Intelligent and Hybrid Techniques to Predict Short-term Electricity Prices: A Review

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Abstract— **In the last years, efforts have been made to present effective tools to predict electricity market prices. These tools are required in face of players' competition in deregulated electricity markets. For the short-term prediction, i.e., from one day to one week, several intelligent techniques have been proposed for the various electricity markets around the world, either alone or combined to form hybrid techniques. In light of the recent advances in the field, this paper presents a review on the application of intelligent/hybrid techniques to predict electricity prices in the short-term. Hence, this paper provides valuable information of past/present works on the topic, serving also as an excellent basis for future developments.**

Index Terms—**Electricity prices, hybrid techniques, intelligent techniques, prediction, short-term.**

I. Introduction

NOWADAYS, in competitive electricity markets the most important signal is the electricity market price (EMP) [1]. A deregulated electricity sector has been replacing the traditionally vertically integrated structure [2], and this evolution increases the complexity in analyzing the behaviour of EMPs [3]. In this context, the research field on EMPs prediction has grown to be one of the major research fields in power systems [4]. An accurate prediction of EMPs allows power producers to achieve maximum profit, and allows power consumers to protect themselves against high prices or to maximize their resources [5].

It is known that EMPs behavior is associated with high frequency, non-constant mean, non-stationary, non-linearity, calendar effect, among others [6], [7]. Due to this behavior, the EMPs prediction task is very challenging, crucial for the decision support of market agents, especially with the advent of smart grids [8]. In the last years, publications have been arising in the technical literature regarding EMP prediction in the short-term, i.e., from one day to one week, divided into two major groups: hard and soft computing techniques [9].

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The hard computing techniques include auto regressive integrated moving average (ARIMA) [10], generalized autoregressive conditional heteroskedastic (GARCH) [11], a combination of ARIMA with neural networks (NNs) [12] or support vector regression [13], and other hybrids [14]-[16].

Those hard computational techniques require an exact model of the problem, needing also a considerable number of physical input data [17], which results in a high computational burden. These techniques will not be addressed in this paper.

The soft computing techniques include NNs [18], adaptive wavelet NN (AWNN) [19], hybrid techniques [20], cascaded neuro-evolutionary algorithm (CNEA) [21], composite NN [22], evolutionary techniques [23], and many others.

Usually, soft computing techniques may work with an input-output mapping learned from historical data examples, not requiring the system modeling. Hence, these approaches can be much more efficient computationally and as accurate as the hard computing techniques, if the correct inputs are considered.

This paper presents a review of the state-of-the-art in the last years concerning soft computing techniques to predict the behavior of EMPs in the short-term.

The paper is organized as follows. Section 2 discusses the applicability of intelligent/hybrid techniques for EMPs prediction, from 2007 onwards. For papers related to these topics that have been published before 2007, the interested reader is referred to [17]. Section 3 provides a brief description of some intelligent techniques, such as NNs, neuro-fuzzy systems and evolutionary particle swarm optimization (EPSO), and also some preprocessing techniques such as wavelet transform (WT) or mutual information (MI). Section 4 presents the reported results in the technical literature, using the tabular form to highlight the techniques used, electricity markets, time horizons and historical data years considered, as well as some typical values for the prediction errors. Finally, Section 5 concludes the paper.

II. Intelligent/Hybrid Techniques Applications

In 2007, a technique was proposed based on NN with Levenberg-Marquardt algorithm to predict the EMPs in mainland Spain with historical data of the year 2002 for all four seasons of year, and also to predict the EMPs in Californian market of year 2000 for 168h-ahead, reporting a lower computation time in comparison with the ARIMA technique [18].

In 2008, a hybrid method was proposed corresponding to the combination of WT and cascaded NN (CNN) with evolutionary algorithms to predict the EMP in the Californian market with historical data of 2006, for 168h-ahead [24].

Also in 2008, a non-parametric technique of dimensional reduction was reported [25], integrating a locally linear embedding to predict EMPs in the New York Independent System Operator's (NYISO) with historical data of 2005 and 2006.

