Electric Power Systems Research 165 (2018) 214–228

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Hybrid model using three-stage algorithm for simultaneous load and price forecasting

Mehrdad Setayesh Nazar[a], Ashkan Eslami Fard[a], Alireza Heidari[b], Miadreza Shafie-khah[c], João P.S. Catalão[c,d,e,*]

[a] Faculty of Electrical Engineering, Shahid Beheshti University, A.C., Tehran, Iran
[b] The University of New South Wales, Sydney, Australia
[c] C-MAST, University of Beira Interior, 6201-001 Covilhã, Portugal
[d] INESC TEC and Faculty of Engineering of the University of Porto, 4200-465 Porto, Portugal
[e] INESC-ID, Instituto Superior Técnico, University of Lisbon, 1049-001 Lisbon, Portugal

ARTICLE INFO

Keywords:
Feature selection
Mutual information
Neural network
Price and load forecasting
Wavelet transformation

ABSTRACT

Short-term load and price forecasting is an important issue in the optimal operation of restructured electric utilities. This paper presents a new intelligent hybrid three-stage model for simultaneous load and price forecasting. The proposed algorithm uses wavelet and Kalman machines for the first stage load and price forecasting. Each of the load and price data is decomposed into different frequency components, and Kalman machine is used to forecast each frequency components of load and price data. Then a Kohonen Self Organizing Map (SOM) finds similar days of load frequency components and feeds them into the second stage forecasting machine. In addition, mutual information based feature selection is used to find the relevant price data and rank them based on their relevance. The second stage uses Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) for forecasting of load and price frequency components, respectively. The third stage machine uses the second stage outputs and feeds them into its MLP-ANN and ANFIS machines to improve the load and price forecasting accuracy. The proposed three-stage algorithm is applied to Nordpool and mainland Spain power markets. The obtained results are compared with the recent load and price forecast algorithms, and showed that the three-stage algorithm presents a better performance for day-ahead electricity market load and price forecasting.

1. Introduction

Load and market price forecasting are important tasks for system operators in restructured power systems [1,2]. An Independent System Operator (ISO) is responsible for its system security and cost reduction; these tasks are highly dependent on hourly load and market price forecasting according to the fact that the hourly market price is dependent on hourly load [3]. Over the years, extensive works have been performed on the load and price forecasting methods that can be classified into three main categories [4,5]. The first category is classical statistical methods that use linear analysis [6]. The second category deals with intelligent forecasting algorithms that are used for non-linear forecasting problem. The third category encounters new heuristic ideas in the forecasting paradigms that consist of combined and hybrid models [6]. Other methods can be recognized as a combination of the above categories [7].

The classical statistical methods like Kalman filtering [8], Autoregressive Integrated Moving Average (ARIMA) [9], exponential smoothing [10], state space model [11], and Box-Jenkins models [12] are based on statistical models. The Intelligent techniques include Support Vector Machine (SVM) [13], Support Vector Regression (SVR) [14], fuzzy inference model [15], Knowledge-Based Expert System (KBES) [16], and Artificial Neural Network (ANN) [17], [18]. Hybrid load and price forecasting techniques are the most common methods that show more accurate and acceptable results as compared to custom separate load and price methods [19–21]; thus, in this paper, a hybrid method is proposed. The wavelet decomposition techniques have been used in some hybrid models [22,23] to decompose high and low frequency components of load and price to a set of sub-series. It facilitates the analysis of complex feature of load and price profile, and each part of the sub-series can be predicted easier than that of the original signal. This method is considered in this paper. In Ref. [22], Wavelet

* Corresponding author at: Faculty of Engineering of the University of Porto, R. Dr. Roberto Frias, 4200-465 Porto, Portugal.
E-mail address: catalao@ubi.pt (J.P.S. Catalão).

https://doi.org/10.1016/j.epsr.2018.09.004
Received 19 February 2018; Received in revised form 25 July 2018; Accepted 7 September 2018

Nomenclature

Index sets

j	Decomposed level index of wavelet decomposition
k	Scaling index of wavelet decomposition
l	Length of signal index of wavelet decomposition
t	Discrete time index

Parameters

a	Spread control of mother wavelet filter
b	Translation parameter of mother wavelet filter
c	Scaling function of fine scale coefficient for mother wavelet filter
m	Integer value for mother wavelet filter
n	Integer value for mother wavelet filter
n	Number of step in primary load and price forecast
η	Correction rate for primary load and price forecast
φ	Scaling function of coarse scale coefficients for mother wavelet filter
ξ	Forecast horizon for mother wavelet filter
Ψ	Mother wavelet function
ω	Scaling functions of fine scale coefficient for mother wavelet filter
Δ	Predefined parameter for primary load and price forecast

