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A new short-term load forecast method based on neuro-evolutionary algorithm and chaotic feature selection

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ABSTRACT

In competitive environment of deregulated electricity market, short-term load forecasting (STLF) is a major discussion for efficient operation of power systems. Therefore, the area of electricity load forecasting is still essential need for more accurate and stable load forecast algorithm. However, the electricity load is a non-linear signal with high degree of volatility. In this paper, a new forecasted method based on neural network (NN) and chaotic intelligent feature selection is presented. The proposed feature selection method selects the best set of candidate input which is used as input data for the forecasted. The theory of phase space reconstruction under Taken's embedding theorem is used to prepare candidate features. Then, candidate inputs relevance to target value are measured by using correlation analysis. Forecast engine is a multilayer perception layer (MLP) NN with hybrid Levenberg–Marquardt (LM) and Differential Evolutionary (DE) learning algorithm. The proposed STLF is tested on PJM and New England electricity markets and compared with some of recent STLF techniques.

Introduction

Short-term load forecasting (STLF) plays a key role in operation of both traditional and deregulated power systems. In deregulated electricity market, STLF is a useful tool for economic and reliable operation of power system. Many operating decisions are based on load forecast such as: dispatch scheduling of generating production, reliability and security analysis and maintenance plan for generators [1]. Therefore, load forecasts are vital for the market players in competitive electricity market [2]. Hence, improving the accuracy of STLF can increase the appropriateness of planning and scheduling and reduce operational costs of power systems.

Load forecasting algorithms are includes traditional methods and modern intelligent methods [3]. Traditional methods based on mathematical statistics including regression analysis method [4], Kalman filtering method [5], autoregressive integrated moving average (ARIMA) [6], Box–Jenkins models [7], state space model [8], exponential soothing [9], and etc. These methods have the advantage of mature technology and simple algorithm, but these are based on linear analysis and none of them can forecast the non-linear load series accurately [3].

The modern intelligent forecasting methods have shown better performance for non-linearity of the time series. Also, they do not require any complex mathematical formulations or quantitative correlation between inputs and outputs. Effective utilization of intelligent algorithms in the context of ill-defined processes (such as load time series), have led to their wide application in STLF [10,11]. The intelligent algorithms including artificial neural network (ANN) based methods [11–13]. It seems that the ANN learned well the training data, but it may encounter great forecast error in the test phase. The area of the electricity load forecasting is still essential need for more accurate load forecast. Especially, there is a requirement for efficient feature selection and input/output mapping algorithm. Knowledge based expert system (KBES) approach [14,15], extracts rules from received relevant information. However, the training procedure of a KBES model is a time-consuming procedure.

Electricity load is a time variant, non-linear and volatile signal. Design of the input vector to the forecast engine is an important pre-processing phase. It plays an important role in forecast accuracy. There are two general approaches for designing of the input vector: wrapper and filter methods [16]. Feature selection is wrapped around a learning algorithm in the wrapper methods. In this method, the usefulness of a feature is judged by the estimated accuracy of the learning algorithm directly. For the electricity load forecasting with a large number of features, these methods are

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computationally expensive [16,17]. Filter methods are data filtering or data pre-processing or methods and features are selected based on intrinsic characteristics. In filters, the characteristics of the feature selection are uncorrelated to those of the learning methods; therefore they have better generalization property [16,17].

This paper is proposed a robust forecast method based on chaotic feature selection algorithm and hybrid neuro-evolutionary algorithm. Chaotic time series are a kind of between regular and random systems. Chaos theory is used to scrutiny the behavior of the dynamical systems that are extremely sensitive to initial conditions such as noise and error [18,19]. Any slight changes in initial conditions can lead to disproportionately high consequences. We are used the theory of phase space reconstruction under Taken's embedding theorem to design input vector. Correlation analysis is used to determine relevance of the features to the target value. The proposed feature selection consists of three adjustable parameters: embedding dimension, delay-time, and number of selected relevant candidate. In order to best-tune adjustable parameters, a kind of cross validation technique is incorporated. The forecast engine of the proposed method is a multilayer perception layer NN with hybrid Levenberg–Marquardt (LM) and Differential Evolutionary (DE) learning algorithm. Contribution of our proposed STLF method can be summarized as follows:

(1) A new feature selection algorithm based on chaotic time series analysis is proposed.
(2) An efficient forecast engine based on combination of ANN and DE is presented for short term load forecasting.