In [26], a technique based on NN was reported to predict EMPs in the Spanish market for 24h-ahead, considering historical data of years 2002 and 2003. The AWNN technique was reported to predict EMPs in the Spanish and PJM markets for 168h-ahead, considering historical data of years 2002 and 2004, respectively [19].

Still in 2008, another technique based on NN was proposed to predict EMPs in the PJM market for the next 168h, considering historical data of year 2002 [27].

In 2009, a hybrid technique based on modified relief algorithm, MI and CNN was proposed to predict EMPs for 168h-ahead on the PJM and Spanish markets considering historical data of years 2006 and 2002, respectively [4].

Moreover, in [21], the CNEA technique was proposed also for the PJM and Spanish markets, while in [28] a hybrid technique based on modified relief and CNN algorithm with correlation analyses was proposed to predict EMPs in the Spanish and Australian market (ANEM).

In [29], a technique based on a mixed model with iterative NN and MI was proposed to predict EMPs in NYISO and Spanish market. Still in 2009, a technique based on self-adaptive radial basis NN with fuzzy inference was proposed to predict the next 24h EMPs of the ANEM market, considering historical data of year 2006 [30]. Further, in [31], a technique based on sensitive analysis and NN algorithm was proposed to predict the next 24h EMPs in the PJM market, considering historical data of year 2006.

In 2010, a hybrid technique based NN with evolutionary algorithms was proposed to predict the 168h-ahead EMP of the PJM and Spanish markets, considering historical data of year 2006 and 2002, respectively [6].

In [12], a technique based on ARIMA and NN was proposed to predict 168h-ahead EMP in the ANEM market, considering historical data of year 2006. In [32], a technique based on recursive model combined with NN was proposed to predict 24h-ahead EMPs in the PJM market, considering historical data of year 2006. Still in 2010, a technique based on NN with enhanced radial basis function network algorithm was proposed to predict the EMPs for 24h and 168h-ahead of PJM market [33].

In 2011, a hybrid technique based on a combination of WT, particle swarm optimization (PSO) and fuzzy algorithm was proposed to predict EMPs in the Spanish market for 168h-ahead, considering the historical data of 2002 [2]. In [5], a technique based on WT, PSO and adaptive neuro-fuzzy inference system (ANFIS) was proposed also for the Spanish market. In [34], EPSO and ANFIS were combined to predict the 168h-ahead EMPs in the Spanish market.

In 2012, a technique called extreme learning machine was proposed to predict EMPs in the ANEM market for 168h-ahead, considering historical data of years 2006 e 2007 [35]. Besides, in [22], a technique that combined MI and composite NN algorithms was proposed to predict 168h-ahead EMPs of the PJM and Spanish markets with historical data of years 2006 and 2002, respectively. In [20], a technique that combined WT, inference system and NN algorithm was proposed to predict EMPs in the Ontario market for 24h and 168h-ahead, considering historical data of year 2010.

Still in 2012, a grey model based on PSO was proposed to predict EMPs in the Nord Pool, Californian and Ontario markets for 24h-ahead, considering historical data of 2007, 2000-2003 and 2006, respectively [36]. In [9], PSO and ANFIS algorithms were combined to predict 168h-ahead EMPs of the Spanish market, considering historical data of 2002.

Finally, in 2013, a hybrid technique called panel co-integration and particle filter was proposed to predict 168h-ahead EMPs of the PJM market, considering historical data of 2008 [37].

III. Description of Selected Intelligent Techniques

Intelligent techniques are especially useful for predicting the stochastic, non-stationary, volatile and unstable behavior of electricity market prices with rather low computational burden, in comparison with hard computing techniques. NN, ANFIS and EPSO techniques will be described in more details hereafter, along two preprocessing techniques: WT and MI.

A. Neural Networks

NNs are structures composed by interconnected neurons, which simulate the behavior of the human brain in processing information [19]. Each neuron is a weighted summation of its input data, communicating with others neurons with added bias result. The information passes across some known transfer functions, such as sigmoid, hyperbolic tangent, linear, and others [18].