Variables

cov	Covariance
r	Correlation coefficient between two random variables
$x(\varpi+1)$	Model state matrix
$y(\varpi)$	Measured signal
$y(\varpi)$	Kalman load forecast
$A(\varpi)$	State transition matrix
$C(\varpi)$	Output matrix
E	Expected value
$K(\varpi)$	Kalman gain
$L\ (t)$	Primary load forecast variable
M, N	Fuzzy membership functions of ANFIS
$P(\varpi + 1)$	Error covariance matrix
Q_1	Noise covariance matrix
Q_2	Error covariance matrix
V	Actual value of prices or load
$\overline{V}$	Average forecasted value
$\hat{V}_h$	Forecasted value of prices or load
$\iota(\varpi)$	Measured error
σ	Standard deviations
$\chi(\varpi)$	System error
Θ	Probability mass function
Ξ	Joint entropy
Υ	Firing strength of the ANFIS rule

Transform (WT) and Adaptive-Network-based Fuzzy Inference System (ANFIS) are used. WT decomposes price series into a set of constitutive series, and these series are forecasted using ANFIS. In Ref. [23], the wavelet pre-processed time series are used after removing the higher frequency (fast changing) components.

Any market-based load forecasting method cannot work well without considering price as an input. One of the hybrid methods for solving this problem is an iterative model that considers the full dependency of price and load [24–26]; this model is also considered in this paper. A mixed load and price forecasting method is proposed in Ref. [24] that consists of a two-level forecast algorithm. The first level uses forecasters for the price and load forecasting. The second level uses two final forecasters that they are equipped with Feature Selection (FS) algorithm. These hybrid methods assume that the Market Clearing Price (MCP) curve has a non-constant variance and average without any pattern [25,26]. Ref. [25] proposes a method that uses the cooperative co-evolutionary approach with adjustable connections in a recursive procedure. In addition, similar days-based methods have been used to investigate the days with similar characteristics including similar week/day indexes or weather parameters during the last two or three years [26]. The major drawbacks of these methods are in the way of finding the similar days and creating a linear function of the past load patterns. For solving this problem, a combination of similar days-based methods and machine learning algorithms is proposed in Ref. [27], in which similar days are selected by the felt temperature, and after wavelet decomposition, each frequency pattern is fed into an ANN as a machine-learning algorithm. This method is also considered in this paper.

The ANN-based load-forecasting methods are among the most popular forecasting algorithms, and many researchers have used unsupervised learning ANN (for example, Self-Organizing Map (SOM)) for better performance of Multi-Layer Perceptron (MLP) forecasting algorithms [28–31]. Selecting the best fitting data (as inputs) might be an important issue in load-forecasting methods. The most common inputs for ANN-based methods used in the previous works include weather data [28], historical loads [29], historical prices [30] and week/day index [31]. The historical MCP curve has a different characteristic from load curve, and no similar curve exists among the historical price data; this fact increases the complexity of the price-forecasting problem [31]. Mutual Information (MI) method is one of the FS techniques that can find the most relevant data and rank them according to their relevance to the target, which decreases the redundancy of data set and is not time-consuming [19]. Elimination of unimportant and redundant data and reducing computational complexity are the main advantages of this method [32,33]; this method is considered in this paper.

Several optimization algorithms have been proposed to optimize the parameters of the hybrid forecasting methods [4,7,34–37]. For example, Ref. [34] uses fuzzy clustering to find the similar days; the proposed method combines the classical methods into one hybrid method that makes the forecasts based on a combination of recent historical data and similar day data. It consists of three units: a pre-processing unit, which is responsible for detecting that a season has changed and searching for similar days; the second unit is an SVM-based hourly predictor, and the third unit is for optimizing the SVM parameters based on the Particle Swarm Optimization (PSO). In Ref. [35], a hybrid model based on a modified firefly algorithm SVR reduces the possibility of trapping in local optima when increasing the convergence criterion. In Ref. [36], an algorithm that uses PSO-SVM is proposed, and the obtained results are compared to the classical training methods results. In Ref. [37], a hybrid model developed to forecast air conditioning electrical load, and comparisons are made among the applied methods to prove the advantages and applicability of the proposed method.

It was observed that using optimization-based techniques for FS of Simultaneous short-term Price and Load Forecasting (SPLF) might not lead to an acceptable trade-off between accuracy and computational burden. It only increased the complexity of the proposed model and computational efforts without considerable improvement of the algorithm accuracy. Thus, optimization-based FS methods are not used in this paper; rather MI-based FS method has been used.

The authors had many attempts to define a proper general layout for soft computing algorithms and to solve the high error problem of the simultaneous price and load forecasting methods. The results of different competitive soft computing paradigms were compared, and finally, the proposed layout and its soft computing algorithms were