DEEPSO to Predict Wind Power and Electricity Market Prices Series in the Short-Term

J.N.D.L. Gonçalves
FEUP
Porto
Portugal
ee10191@fe.up.pt

G.J. Osório
C-MAST/UBI
Covilha,
Portugal
gjosilva@gmail.com

J.M. Lujano-Rojas
UBI, Covilha, and
INESC-ID/IST-UL, Lisbon,
Portugal
lujano.juan@gmail.com

T.D.P. Mendes
C-MAST/UBI
Covilha,
Portugal
tiagomendestdi@gmail.com

J.P.S. Catalão
INESC TEC and FEUP, Porto,
C-MAST/UBI, Covilha, and
INESC-ID/IST-UL, Lisbon, Portugal
catalao@fe.up.pt

***Abstract* – With the advent of restructuring electricity sector and smart grids, combined with the increased variability and uncertainty associated with electricity market prices (EMP) signals and players' behavior, together with the growing integration of renewable energy sources, enhancing prediction tools are required for players and different regulators agents to face the non-stationarity and stochastic nature of such time series, which must be capable of supporting decisions in a competitive environment with low prediction error, acceptable computational time and low computational complexity. Hybrid and evolutionary approaches are good candidates to surpass most of the previous concern considering time series prediction. In this sense, this work proposes a hybrid model composed by a novel combination of differential evolutionary particle swarm optimization (DEEPSO) and adaptive neuro-fuzzy inference system (ANFIS) to predict, in the short-term, the wind power and EMP, testing its results with real and published case studies, proving its superior performance within a robust prediction software tool.**

***Index Terms* – Differential evolutionary particle swarm optimization; Electricity market prices; Forecasting; Short-term, Wind power.**

I. Introduction

With the increasing concern in higher integration of renewable power generation, namely the wind power, even considering all the economic and environment features, nonetheless, due to its stochastic, unpredictable and uncertainty behaviour motivates harder and costly operations in electrical framework, and consequently, motivates more uncertainty and competition in regulated electricity markets, making more difficult to all market players make their strategic bids without accurate, reliable and proficient prediction tools to support their decisions.

One way to mitigate some of the problems described above for a correct and sustainable management of electrical system, involves the integration of energy storage systems, which makes the electrical system more flexible in the presence of renewable energy versus the conventional energy production, incrementing the quality management of energy flows, via increasing the renewable penetration, and helps to mitigate the operational costs, however, their implementation is very costly, and often, it is still in experimental phases in some cases [1-2].

Another way, more economical and versatile, is the usage of predictive tools to determine the future behaviour of the wind potential, making possible the creation of a portfolio of possible generation, even considering the predicted profile of EMP, which are also influenced by external, society an environmental factors, and electricity agents' behaviours [3].

In recent years the efforts carried out by the scientific community has been massive to present more viable an reliable solutions which allow to mitigate the countless problems in the electrical system, and its reflection is present on larger proliferation of techniques and predictive approaches as shown by example in [4] or even in [5].

Considering the widespread state-of-the-art in the areas of predicting the wind power or EMP, is necessary to consider some different aspects, such as, the family where the proposed methodology is includes, the time horizon prediction used and also the prediction field [6]. Thus, starting from the field of wind power, the prediction methodologies can belong to the family of physical and statistical methodologies where the latest show accurate response in time [7]. Also, when it is considered the field of EMP prediction the methodologies may be categorized in hard and soft computing methodologies, where soft computing methodologies proved to be the most proliferated due to their versatilities, ease implementation and understanding [8]. Regarding the time horizon prediction, the scientific community considers with some unanimity the three horizons, very-short, short, and long-term horizons, as described in [9]. For instance, in [10] was presented a comparison study between different hybrid models and conventional models such as persistence, neural networks (NN) and fuzzy-NN to predict the wind speed behavior using different original wind speed series divided in three cases studies with different time steps from a Chinese Qinghai wind farm. In [11] was presented a hybrid model composed by NN and improved simplified swarm optimization to predict the wind power behavior from an important wind farm located in Taiwan, considering the wind speed and wind power data for several years predicting for the daily wind power prediction set. In [12] was presented a hybrid model combining mutual information (MI), wavelet transform (WT), evolutionary particle swarm optimization (EPSO), and ANFIS to predict in short-term, the wind power behavior of wind farm connected to the Portuguese transmission system operator, considering intervals of 3 hours ahead with a time-step of 15 minutes, predicting the wind power behavior till 24hours ahead. In [13] was presented a power prediction methodology combining pre-processing model, back-propagation NN and genetic algorithm to predict with historical data the electrical power for 24 hours ahead with a time step oh 30 minutes and comparing the results with other obtained with different NN models proving the superiority of hybrid model proposed.