Fig. 1 represents a hypothetic NN structure with three layers. Layer1 represent the input layer, with some neurons receiving the input data signal and computing the transfer characteristic to the next layer. Layer2 represents the hidden layer where it is possible to combine the previous results with some aforementioned transfer function, sending the results to Layer3. This Layer 3, or output layer, is where the final results are computed by combining with another transfer function. This type of NN is called feed-forward network or, specifically in this case, a three-layered feed-forward network.

To predict EMPs with NNs, two steps are usually required: the training process, where historical input data sets are provided to the NN, and the learning process, where the NN constructs a mapping way by computing the biases and weights, in order to minimize the error between prediction results and real results, a process repeated until convergence is found [22]. A learning algorithm can be the Levenberg-Marquardt algorithm, explained for instance in [18], while other algorithms can be found in [6], [12] and [26].

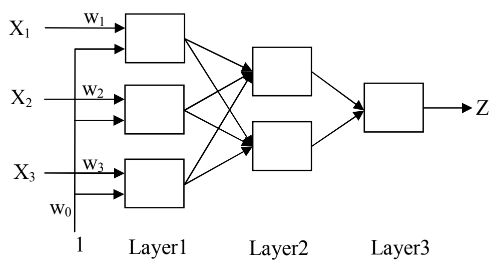

Fig. 1. NN structure.

B. Neuro-Fuzzy Systems

NN and fuzzy algorithms are complementary algorithms that can be used to predict EMPs, combining the advantages of both in a hybrid structure like ANFIS.

This combination is possible due to the low computational requirements of well-structured NN architectures [5], which can be useful to deal with a large number of data, combined with a high response given by fuzzy algorithms.

The NN architecture has the self-learning capability that is essential to the fuzzy architecture to self-adjust its parameters [2].

In ANFIS method the NN computes automatically the fuzzy rules of data-inputs and, due to the self-learning process, their membership functions are adaptively adjusted [35]. The general ANFIS architecture consists of fuzzification, rules, normalization data, desfuzzification, and signal reconstruction by the respective layers, also called multi-layer feed-forward network [5].

Fig. 2 presents a hypothetic architecture of the ANFIS, as a generic five-layered feed-forward network.

Each layer has a specific purpose: Layer1 is an adaptive layer where each node has a membership function node, with linguistic labels associated. Nodes A_n and B_n have a specific bell function, as described in [9]. Layer2 is responsible for the firing strength, where node Π_n computes the output signal with a multiplication of inputs signals. In Layer3, each node N computes the measured of firing rules strength with the sum of every firing strength rules. In Layer4, every node measures the contribution of each rule for the global input. Finally, Layer5 computes the sum of all inputs in this node. The ANFIS can use least-squares or back-propagation gradient descent methods.

C. Evolutionary Particle Swarm Optimization

EPSO incorporates a selection procedure to the original PSO algorithm (where its principle is based on the simulation of the behavior of migratory bird applied to predict the future behavior of signals), and self-adapting properties for its parameters.

EPSO has some important features: 1) replication: where each data signal is replicated; 2) mutation: where each data signal has its weight mutated; 3) reproduction: where each mutated signal generates a new set of data signals according with the movement rule; 4) evaluation: where the fitness of each data signal is computed; and 5) selection: made by stochastic tournament, where the best data signal is chosen to create a new data signal [38]-[39].

EPSO technique provides quicker convergence in comparison with the original PSO, with the inertia, memory and cooperation parameters undergoing mutation in an evolutionary process. Hence, EPSO is classified as a self-adaptive technique, which uses the mutation and selection of strategic parameters to predict new signals.

Fig. 3 presents the movement rule and principal parameters related to EPSO. In Fig. 3, the signal is represented by point P_i (initial position) going to point P_f (final position), given by vector velocity, which is dependent on inertia, memory, and cooperation parameters in relation with other signals. The weights of all parameters are represented in the starting point the of signal. This figure also provides the time dimension (x_t) axis and forecasted value of data signal dimension (x_p) axis.

D. Wavelet Transform

WT is used in the preprocessing of input data for forecasting algorithms. WT expresses the non-stationary of a time varying data signal, with sensibility to its irregularities [24]. This tool has the capability to illustrate the different aspects of the data signal without losing their behavior [5]. The filtering effect is achieved due to noise reduction of the input data signal without appreciable degradation, as discussed in [19].

