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Modeling data uncertainty on electric load forecasting based on Type-2 fuzzy logic set theory

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A B S T R A C T

Real applications based on type-2 (T2) fuzzy sets are rare. The main reason is that the T2 fuzzy set theory requires massive computation and complex determination of secondary membership function. Thus most real-world applications are based on one simplified method, i.e. interval type-2 (IT2) fuzzy sets in which the secondary membership function is defined as interval sets. Consequently all computations in three-dimensional space are degenerated into calculations in two-dimensional plane, computing complexity is reduced greatly. However, ability on modeling information uncertainty is also reduced. In this paper, a novel methodology based on T2 fuzzy sets is proposed i.e. T2SDSA-FNN (Type-2 Self-Developing and Self-Adaptive Fuzzy Neural Networks). Our novelty is that (1) proposed system is based on T2 fuzzy sets, not IT2 ones; (2) it tackles one difficult problem in T2 fuzzy logic systems (FLS), i.e. massive computing time of inference so as not to be applicable to solve real world problem; and (3) membership grades on third dimensional space can be automatically determined from mining input data. The proposed method is validated in a real data set collected from Macao electric utility. Simulation and test results reveal that it has superior accuracy performance on electric forecasting problem than other techniques shown in existing literatures.

1. Introduction

Electricity load forecaster is an important function in planning and operation of electric power system. However, due to its stochastic and uncertainty characteristics, it has been one challenging problem in electric industries to accurately forecast future load demand. In past decades, many soft-computing based methodologies were proposed and possessed a leading position. They are expert systems (Rahman and Bhatnagar, 1988; Ho et al., 1990), neural networks (Xiao et al., 2009; Su and Zhang, 2007; Lauret et al., 2008) and fuzzy logic systems (Chow and Tram, 1997; Ranaweera et al., 1996; Mastorocostas et al., 1999). In addition, different levels of hybridization on referred methods were also proposed (Lopes et al., 2005; Liao and Tsao, 2006; Zhang et al., 2008; Chang et al., 2011; Hanmandlu and Chauhan, 2011) in order to enhance pros and complement cons of each individual method. However, among them the fuzzy neural networks (FNN) based systems are the most promising due to its parallel computing, certain fault tolerance and capability of modeling data uncertainties.

All referred FNN based systems use fuzzy rules, whose input, antecedent and consequent fuzzy sets use membership functions (MF) represented in two-dimensional plane. These systems are called T1 fuzzy logic systems (FLS). However, words/information can give different meanings to different people in the real world. T1 fuzzy sets/systems cannot handle uncertainty about noisy data and different information meanings properly.

T2 fuzzy sets was firstly introduced as an extension of an ordinary T1 fuzzy sets, in which membership function is represented in three-dimensional space, i.e. membership grades themselves are also T1 fuzzy sets and are called as secondary memberships. Although it was introduced by Prof. Zadeh in 1975 (Zadeh, 1975), it remained in silence for a long time until it got attention by Karnik et al. (1999). After that, a series of publications about development and consolidation on this theory were presented (Karnik and Mendel, 2001a,b; Mendel and John, 2002; Starczewski, 2006; Mendel, 2007). A complete theory of T2 fuzzy sets/systems can be referred in Mendel (2001). Unfortunately, real applications based on T2 fuzzy set theory are still rare. The main obstacles are that (1) T2 FLS requires massive computation because operations of fuzzy sets required in rule inference of FLS are computed in three-dimensional space. Due to this high level of computational complexity, it is still not suitable in practice. (2) In output process, there is a type-reduction process followed with a defuzzification computation. This process which is not required in T1 FLS is also a high level of intensive

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computation. (3) Although T2 fuzzy sets are believed to be able to enhance modeling uncertainty about noisy data and different information meanings, there are still no practical approaches about how to determine those secondary memberships. As a result, T2 FLS are obstructed to use in practice such that almost all real-world applications were based on its simplified version, i.e. IT2 fuzzy sets (Liang and Mendel, 2000; Wu and Mendel, 2002; Lee et al., 2003; Wang et al., 2004; Mendel, 2004; Mendel et al., 2006; Hagras, 2006; Mendez and Castillo, 2005), in which secondary MFs are defined as interval sets, i.e. secondary memberships are either zero or one. Such simplification makes the use of T2 FLS be practical due to that all computations in three-dimensional space are degenerated into calculations in two-dimensional plane. But on the other hands, ability on modeling uncertainty in data or linguistic information is also reduced accordingly.

In this paper, a novel methodology T2SDSA-FNN (Type-2 Self-Developing and Self-Adaptive Fuzzy Neural Networks) is proposed. The novelty is that it can greatly reduce the computing time of inference required for T2 FLS so as to integrate with powerful searching engine genetic algorithm (GA) to determine automatically the secondary membership function in the third dimensional space. Adopting such a methodology into electric load forecast in Macao power system, simulation and test results reveal that it has superior accuracy and speed performance than other techniques.

2. Review of type-2 fuzzy set theory

Some key definitions about T2 fuzzy sets (Mendel, 2001) are listed below, which will be used in this paper afterwards.

Definition 1. T2 fuzzy set in point-value representation.

As shown in Fig. 1, one T2 fuzzy set $\tilde{A}$ is characterized by T2 membership function $\mu_{\tilde{A}}(x,u)$, in which $0 \le \mu_{\tilde{A}}(x,u) \le 1$, i.e.

$$\tilde{A} = \{((x,u),\mu_{\tilde{A}}(x,u))\,|\,\forall x \in \mathbf{X}, \forall u \in \mathbf{J_x} \subseteq [0,1]\} \quad (1)$$

where

x: primary variable of one T2 fuzzy set, $x \in \mathbf{X}$.
u: secondary variable of one T2 fuzzy set, in which $u \in \mathbf{J_x}$.
$\mathbf{J_x}$: primary membership of x, in which $\mathbf{J_x} \subseteq [0,1]$.
$\mu_{\tilde{A}}(x,u)$: secondary grade at point (x, u).