978-1-5090-4650-8/16/$31.00 ©2016 IEEE

In [14] was proposed Wavelet NN considering the hidden neurons constructed based on multi-dimensional Morlet wavelets, trained by improved clonal selection algorithm for wind power prediction, considering the real hourly data of system level wind power generation in Alberta, Canada, divided in set of 6 hours to predict one weak ahead.

Considering EMP prediction, for instance in [15] was presented a full study of hybrid prediction models applied in electrical system and proposed two hybrid forecasting models to predict the next-day base load electricity prices on the APX power exchange for Great Britain. In [16] was proposed a recurrent NN prediction model for the day ahead deregulated EMP using Elman network, considering historical data from markets of mainland Spain and New York, presenting the results under a time step of 1 hour ahead till 168 h ahead.

In [17] was presented a hybrid prediction model combining MI, WT, EPSO and ANFIS methodologies to predict the EMP series from different markets in different spatial years, and different time ahead prediction without exogenous data. The markets under study were the mainland Spain market from years 2002 and 2006, and PJM market from year 2006, considering also different horizon prediction time between 24 till 168 hours ahead with a time step of 1 hour.

In [18] was proposed a prediction model for short-term spot prices in the Nordic power market, considering a Cuckoo search Levenberg–Marquardt (CSLM)-trained, CSLM feed-forward NN (CSLM-FFNN) for the solved process that combines the improved Levenberg Marquardt and Cuckoo search algorithms. The proposed considered the power generation and system load as input sets to facilitate the efficient use of transmission and power generation resources by direct market participants. The model was tested with real data from Nord Pool and mainland Spain markets data from years 2009, and 2002, respectively.

In [19] was presented a hybrid prediction model for hourly electricity price prediction considering the real data of 2001 from New England area. The proposed model was implemented in two steps. In the first step, a set of relevance vector machines (RVM) was adopted for an individual prediction. In second step, the previous predictions were aggregated to create a linear regression ensemble. Thus, was considered a micro-genetic algorithm to create the final EMP prediction forecast

In this work, and in line with the features demonstrated by hybrid prediction methodologies above, is proposed a novel model to predict the wind power and EMP behavior in the short-term. In detail, in case of predicting wind power behavior, the prediction will made with a range of 3 hours ahead with a time step of 15 minutes and refreshing the system till complete a time horizon of 24 hours ahead. In the case of EMP prediction, the prediction will for 168 hours ahead with a time step of 1 hour. In both prediction methodologies, it will be used, for the first time in this field of knowledge the combination of differential evolutionary particle swarm optimization (DEEPSO), which is itself a hybrid method, combined with adaptive neuro-fuzzy inference system (ANFIS), hybrid by nature also.

For a reliable and free ambiguity comparison of proposed prediction methodology, no exogenous data will be used in both case of study, and the real historical data used will be comparable to those data used in reported and published models [12] and [17]. The remaining manuscript is described as follows: Section 2 describes the concepts used to create the predictive tool, and also the algorithm used for wind power or EMP prediction. Section 3 describes the criteria used for validate and compare the capabilities of the proposed prediction methodology with previous and published methodologies, and the data used to carry out the prediction. Section 4 reports the results obtained for wind power and EMP predictions and the comparison carried out, and finally, Section 5 presents the main conclusions drawn in this work.

II. Proposed Hybrid Model

The proposed hybrid model, hereafter called hybrid prediction model (HPM), is an innovative mixture of DEEPSO and ANFIS models. The DEEPSO model offers augmented ANFIS capabilities, by helping to tuning its membership functions, attaining a lower prediction error.