This technique runs by decomposition of the data signal in some predefined levels, divided in approximation levels and details levels of the data signal. The approximation levels are responsible for the general information of the original data signal, which can be divided into their lower and higher frequency representation, and by details levels, showing the difference between approximations [24].

The WT structure uses a mother function, such as Daubechies 4 [5], [19], which provides an appropriate trade-off between smoothness and length. Fig. 4 represents a typical WT structure, divided by some decompositions levels, where A_n to A_{n+1} represent approximations levels, an D_n to D_{n+1} represent details levels of the original data signal input.

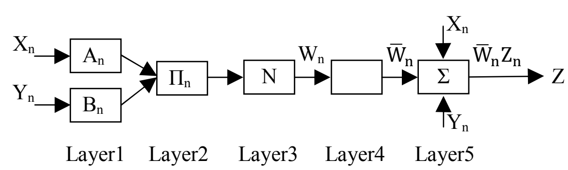

Fig. 2. ANFIS structure.

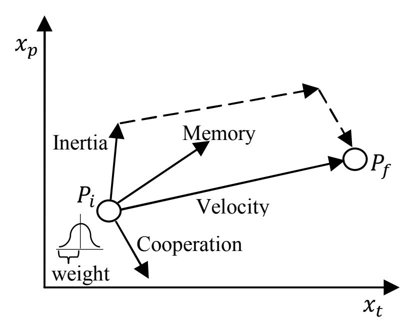

Fig. 3. EPSO graphical movement rule.

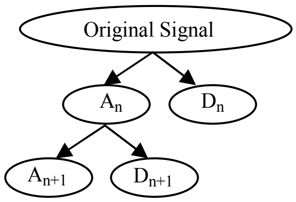

Fig. 4. WT Signal Decomposition.

E. Mutual Information

MI is based on entropy information theory. This tool allows understanding the complexity of the data signal, quantifying its disorder state [21].

MI follows some rules in the entropy of data, comprehended between 0 and 1, depending on the probability of each individual event [28].

Moreover, the entropy can be extended in a joint distribution of random variables. So, MI quantifies the level of information between a group of data that can be used to reduce the computation effort, allowing preprocessing the information that later on will allow increasing the performance of the algorithms [22].

MI defines the best data to be used with lower entropy between signal data sets, each sharing a substantial portion of the necessary information to help in the prediction tools [28].

Fig. 5 represents a simplified representation of the MI technique.

IV. Reported Results

This section shows the results obtained with several recently reported EMP techniques, considering different electricity markets and time horizons.

Table I shows the different electricity markets used as case study to evaluate the techniques reported in the technical literature. The symbol "+" means that the authors in their paper used more than one time horizon to report the predicted results for the indicated market.

Table II shows the year of historical data used in the case study of each paper, for a specific electricity market, i.e., Australian ANEM (AN), Californian (Ca), Nord Pool (NP), New York ISO (NY), Ontario (On), PJM (PJ), and Spanish (Sp) markets, respectively. No paper was found using historical data of years 2001 or 2009, so these years do not appear in Table II.

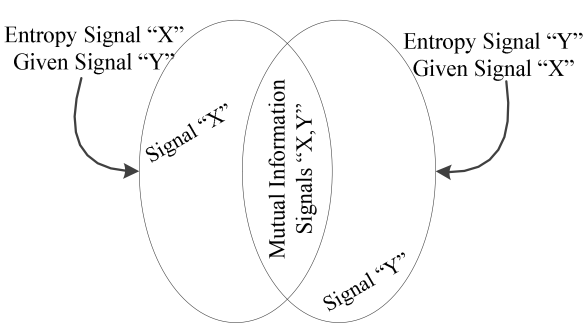

Fig. 5. Simplified MI Representation.

