends are significantly different, as expected, and IPSO–ANN model can be utilized to forecast long-term EEC up to 2030 with mean absolute percentage error of 1.94 and 1.51% for Iran and the U.S., respectively.

1. Introduction

Electrification plays a crucial role in promoting economic growth and social welfare for all economies. The electric power sector receives significant resources from governments and international development agencies, as in the period of 2021–2030, the total investment for the electricity sector infrastructure is expected to be $3.9 trillion [1]. While the world electricity generation has experienced a higher increase as compared with growth in total primary energy supply, the need for additional generation capacities an investment is not the same for all economies. Developing economies require additional generation capacities for industrialization and rural electrification, whereas, it is the increase in use of electric appliances that imposes additional need for electricity generation in developed economies [2].

Technological diversities and the share of power plants in electricity generation vary, as they depend on the availability and type of indigenous energy resources [3]. Electrical energy is generated by different types of power plants such as thermal, nuclear, and renewable. Renewable energy, categorized in hydraulic power, geothermal, solar, wind power, biomass, and marine, had a growth rate and consequently cost decrease in electricity generation but still conventional power plants are more economical than most of them. Hydropower is one of the renewable energy forms which is competitive with conventional power plants. It has a significant share of power plants generation in both developing and developed countries in 2011 e.g., the share of hydropower for China and India as developing countries and the U.S. and Japan as developed countries are 22, 19, 7, and 17%, respectively [1]. Developing countries use small-scale renewable energy technologies such as solar photovoltaic, solar thermal, biogas, and small hydropower for rural household lighting, community street lights, and community water pumping because they are likely to be most cost-competitive with conventional alternatives. Also, biomass, due to its low cost and indigenous nature, is widely used in developing countries, mostly for cooking and heating. For instance, about 81% of sub-Saharan African households rely on wood-based biomass to satisfy their energy needs in 2011 [2]. Nuclear and marine power plants are not pursued significantly in developing countries, as compared with other renewable energy forms, because nuclear power plants need high standard technology to minimize both the occurrence and harmful consequences of serious incidents involving nuclear materials and technology. Thus, additional costs and experience might be expected for these power plants. The U.S.

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and Japan as developed countries generate 19 and 17% of electrical energy by nuclear power plants, respectively, and for China and India, the same shares are about 1 and 2%, respectively [1]. Both developing and developed countries invest on wind power as the share of wind energy in electricity generation for China and the U.S. were 6 and 3.5%, respectively, in 2011 [1]. Also, geothermal energy is used for electricity generation in both developing and developed countries when it is available.

The developing and developed economies are generally identified based on HDI (human development index), which is a composite measure of health, education, and income. HDI is a yearly index and takes on higher values, when electrical energy consumption (EEC) increases in a country, for instance, in 2010, HDI for developing economies such as Iran, Lebanon, and India was recorded as 0.705, 0.736, and 0.541, whereas for the U.S., New Zealand, Greece, and Italy, as developed economies, it was the reported as 0.908, 0.907, 0.887, and 0.872, respectively [4].

The electricity production in industrialized developed economies is usually much higher than that in developing economies, for example, the average annual electricity production in the U.S. at 12,914 kWh/capita was nearly six times that of Iran during 2007–2011 period [5]. Based on data reported by World Bank [6], shown in Table 1, the growth rate in EEC for Iran and the U.S. for 2000–2010 period are 68 and 8%, respectively. Table 1 shows that the average EEC growth rates for developing and developed countries are different but the mean of average EEC growth rates is about 4%, as forecasted by IAEA [1]. It is also observed in Table 1 that the EEC averages for various developing and developed countries, in 2010, are 2341.1 kWh/capita corresponding to 8.4×10^5 GWh and 8445.9 kWh/capita corresponding to 11.8×10^5 GWh, respectively, and the difference of 6104.8 kWh/capita will be required on average, by developing countries to improve their economies and match that of developed countries for better HDI (as directly related to kWh/capita).

To achieve the needed growth and regardless of different trends of EEC for developing and developed countries, continuous monitoring of EEC and socio-economic indicators such as, GDP (gross domestic product), energy IMP (imports), energy EXP (exports), and POP (population) [7–10] for proper and accurate forecasting is necessary.

