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Novel effects of demand side management data on accuracy of electrical energy consumption modeling and long-term forecasting

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ABSTRACT

Worldwide implementation of demand side management (DSM) programs has had positive impacts on electrical energy consumption (EEC) and the examination of their effects on long-term forecasting is warranted. The objective of this study is to investigate the effects of historical DSM data on accuracy of EEC modeling and long-term forecasting. To achieve the objective, optimal artificial neural network (ANN) models based on improved particle swarm optimization (IPSO) and shuffled frog-leaping (SFL) algorithms are developed for EEC forecasting. For long-term EEC modeling and forecasting for the U.S. for 2010–2030, two historical data types used in conjunction with developed models include (i) EEC and (ii) socio-economic indicators, namely, gross domestic product, energy imports, energy exports, and population for 1967–2009 period. Simulation results from IPSO-ANN and SFL-ANN models show that using socio-economic indicators as input data achieves lower mean absolute percentage error (MAPE) for long-term EEC forecasting, as compared with EEC data. Based on IPSO-ANN, it is found that, for the U.S. EEC long-term forecasting, the addition of DSM data to socio-economic indicators data reduces MAPE by 36% and results in the estimated difference of 3592.8 MBOE (5849.9 TW h) in EEC for 2010–2030.

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1. Introduction

During 2000–2011 period, while total energy consumption in the world had a growth rate of 2.4%, electrical energy consumption (EEC) experienced a growth rate of 3.4% [1]. With such dynamics, underestimation of EEC leads to potential outages that are damaging to the economy, whereas, its overestimation leads to unnecessary installed capacity resulting in wasted financial resources [2]. At the same time, governments and utility companies continuously emphasize improving EEC through implementation of demand side management (DSM) programs, as it could play a vital role in meeting future energy security requirements. DSM programs are designed to influence the utilities customers energy utilization for load leveling and optimization of the whole power system from generation to end use. DSM data are collected based on EEC savings from implementation of energy efficiency measures and utilization of low-energy technologies including automatic daylighting controls and compact fluorescent lamps, heat pumps with high coefficient of performance for air conditioning, and high efficiency motors [3].

Recent experiences with increasing prices for energy carriers and the commitment to international initiatives on reduction of greenhouse gas emissions have revitalized the debate on the implementation of DSM policies that aim at gradual curtailment of EEC and, it is certain that, in the long term, electrical generation expansion planning is influenced by such policies.

Atilcol analyzed the electricity load of the commercial sector of Northern Cyprus and concluded that it is possible to reduce the end-use demand by at least 58% by the application of DSM programs [4]. For electrical energy system planning of Tamil Nadu state in India, several DSM programs, including substitution of fluorescent and incandescent lamps with compact fluorescent lamps, replacing existing refrigerators with more efficient types, and penetration of renewable resources in both demand and supply side have been examined [5]. The results of that study show that the noted DSM programs decrease EEC and consequently the annual electrical energy generation costs. In a study by Amirnekooei et al., a reference energy system for Iran is developed and the effects of several DSM programs to enhance future generation expansion planning are examined [6].

For the U.S., in a study in 2003, nearly 92 DSM-related technologies were listed for providing strategic conservation, peak clipping, peak shifting, valley filling, flexible demand, and strategic growth on the utility load shape [7]. The implementation of DSM in the U.S. has resulted in considerable reduction of EEC (1170.53×10^6 MW h) during 1989–2010 period and, the continuation of this trend is expected to affect the U.S. generation expansion in the long term [8].

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Nomenclature

ABC	artificial bee colony
ACF	autocorrelation function
ACO	ant colony optimization
AI	artificial intelligence
AIC	Akaike's information criterion
ANN	artificial neural network
AR	auto regressive
ARIMA	auto regressive integrated moving average
ARMA	auto regressive moving average
DSM	demand side management
EEC	electrical energy consumption
EXP	energy export
FWNN	fuzzy wavelet neural network
GD	gradient descent
GDP	gross domestic product
GM	Grey model
IMP	energy import
IPSO	improved particle swarm optimization
KBES	knowledge based expert system
MA	moving average
MAPE	mean absolute percent error
MLP	multi-layer perceptron
PACF	partial autocorrelation function
POP	population
PSO	particle swarm optimization
RMS	relative root mean square
SARIMA	seasonal auto regressive integrated moving average
SFL	shuffled frog-leaping

The effects of different data types and modeling methodologies on the accuracy of EEC forecasting has been examined by substantial numbers of studies (Table 1). EEC forecasting is usually based on historical EEC data and other influential indicators, such as, socio-economic, demographic, and climatic indicators [9]. For example, it has been shown that EEC, employment, and real income in Australia are co-integrated and, in the long term, unidirectional causality runs from employment and income to EEC [10]. Further, the relation between EEC and socio-economic indicators, namely, gross domestic product (GDP), energy imports (IMP), energy exports (EXP), and population (POP) has been examined in several studies [11–13] and it is shown that GDP and POP have substantial impact on EEC, where their combined effect can be shown by GDP/capita. The ratio GDP/capita is affected by economic state of countries, developing or developed, and it has been shown that it has a directional or bidirectional effect on EEC [13,14].

