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A systematic design of interval type-2 fuzzy logic system using extreme learning machine for electricity load demand forecasting

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ABSTRACT

This paper presents a novel design of interval type-2 fuzzy logic systems (IT2FLS) by utilizing the theory of extreme learning machine (ELM) for electricity load demand forecasting. ELM has become a popular learning algorithm for single hidden layer feed-forward neural networks (SLFN). From the functional equivalence between the SLFN and fuzzy inference system, a hybrid of fuzzy-ELM has gained attention of the researchers. This paper extends the concept of fuzzy-ELM to an IT2FLS based on ELM (IT2FELM). In the proposed design the antecedent membership function parameters of the IT2FLS are generated randomly, whereas the consequent part parameters are determined analytically by the Moore–Penrose pseudo inverse. The ELM strategy ensures fast learning of the IT2FLS as well as optimality of the parameters. Effectiveness of the proposed design of IT2FLS is demonstrated with the application of forecasting nonlinear and chaotic data sets. Nonlinear data of electricity load from the Australian National Electricity Market for the Victoria region and from the Ontario Electricity Market are considered here. The proposed model is also applied to forecast Mackey-glass chaotic time series data. Comparative analysis of the proposed model is conducted with some traditional models such as neural networks (NN) and adaptive neuro fuzzy inference system (ANFIS). In order to verify the structure of the proposed design of IT2FLS an alternate design of IT2FLS based on Kalman filter (KF) is also utilized for the comparison purposes.

Introduction

Electricity is an essential service which plays a vital role to facilitate our convenience. It has illuminated our planet and has drawn us where one can feel the practicability of an industrialized world. The mounting demand of electricity is proportional to the increase in population, economic buildup, adaptations of the latest use of technologies and some climatic changes. A continuous supply to the demand is vital for an efficient and reliable electricity network. Planning of the electricity systems is vital so that the demand and supply can be matched. In order to be able to plan the electricity systems in its three major aspects of generation, transmission, and distribution, it is necessary to analyze huge amount of information available in power system data-bases [1,2].

Electricity generation systems, that rely on the traditional electricity planning, regularly face the supply/demand mismatch issues due to the inaccurate forecasts of the load demand. Most of these traditional power grids are not designed to be compliant with the rapidly changing climate, the high energy-efficiency demand and/or the use of the latest technologies. Smart grid, also known as intelligrid, interagrid and future grid [3], is likely to address the limitations of the traditional grid. Smart grid can be defined as "an electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in as integrated fashion across electricity generation, transmission, substations, distribution and consumption to achieve a system that is clean, safe, secure, reliable, resilient, efficient, and sustainable" [4]. Availability of the reliable load demand forecasting is required to ensure the security and stability of the smart grid. The utility providers need load demand forecasting tools to take into account the changes in demand; decided by the consumer. These tools provide useful information to the utilities to plan the resources and to balance the supply–demand, thus ensuring continuity and reliability of service provision [5]. The consumers can manage electricity load demand consumption by adjusting its usage during on/off-peak hours. Practicing such a mechanism will

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Acronym

ANFIS	adaptive neuro fuzzy inference system
ELM	extreme learning machine
FLS	fuzzy logic system
IT2	interval type-2
IT2FLS	interval type-2 fuzzy logic system
IT2FELM	IT2FLS trained using extreme learning machine
IT2FKF	IT2FLS trained using KF method
KF	Kalman filter
MAPE	mean absolute percentage error
NN	neural network
NEM	Australian National Electricity Market
OEM	Ontario Electricity Market
RMSE	Root Mean Square Error
SLFN	Single hidden layer feed-forward neural networks
T1	type-1
T1FLS	type-1 fuzzy logic system
T2	type-2
T2FLS	type-2 fuzzy logic system

help to reduce their electricity bills. With the emergence of smart grid and distributed generation technologies in recent years, new and advanced load demand forecasting models are required to be introduced.

Rigorous studies on the short term load forecasting have been published [6–9]. Statistical and computational intelligence models are the two paradigms that are mostly used for forecasting the electricity load demand. The later is gaining more attention in incorporating the nonlinearity of the load demand data. Being able to approximate the nonlinear relationship between the input(s) and output, neural networks (NN) and fuzzy logic systems (FLS) were extensively applied to the load forecasting among other computational intelligence models [6,7,10–12]. A new cascade NN based method was proposed for the short-term load forecasting in the deregulated electricity market [13]. A novel integrated technique, random fuzzy NN, was presented for tackling uncertainties of electric load forecasting [14]. Fuzzy logic and wavelet transform integrated generalized NN was described and applied to the short term week day electrical load forecasting problem [12]. Short-term load forecasting models were developed by using fuzzy logic and adaptive neuro-fuzzy inference system (ANFIS) [15]. Some of our group's recent work on computational models for load demand forecasting can be seen in [16–19,11].