A. Adaptive Neuro-Fuzzy Inference System

ANFIS is a well-known hybrid combination of NN and Fuzzy algorithms combining useful features such as low computational requirements, possibilities to deal with a large number of data, and high response features. Furthermore, it has self-learning capabilities which helps to self-adjust its parameters [17]. The general ANFIS structure is based on several layers providing the fuzzification, rules, normalization data, desfuzzification, and data reconstruction process as described in [9], [12]. In Fig. 1 is described the universal ANFIS structure.

B. Differential Evolutionary Particle Swarm Optimization

DEEPSO is a hybrid successful combination from EPSO model, which is itself a hybrid combination of its ancestor model, i.e., particle swarm optimization, where the weight factors have self-adaptive features, combined with evolutionary programming bringing self-adaptive operators [20], and differential evolution algorithm, which provides a new solution from current particle of the swarm by adding a fraction difference between two other points experimented from the swarm evaluated [21]. DEEPSO formulation is similar with EPSO [22], however the movement rule has new notation, i.e.:

$$X_i^{new} = X_i + V_i^{new} \quad (1)$$

$$V_i^{new} = w_{i0}^* V_i + w_{i1}^* \left(X_{r1}^i - X_{r2}^i\right) + P\, w_{i2}^* \left(b_g^* - X_i\right) \quad (2)$$

where:

$$w_{ik}^* = w_{ik} + \tau N(0,1) \quad (3)$$

$$b_g^* = b_g \left(1 + w_g N(0,1)\right) \quad (4)$$

Components X_r^i should be any pair of different particle already tested, ordered to minimize at the end, i.e.,

$$f\left(X_{r1}^i\right) < f\left(X_{r2}^i\right) \quad (5)$$

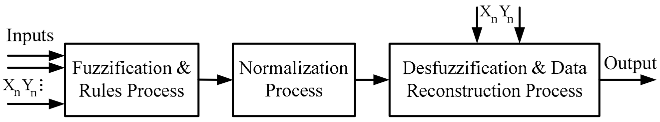

Fig. 1. Universal ANFIS structure.

From (1)-(5), X_i^{new} is the new position of the particle, V_i^{new} is the new velocity found, P is a diagonal binary matrix containing value 1 when probability is p, and 0 with $(1-p)$, w_{ik}^* are the mutated weight of inertia, memory and cooperation of the swarm, given by a learning parameter τ (fixed or mutated) and $N(0,1)$ is a random Gaussian variable with 0 mean and variance 1. Also, b_g^* is the global position provided by new weight w_g collected from a diagonal matrix, having a self-adaptive feature and in this sense suffers mutation [20], [21].

Components X_{r1}^i and X_{r2}^i assures that a suitable pull is done considering macro-gradient points in a descending direction depending from the structured comparison of $f(X_{r1}^i)$ and $f(X_{r2}^i)$. In this sense, in DEEPSO the component X_{r2}^i is assumed as $X_{r2}^i = X_i$, and component X_{r1}^i is sampled from the set of best ancestors from the swarm of n particles, i.e., $S_{bA} = \{b_1, b_2, \ldots, b_n\}$ [22]. The universal idea behind of DEEPSO movement is briefly expressed in Fig. 2.

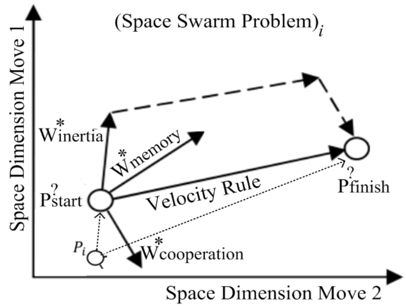

Fig. 2. DEEPSO universal particle movement rule.