1.1. Literature review on EEC forecasting

While short and mid-term forecasting methodologies are used for operation of power generation facilities, long-term forecasting of energy demand and consumption forms the basis of power system expansion planning for both developing and developed economies. Over the past decades, numerous investigations have been conducted to improve the accuracy of EEC forecasting, however, most of the methodologies are dedicated to short-term forecasting periods (a few minutes to 24 h) [11–15] or intermediate-term forecasting periods (a few days to several months) [16,17]. Studies focusing on long-term EEC forecasting have been limited, as discussed below.

For long-term planning, all approaches used for EEC forecasting require historical data and they are categorized into parametric and AI (artificial intelligence) based methodologies. Table 2 outlines the summary of studies on EEC forecasting based on various methodologies for different countries, and it is observed that parametric methods, in comparison with AI-based methodologies, result in higher MAPE (mean absolute percent errors) or less accuracy in EEC forecasting. The calculated MAPEs for each country depend on the EEC pattern, the applied models and input data types of each.

The parametric methods benefit from mathematical modeling, where the model parameters are estimated using statistical techniques. Parametric EEC forecasting methods are classified under two schemes, namely, time series methods and regression methods [16].

One of the most important and widely used time series models is the ARIMA (auto regressive integrated moving average) model. The popularity of the ARIMA model is due to its use of statistical properties as well as the well-known Box–Jenkins methodology and GM (Grey model) in the modeling process [18].

The GM popularity in time series forecasting is due to its simplicity and ability to characterize an unknown system by using few data. Further, GM is more practical and user friendly, as compared to Box–Jenkins model and AI-based techniques which require more modeling effort and time for parameters identification [19]. Bianco et al. have used trigonometric GM with rolling mechanism to forecast the nonresidential EEC up to 2020 for Romania and accuracy criterion is described in terms of the MAPE calculated as 0.6% [20].

Although ARIMA models are quite flexible as they can represent several different types of time series, namely, pure AR (auto regressive), pure MA (moving average) and combined ARMA (AR and MA) series, their major limitation is the pre-assumed linear form of the model.

Regression methods are divided into the linear and nonlinear models, where linear regression methods are most popular in forecasting and prediction [3,21–23]. Similar to time series models, linear regression methods are based on linearity assumption. Thus, the noted models could not fully suffice the needs for EEC forecasting

Table 1
Annual EEC ($\times 10^{-5}$)(GWh) and HDI for several developing and developed countries [6].

	Year	Developing						Developed			
		China	India	Iran	Lebanon	Romania	Turkey	Greece	Italy	New Zealand	U.S.
EEC	2000	13.6	3.76	1.21	0.09	0.42	0.99	0.53	2.78	0.35	40.2
	2001	14.7	3.84	1.30	0.09	0.43	0.97	0.53	2.84	0.35	38.4
	2002	16.4	4.03	1.41	0.10	0.43	1.03	0.54	2.91	0.37	40.3
	2003	19.1	4.27	1.54	0.11	0.46	1.10	0.58	2.95	0.37	40.5
	2004	22.0	4.56	1.67	0.10	0.47	1.20	0.59	3.02	0.38	41.5
	2005	25.0	4.83	1.76	0.11	0.48	1.29	0.59	3.07	0.39	42.7
	2006	28.6	5.32	1.87	0.10	0.49	1.42	0.60	3.14	0.39	42.7
	2007	32.8	5.91	1.95	0.11	0.50	1.54	0.63	3.15	0.39	43.2
	2008	34.6	6.17	1.99	0.11	0.51	1.60	0.63	3.15	0.39	43.4
	2009	37	6.61	2.03	0.12	0.46	1.55	0.61	2.97	0.39	41.6
	2010	39.4	6.99	2.09	0.14	0.43	1.70	0.61	3.07	0.41	43.3
EEC average growth rate (%)		189	85	68	54	3	73	15	10	16	8
HDI	2010	0.69	0.55	0.74	0.74	0.78	0.75	0.87	0.88	0.92	0.93