TABLE I
ELECTRICITY MARKETS USED AS CASE STUDY AND THE TIME HORIZONS

	Spanish	Californian	NYISO	PJM	Ontario	ANEM	Nord Pool
Ref. [2]	168h						
Ref. [4]	168h			168h	+168h		
Ref. [5]	168h						
Ref. [6]	168h			168h			
Ref. [9]	168h						
Ref. [12]						168h	
Ref. [18]	168h	168h					
Ref. [19]	168h			168h			
Ref. [20]					+24h		
Ref. [21]	168h			24h			
Ref. [22]	168h			168h			
Ref. [24]		168h					
Ref. [25]			+24h				
Ref. [26]	24h						
Ref. [27]				168h			
Ref. [28]	168h					24h	
Ref. [29]	168h		+168h				
Ref. [30]						24h	
Ref. [31]				24h			
Ref. [32]				+24h			
Ref. [33]				+24h			
Ref. [34]	168h						
Ref. [35]						168h	
Ref. [36]		24h			24h		24h
Ref. [37]				+24h			

TABLE II
YEAR OF HISTORICAL DATA USED IN THE CASE STUDY

	2000	2002	2003	2004	2005	2006	2007	2008	2010
Ref. [2]		Sp							
Ref. [4]		Sp/On				PJ			
Ref. [5]		Sp							
Ref. [6]		Sp				PJ			
Ref. [9]		Sp							
Ref. [12]						AN			
Ref. [18]	Ca	Sp							
Ref. [19]		Sp		PJ					
Ref. [20]									On
Ref. [21]		Sp				PJ			
Ref. [22]		Sp				PJ			
Ref. [24]						Ca			
Ref. [25]					NY	NY			
Ref. [26]		Sp	Sp						
Ref. [27]		PJ							
Ref. [28]		Sp	AN						
Ref. [29]		Sp		NY					
Ref. [30]						AN			
Ref. [31]						PJ			
Ref. [32]						PJ			
Ref. [33]		PJ							
Ref. [34]		Sp							
Ref. [35]						AN	AN		
Ref. [36]	Ca		Ca			On	NP		
Ref. [37]								PJ	

Table III presents some results regarding the mean absolute percentage error (MAPE) for the ANEM market. Tables IV and V presents MAPE results for the Spanish and PJM markets, respectively. These tables illustrate the performance of the different prediction techniques, in some commonly used electricity markets as case studies.

TABLE III
MAPE RESULTS FOR EMP PREDICTIONS IN THE ANEM MARKET

	Winter	Spring	Summer	Fall	Average
Ref. [12]	13.85	9.99	15.58	13.04	13.18
Ref. [35]	8.34	10.26	21.88	12.74	13.30

TABLE IV
MAPE RESULTS FOR EMP PREDICTIONS IN THE SPANISH MARKET

	Winter	Spring	Summer	Fall	Average
Ref. [2]	3.38	4.01	9.47	9.27	6.53
Ref. [4]	4.21	4.76	6.01	5.88	5.22
Ref. [5]	3.37	3.91	6.50	6.51	5.07
Ref. [6]	4.28	4.39	6.53	5.37	5.14
Ref. [9]	3.65	4.19	6.76	6.53	5.28
Ref. [18]	5.23	5.36	11.40	13.65	8.91
Ref. [19]	3.62	4.85	9.48	9.50	6.86
Ref. [21]	4.88	4.65	5.79	5.96	5.32
Ref. [28]	4.32	4.31	6.37	6.22	5.30
Ref. [29]	4.22	4.39	5.55	5.66	4.95
Ref. [34]	3.59	4.10	6.39	6.40	5.12

TABLE V
MAPE RESULTS FOR EMP PREDICTIONS IN THE PJM MARKET

	Winter	Spring	Summer	Fall	Average
Ref. [4]	4.79	4.34	4.59	4.49	4.55
Ref. [19]	6.36	5.98	5.95	6.65	6.24
Ref. [27]	6.16	5.60	8.40	5.52	6.42
Ref. [37]	5.60	7.30	7.30	6.30	6.63

V. CONCLUSION

This paper presented an overview of intelligent/hybrid techniques applications to electricity market prices prediction. The most recent advances have been presented and discussed. The electricity markets, time horizons and historical data years considered in the several publications have been presented in tabular form, as well as comparative mean absolute percentage errors achieved. The information provided here is aimed to provide both a valuable database and a good starting point for future developments in the field.

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