Type-2 fuzzy logic system (T2FLS) as an extension of the conventional type-1 fuzzy logic system (T1FLS) is increasingly utilized in modeling real world problems [20–25]. In contrast to T1FLS, a T2FLS assigns a fuzzy number to the membership grades [26,27]. Experimental results have been reported presenting improvements of the T2FLS over its T1 counterpart in terms of accuracy [28–30]. Because of the large computing resources required for the computationally intensive T2FLSs, IT2FLS is introduced as its simplest version. Using IT2FLSs, the membership grade for every point is a crisp set in an interval $[0,1]$ rather then fuzzy. Though improvements of IT2FLSs to its earlier version have been evidenced, yet it still lacks a systematic and coherent design procedure. In order to determine the parameters of an IT2FLS optimally, various learning algorithms are proposed in literature that include dynamical optimal training method [31], back propagation based learning method [32], genetic and other bio-inspired algorithms [33–36], self-organizing with ant colony optimization [37], rule reduction of IT2FLSs using singular value decomposition [38] and extended Kalman filter based learning algorithm [39]. Castillo et al. [40] presented a concise review on the optimization of T2FLSs using bio-inspired algorithms. They stated that "the use of bio-inspired optimization methods have helped in the complex task of finding the appropriate parameter values and structure of fuzzy systems". However the computation burden of the classical learning algorithms for IT2FLSs is still an issue.

These learning algorithms are usually very slow and require iterative tuning of the parameters to achieve good learning performance. Also the distressing issues of learning algorithms i.e. stopping criteria, learning rate, learning epochs and local minima may not be handled by the conventional learning algorithms. An adaptive interval type-2 fuzzy control based on gradient descent algorithm [41] was presented to overcome the divergence of bio-inspired algorithms. Due to the researchers' interests and initiatives in this area, advanced learning algorithms are presented during the past several years with improved performances [42,43]. Huang et al. [44,45] introduced the theory of ELM that can solve the stated issue of conventional training methods. Moreover, it easily achieves good generalization performance at extremely fast learning speed.

ELM is originally proposed for the SLFN. From the functional relationship between FLS and NNs [46,47], it is observed that under some mild conditions FLS can be interpreted as a special case of SLFN and can be trained using its learning algorithms. Evolutionary fuzzy-ELM is proposed to analyze mammographic risk [48]. A hybrid model of FLS and ELM was presented as a fault detection method for improving the efficiency of circulating water systems in power generation plant [49]. ELM based fuzzy inference system has been presented in [50] where membership functions for the fuzzy rules were obtained through ELM and the consequent part was determined through multiple ELMs. An online sequential fuzzy-ELM is proposed for function approximation and classification problems [51]. In these designs of fuzzy-ELM the antecedent part parameters were generated randomly, and the consequent part parameters were determined analytically. After successful application of T1FLS into vast application areas; researchers are now finding their way to solve the dynamic and uncertain problems using the extensions of classical FLS. A hybrid model of ELM and T2FLSs was proposed to deal with uncertainty in permeability prediction as well as to boost the generalization ability of ELM [22]. The emphasis of the study was to examine the viability of using T2FLS as a preprocessor for improved generalization of ELM. A challenge to develop an efficient learning algorithm for T2FLSs was taken by Deng at el. in [52].

Motivated by the superior performances of the fuzzy-ELM in different fields, it is suggested to design alike model in the field of electricity load demand forecasting. In this paper, the ELM strategy is used to tune the parameters of an IT2FLS for modeling nonlinear and chaotic data sets. Based on the working principle of ELM, the antecedent part parameters of the IT2FLSs are generated randomly, while the consequent part parameters are initialized and later refined using the Moore–Penrose pseudo inverse.

The rest of this article is structured as follows. Section 'Backgro und' introduces the basic concepts of IT2FLSs and ELM. The methodology utilized for the research work of this paper is described in section 'Methdology of IT2FELM'. Section 'Simulation result' presents the case studies and discussion on the empirical results. Concluding remarks are provided in section 'Conclusions'.