To the best of our knowledge, the proposed prediction method has been thoroughly discussed in next section. For STLF, forecast step is often on hour and forecast horizon is limited to one weak ahead although its usual horizon is the next day [1,11]. This paper is focused on hourly load forecast and forecast horizon is limited to 1 day ahead, though the proposed method can be extended to daily peak load prediction and mid-term or long-term forecasting easily.

The remaining parts of the paper are organized as follows. Proposed STLF method is described in Section 2. In the third section, the numerical results of the proposed method is illustrated and compared with recent STLF methods. Finally conclusion is discussed in Section 4.

Proposed feature selection method

Phase space reconstruction

Phase space reconstruction is the process of finding a space in which the dynamics are smooth and no intersections or overlaps occur in the orbits of the attractor. Embedding theorem of the Taken provides the conditions under which a chaotic time-series can be reconstructed into a M-dimensional vector with two conditions: the embedding dimension and the time delay [20].

Given an chaotic time series $\{x(t)\},\ t = 1, 2, \cdots, N$ (load time-series), selecting the embedding dimension M and the delay-time t_0, the phase space can be explained as follows:

$$\begin{aligned} X_1 &= [x(1),\ x(1+t_0),\ \ldots,\ x(1+(M-1)*t_0) \\ X_2 &= [x(2),\ x(2+t_0),\ \ldots,\ x(2+(M-1)*t_0) \\ &\vdots \\ X_L &= [x(L),\ x(L+t_0),\ \ldots,\ x(L+(M-1)*t_0) \end{aligned} \tag{1}$$

where $L = N - (M-1)*t_0$ is the length of the reconstructed phase space and X_t is a point or vector in the construction phase space.

Intelligent feature selection

One of the key issues for the success of STLF is the design of input vector [21]. The main idea of the proposed feature selection technique is to reconstructed chaotic time-series into a M-dimensional phase space with length of L for reconstructed phase space and choose a subset of candidate inputs that high relevance to the target. For this purpose in Eq. (1), the X_1 is assumed as target and $X_2, X_3, \ldots, X_L$ are assumed as input variables correspond with one, two, and $(L-1)$ hours ago, respectively. Correlation analysis is commonly used to measure candidate relevance [21–23]. Correlation analysis concept has been thoroughly discussed in [22]. The correlation coefficient (e.g. $corr(V,\ W)$) between two random variables V and W with expected values μ_V and μ_W, and standard deviations σ_V and σ_W is defined as:

$$corr(V,W) = \frac{\mathrm{cov}(V,W)}{\sigma_V\sigma_W} = \frac{E[(V-\mu_V)(W-\mu_W)]}{\sigma_V\sigma_W} \tag{2}$$

where E is the expected value operator and cov is the covariance. The correlation is defined only if both of the standard deviations are finite and both of them are nonzero. It is a corollary of the Cauchy–Schwarz inequality that the correlation coefficient cannot exceed 1 in absolute value. Also, The correlation is symmetric (i.e. $corr(V,\ W) = corr(W,\ V)$). Absolute value of correlation coefficient between 0 and 1, indicate the degree of linear dependence between the variables. In this approach the zero and 1 are explain less and perfect relationship, respectively.

The proposed feature selection method has three adjustable parameters: embedding dimension, delay-time, and number of selected input with highest relevancies. In order to fine-tune the adjustable parameters, this paper has been incorporated a kind of cross-validation technique. Selection of the validation set, which is unseen for the forecaster influence efficiency of the cross-validation technique [11,24]. The day before the forecast day is considered as validation set and the 39 days before considered as training set. To fine-tune the adjustable parameter we are used to step procedure. At first step, number of selected input is assumed constant and Training phase is executed with different values embedding dimension and delay-time and minimum of the validation set error is selected as the optimal point. Then, phase space reconstruction parameters are assumed constant and previous step executed for number of selected input to find optimal point.

Forecast engine

Multi-layer perception NN

Artificial neural networks (ANN) are a computer data processing system that simulates the performance of human brain, which is composed of billions of interconnected cells named neurons [27-aien]. It is claimed that the multi-layer perceptron (MLP) network is capable to numerically approximate any continuous function to the desired accuracy [42-aien]. The architecture of the suggested ANN has multi-layer perception (MLP) structure with hybrid LM and DE learning algorithm. LM training algorithm is the one of the most efficient learning mechanism for the prediction [21]. The LM method trains a NN 10–100 times faster than the gradient descent back propagation (GDBP) algorithm [25]. Mathematical details of the LM algorithm are discussed in [26]. In [27] Kolmogorov's theorem express, a problem can be solved with MLP by using one hidden layer, provided it has the proper number of neurons. So, we are used one hidden layer in the MLP in structure NN.