Definition 2. Embedded T2 fuzzy sets.

For discrete universes of discourse X, an embedded T2 fuzzy set $\tilde{A}_e$ has N elements, where $\tilde{A}_e$ contains exactly one element from $\mathbf{J}x_1, \mathbf{J}x_2, \ldots, \mathbf{J}x_N$, namely $u_1, u_2, \ldots, u_N$, each with its associated secondary grade, namely $f_{x_1}(u_1), f_{x_2}(u_2), \ldots, f_{x_N}(u_N)$, i.e.

$$\tilde{A}_e = \sum_{i=1}^{N} \left[f_{x_i}(u_i)/u_i\right]/x_i, u_i \in \mathbf{J_{x_i}} \subseteq [0,1] \quad (2)$$

As seen, set $\tilde{A}_e$ is embedded in set $\tilde{A}$.

Definition 3. Join operation of two T2 fuzzy sets.

Consider two T2 fuzzy sets $\tilde{A}$and $\tilde{B}$, i.e.

$$\tilde{A} = \int_{\mathbf{X}} \mu_{\tilde{A}}(x)/x = \int_{\mathbf{X}} \left[\int_{J_x^u} f_x(u)/u\right]/x, \mathbf{J_x^u} \subseteq [0,1] \quad (3)$$

$$\tilde{B} = \int_{\mathbf{X}} \mu_{\tilde{B}}(x)/x = \int_{\mathbf{X}} \left[\int_{J_x^w} g_x(w)/w\right]/x, \mathbf{J_x^w} \subseteq [0,1] \quad (4)$$

where u and w are dummy variables used to differentiate different secondary membership functions of x in $\tilde{A}$ and $\tilde{B}$ respectively.

Join of $\tilde{A}$ and $\tilde{B}$ is another T2 fuzzy set and is defined as

$$\tilde{A} \cup \tilde{B} \Leftrightarrow \mu_{\tilde{A}}(x) \cup \mu_{\tilde{B}}(x) \equiv \mu_{\tilde{A}\cup\tilde{B}}(x) = \int_{u \in \mathbf{J_x^u}} \int_{w \in \mathbf{J_x^w}} f_x(u) * g_x(w)/(u \vee w), x \in \mathbf{X} \quad (5)$$

where $\cup$ indicates join operation of T2 fuzzy sets, $*$ indicates minimum or product operation, $\vee$ represents maximum operation and $\int\int$ indicates union over $\mathbf{J_x^u} \times \mathbf{J_x^w}$.

Definition 4. Meet operation of two T2 fuzzy sets.

Meet of $\tilde{A}$ and $\tilde{B}$is another T2 fuzzy set and is defined as

$$\tilde{A} \cap \tilde{B} \Leftrightarrow \mu_{\tilde{A}}(x) \cap \mu_{\tilde{B}}(x) \equiv \mu_{\tilde{A}\cap\tilde{B}}(x) = \int_{u \in \mathbf{J_x^u}} \int_{w \in \mathbf{J_x^w}} f_x(u) * g_x(w)/(u \wedge w), x \in \mathbf{X} \quad (6)$$

where $\cap$ indicates meet operation of T2 fuzzy sets.

Definition 5. Complement of a T2 fuzzy set.

Complement of a T2 fuzzy set is another T2 fuzzy set and is defined as

$$\bar{\tilde{A}} \Leftrightarrow \neg\mu_{\tilde{A}}(x) \equiv \mu_{\bar{\tilde{A}}}(x) = \int_{u \in \mathbf{J_x^u}} f_x(u)/(1-u), x \in \mathbf{X} \quad (7)$$

where $\neg$ indicates complement operation of a T2 fuzzy set.

Definition 6. Type-2 FLS inference.

Suppose that a Type-2 FLS depicted in Fig. 2 has M rules, in which each rule has n antecedents and single consequent. It is understandable that multi-consequent rule can also be considered as a group of single-consequent rules. Let l-th rule be

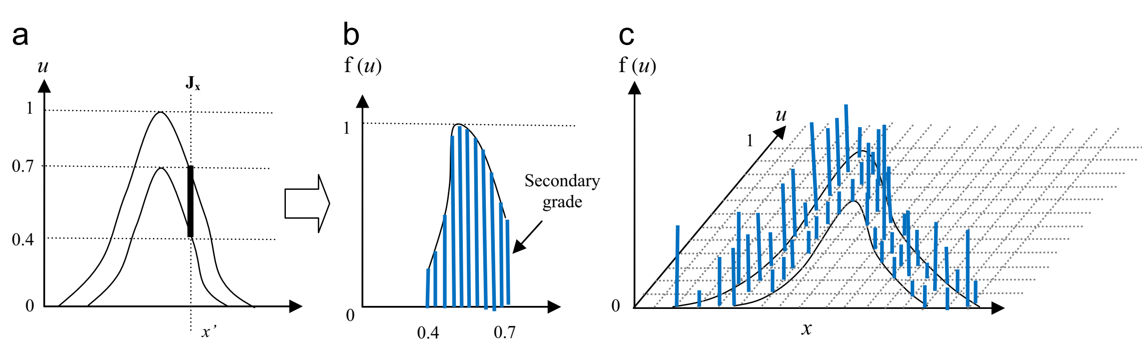

Fig. 1. (a) One T2 fuzzy set projected into x–u plane. (b) Secondary MF (vertical slice) at x'. (c) T2 fuzzy set represented in three-dimensional space (blue bars are secondary grades in third dimensional space). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)