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A collaborative fuzzy-neural approach for long-term load forecasting in Taiwan

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ABSTRACT

Forecasting the long-term load in a country is a critical task for the government. In addition, establishing a precise upper bound for the long-term load avoids unnecessary power plant investment. For these purposes, a collaborative fuzzy-neural approach is proposed in this study. In the proposed approach, multiple experts construct their own fuzzy back propagation networks from various viewpoints to forecast the long-term load in a country. To aggregate these long term load forecasts, fuzzy intersection is applied. After that, a radial basis function network is constructed to defuzzify the aggregation result and to generate a representative/crisp value. The practical case of Taiwan is used to evaluate the effectiveness of the proposed methodology. According to the experimental results, the proposed methodology improved both the precision and accuracy of long term load forecasting by 40% and 99%, respectively. In addition, the proposed methodology made it possible to accurately forecast the average and peak values of the annual energy consumption at the same time.

1. Introduction

The national long-term load is highly controversial in Taiwan. Some people claim that, in order to support the continuing operations of many high-technology industries (including notebooks, personal computers, foundry, dynamic random access memory (DRAM), the thin film transistor liquid crystal display (TFT-LCD), etc.) in Taiwan, the government is responsible for providing adequate power supply in the long term. In contrast, others insist that the country may be contaminated by operating thermal and nuclear power plants. The government should close these power plants and pursue cleaner power technologies instead. Owing to these arguments the construction of the fourth nuclear power plant was suspended in 2001, but recovered after three months, which caused a loss of about 3.5 billion NT dollars. For these reasons, forecasting the long term load is a critical task to the government in Taiwan.

Load forecasting can be categorized as short-term (up to 1 day), mid-term (1 day to 1 year), or long-term (1–10 years) (Willis & Northcote-Green, 1984). In short-term load forecasting, the system administrator is responsible for the hourly scheduling of the generators. The aim is to balance power supply and demand. Long-term load forecasting is a crucial instrument for planning and forecasting future conditions of the electricity network. This study is focused on long-term load forecasting. In other words, the annual energy consumption in a country is estimated. For the annual energy consumption, there are upper and lower bounds that limit the forecast to be within a possible range. It is very important that the peak load can be fully satisfied. However, an upper bound too high is not welcome, as the long-term load may be overestimated in this way, so it is important to establish a precise upper bound for the long-term load.

Load forecasting has attracted a great deal of attention in power system research. Bunn and Farmer (1985) and Bunn (2000) highlighted the importance of short-term load forecasting. Alfares and Nazeeruddin (2002) claimed that the economy of operation and control of power systems are very sensitive to the forecasting error. They also classified the existing load forecasting approaches into nine categories: multiple linear regression, exponential smoothing, iterative reweighted least-squares, adaptive load forecasting, stochastic time series, autoregressive moving average with exogenous variable (ARMAX) models based on genetic algorithms, fuzzy logic, neural networks and expert systems. A good literature review can be found in Matthewman and Nicholson (1968), Abu El-Magd and Sinha (1982), Bunn and Farmer (1985), Gross and Galiana (1987), and Alfares and Nazeeruddin (2002).

Long-term load forecasting can be decomposed into two subproblems: annual electrical peak load estimation and annual energy consumption forecasting. Both the peak and average values of the annual energy consumption are highly uncertain and very difficult to estimate. Fitting the annual energy consumption within a future year with a distribution function is not easy, implying that a stochastic approach might not be applicable. For this reason, some studies proposed a fuzzy approach to forecast the demand or the supply in an industry. In addition, many references were devoted to decision making under fuzzy demand or fuzzy supply forecasts. Therefore, it is reasonable to propose a fuzzy approach to forecast the peak or average value of the annual energy consumption.

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There are two viewpoints when it comes to forecasting the annual energy consumption of a future year. The first viewpoint, the input–output relationship viewpoint, is to determine those factors (e.g. time, day, season, weather, economic conditions, pricing policy, etc.) that are influential to the annual energy consumption and then apply different approaches (e.g. multiple linear regression (MLR), artificial neural network (ANN), etc.) to model the relationship between the annual energy consumption and these factors in order to forecast the future annual energy consumption. Dashti and Afsharnia (2009) classified such factors into three categories: governance factors, social factors, and urban planning factors.

The second viewpoint, the time-series viewpoint, is to treat the fluctuation in the annual energy consumption as a type of time series. Theoretically, there are many approaches, e.g. moving average (MA), weighted moving average (WMA), exponential smoothing (ES), MLR, ANN, auto-regressive integrated moving average (ARIMA), and others, that can be applied to forecast the annual energy consumption. Hippert, Pedreira, and Souze (2001) gave a review and evaluation of neural networks for short term load forecasting. The most popular method for this purpose is called back propagation networks (BPNs). Recently, Lauret, Fock, Randrianarivony, and Manicom-Ramsamy (2008) constructed a Bayesian neural network for load forecasting. Generally speaking, an ANN is suitable for modeling a short-term nonlinear pattern of the annual energy consumption, while traditional approaches such as MA, WMA, and ES have good performances when the trend in the annual energy consumption is stable. This study belongs to the second category.