In general, the approaches used for long-term EEC forecasting are categorized into parametric methods and methods based on artificial intelligence (AI) techniques, as summarized in Table 1.

To address the nonlinearities, black box models such as artificial neural network (ANN) are used instead of mathematical functions whose parameters are estimated through regression type computations [15,16]. The literature shows that AI-based techniques such as ANN [17], support vector machines [18], wavelet networks [19], and expert system methods [20] are employed for EEC forecasting. While, Hsua and Chenb showed that ANN modeling is superior to its regression-based counterpart for long-term forecasting [16], using models in hybrid form or combining several models has become a common practice to improve the long-term forecasting accuracy. For example, to demonstrate the effectiveness of the hybrid method, Zhang proposed a methodology that combines both ARIMA and ANN models to take advantage of the unique strength of each in linear and non-linear modeling [21]. That study reported that the mean square error for ARIMA, ANN, and ARIMA–ANN models, for 35-year forecasts, as 16.13%, 9.89%, and 2.67%, respectively. Padmakumari et al. discussed the application and validation of forecasting results of a hybrid fuzzy-neural technique, which combines ANN and fuzzy logic modeling for long-term EEC modeling for India, and the MAPE for radial basis function ANN model is determined as 1.76%. The input data of a hybrid fuzzy-neural technique are the historical data of EEC for 1987–1998 period [22].

Wang et al. applied three residual modification models to improve the precision of the EEC forecasting by seasonal ARIMA (SARIMA) model in the northwest electricity grid of China where the inputs of the SARIMA model were historical data of EEC [23]. In that study, MAPEs of the single SARIMA and the combined models of particle swarm optimization (PSO)-based Fourier method with SARIMA model are reported as 3.28% and 2.19%, respectively. The results indicate that the forecasting accuracy of the combined model is more satisfactory than the other.

For EEC modeling for the household sector in Iran, multi-layer perceptron (MLP) ANN and regression models are developed and applied for 22 years based on five input variables, including (a) electricity price, (b) television price index, (c) refrigerator price index, (d) urban household size, and (e) urban household income and, the MAPEs are determined as 4.66% and 11.7% for ANN and regression models, respectively [24]. In that study, the results are compared with the study by Azadeh et al. [25], in which ANN based on gradient descent (GD) and time series methods are used. The results from ANN and time series methods are compared by analysis of variance F-test and MAPE is used for determination of the forecasting accuracy. The MAPEs for ANN and time series models are reported as 1.2% and 4%, respectively [25].

In a study by Kiran et al., for EEC forecasting for Turkey, PSO–artificial bee colony (ABC) algorithm is used [26]. Based on data for GDP, IMP, EXP, and POP, the results showed that applying PSO–ABC algorithm results in MAPEs of 4.47% and 3.206% for optimal linear and quadratic models, respectively.

Zhang and Wang developed fuzzy wavelet neural network (FWNN) approach for China EEC modeling, where EEC historical data for 1983–2003 is used to illustrate the applicability of FWNN, as compared with the Grey model (GM) and, MAPEs are determined as 1.65% and 15.99%, respectively [27].

Genetic algorithm (GA) and ANN for EEC forecasting in Iran agriculture sector for 1981–2005 are integrated by Azadeh et al. [28]. The input data include price, value added, number of customers and EEC in the previous periods. In that study, GA is used to optimize the parameters of the input data approximation functions modeled as linear–logarithmic. Then, EEC in agriculture sector is forecasted by ANN with MAPE of 3.68%. In a study by Amjadi et al., EEC modeling, for Iran during 1980–2006, based on historical data of GDP, POP, number of customers, and average price electricity is developed based on linear and non-linear models [29]. It was found in that study that applying PSO and GA, for optimization of models parameters, results in MAPEs of 1.51% and 1.36% for linear and non-linear models, respectively.

Karabulut et al. used genetic programming (GP) for EEC forecasting for Turkey [30]. In that study, historical data of EEC from 1994 to 2005 period are used as input data for GP model and EEC for 2006–2010 period is forecasted with MAPE of 1.16%. In a study by Mohamed and Bodger for New Zealand, a multiple linear regression model using GDP, average price of electricity, and POP,

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