The purposes of long-term load forecasting in this study include:

(1) Generating an accurate annual energy consumption forecast so that long-term power planning can be based on it.
(2) Establishing a precise interval of the annual energy consumption forecast so that it becomes less likely for the government to raise budget unreasonably.
(3) Reducing the risk of power shortage.

Most existing approaches use a single system. However, the forecasting performance could be enhanced by dealing with the problem from different points of view (Chen & Lin, 2008). Pedrycz (2008) proposed the concepts of collaborative computing intelligence and collaborative fuzzy modeling, and developed the so-called fuzzy collaborative system. Based on these ideas, a collaborative fuzzy-neural approach is proposed in this study to enhance the accuracy of the annual energy consumption forecasting. Moreover, in the past studies, the peak value and the average value were separately forecasted for the annual energy consumption, while by the proposed methodology they can be treated at the same time. Forecasting the peak value and the average value separately is problematic because it is possible that the forecast becomes invalid in the sense that the average value higher than the peak value (Fig. 1).

In the proposed methodology, multiple experts construct their own fuzzy back propagation networks (FBPNs) from various viewpoints to forecast the annual energy consumption. Traditionally, there are several ways of solving an FBPN problem. For example, in Chen (2003), all parameters in the FBPN were given in triangular fuzzy numbers (TFNs), and the arithmetic for TFNs was applied to deal with all operations in training the FBPN. However, the accumulation in the fuzziness might prevent FBPN from converging to its minimal value. To tackle this problem, Chen and Wang (2010a) proposed a different FBPN approach that aimed at minimizing the spreads of fuzzy forecasts. In this study, we apply Chen and Wang's FBPN approach. FBPN parameters and the prediction results by an expert are conveyed to other experts. Upon receipt of this information, the expert may choose to repair his/her setting

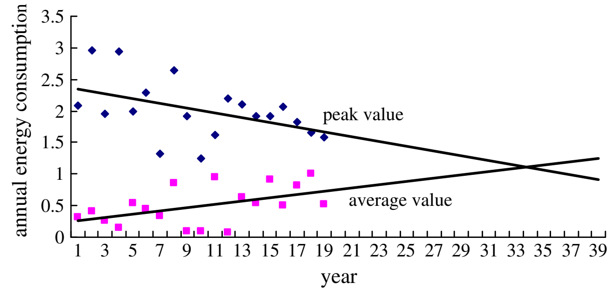

Fig. 1. Problem caused by forecasting the peak value and the average value separately.

in order to obtain a better prediction performance. The fuzzy annual energy consumption forecasts by different experts are aggregated using the fuzzy intersection (FI) approach. Afterwards, the aggregation result is defuzzified with a radial basis function network (RBF). The communication stops when the improvement in the forecasting performance becomes negligible.

The rest of this paper is organized in the following manner. Section 2 details the proposed collaborative fuzzy-neural approach. In Section 3, the practical data of the annual energy consumption in Taiwan are used to demonstrate the application of the proposed methodology. The performance of the proposed methodology is evaluated and compared with those of some existing approaches. Based on the analysis results, some points are made. Finally, some concluding remarks and a view to the future are given in Section 4.

2. Methodology

The proposed methodology is made up of several steps (see Fig. 2) which will be described in the following sections:

(1) Construct FBPNs to generate fuzzy annual energy consumption forecasts.
(2) Apply fuzzy intersection to aggregate fuzzy annual energy consumption forecasts into a polygon-shaped fuzzy number.
(3) Defuzzify the aggregation result with a RBF.
(4) Stop if the improvement in the forecasting performance (either accuracy or precision) is negligible; otherwise, return step (3).

The parameters used in the proposed methodology are defined as follows:

(1) a_t: the annual energy consumption of period t.
(2) $\tilde{h}_l(t)$: the activated signal outputted from hidden-layer node l of the FBPN.
(3) $\tilde{o}_t$: the output from the FBPN, which is the (normalized) fuzzy annual energy consumption forecast of period t. $\tilde{o}_t = (o_{tl}, o_{t2}, o_{t3})$.
(4) s_L: the satisfaction level of the actual value on the left side of the fuzzy forecast.
(5) $s_{U:}$ the satisfaction level of the actual value on the right side of the fuzzy forecast.
(6) $\tilde{w}^h_{il}(t)$: the connection weight between input node i and hidden-layer node l of the FBPN.
(7) $\tilde{w}^o_l(t)$: the connection weight between hidden-layer node i and the output node of the FBPN.
(8) $x_i(t)$: an input to the FBPN; i=1 $\sim K$.
(9) $\tilde{\delta}^o(t)$: the error term of the output-layer node.
(10) $\tilde{\delta}^h_l(t)$: the error term of hidden-layer node l.
(11) $\Delta\tilde{w}^o_l(t)$: adjustment to the connection weight between hidden-layer node l and the output node.