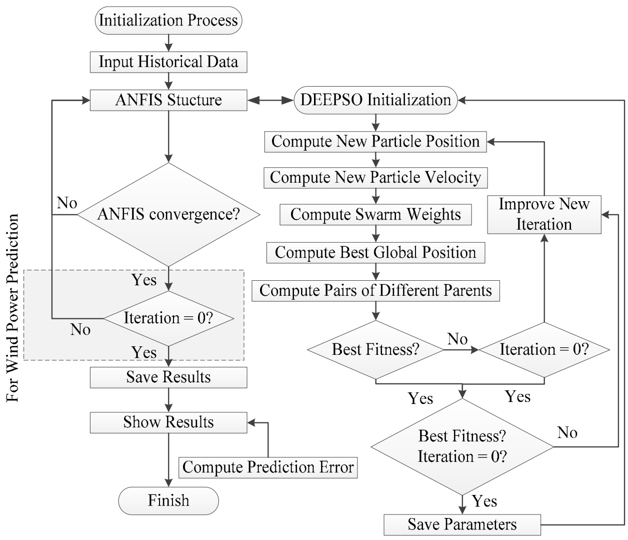

Fig. 3. HPM flowchart.

C. Hybrid Prediction Model.

The HPM model is illustrative described in Fig. 3, giving more focus on the DEEPSO method. The HPM model is designed considering the following steps:

- Step 1. Initialize the HPM model with an historical data matrix of wind power or EMP respectively, considering the prediction time scale on each prediction field.
- Step 2. Train the ANFIS method with the previous sets of historical data. The optimization process of membership function parameters will achieve with DEEPSO method. All parameters considered are summarized in Table I. As in [12] and [17], the ANFIS inference rules are obtained by considering the automatic ANFIS mode, achieving more improvements.
- Step 3. Until the best results or convergence are not reached:
  - Step 3.1. Jump to Step 4 in case of EMP;
  - Step 3.2. Jump to Step 2 in case of wind power prediction, refreshing the historical data matrix. When the best result is found or convergence is reached, the wind power data is predicted for the next three hours till complete 24 hours ahead.
- Step 4. Compute the predicting errors with different criteria to validate the proposed HPM model.

III. Prediction Validation

To compare the proposed HPM model with other models previously published and validated to predict wind power or EMP in short-term, the mean absolute percentage error (MAPE) criterion is commonly used.

The MAPE criterion is described by [12], [17]:

$$MAPE = \frac{100}{N} \sum_{n=1}^{N} \frac{|\hat{p}_n - p_n|}{\bar{p}} \tag{6}$$

$$\bar{p} = \frac{1}{N} \sum_{n=1}^{N} p_n \tag{7}$$

where $\hat{p}_n$ is the data predicted at hour n, p_n is the real data at hour n, $\bar{p}$ is the average value for the prediction time horizon, and N has the length of observed points. Following the same idea from previous criterion, the uncertainty of the HPM model is evaluated using the error variance, described as:

$$\sigma_{e,n}^2 = \frac{1}{N} \sum_{n=1}^{N} \left(\frac{|\hat{p}_n - p_n|}{\bar{p}} - e_n \right)^2 \tag{8}$$

$$e_n = \frac{1}{N} \sum_{n=1}^{N} \frac{|\hat{p}_n - p_n|}{\bar{p}} \tag{9}$$

Moreover, for wind power prediction, the normalized mean absolute error (NMAE) criterion is used [12]:

$$NMAE = \frac{100}{N} \sum_{n=1}^{N} \frac{|\hat{p}_n - p_n|}{P_{installed}} \tag{10}$$

where $P_{installed} = 2700$MW.

TABLE I
PARAMETERS OF DEEPSO AND ANFIS

	Parameters	Type or Size
DEEPSO	Communication Probability	0.10
	Final Inertia Wight	0.01 - 0.15
	Initial Inertia Weight	0.50 – 0.90
	Initial Population Size	100
	Initial Sharing Acceleration	0.50 – 2.00
	Initial Swarm Learning Process	1.00 – 2.00
	Initial Swarm Sharing Process	2.00
	Learning Parameter	1
	Maximum Value of New Position	Set of Max. Inputs
	Minimum Value of New Position	Set of Min. Inputs
	Necessary iterations	100 – 1000
ANFIS	Membership Functions	2 – 15
	Number of Epochs	2 – 50
	Style of Membership Function	Triangular

IV. CASE STUDIES

A. Wind Power Prediction

The HPM model was used to predict the wind power for 3 hours ahead with a time-step of 15 minutes till complete 24 hours ahead (short-term prediction), considering the historical data of wind power in Portugal between 2007 and 2008 as described in [12] where were considered the different seasons of the year. Also, for a fair and clean comparison, only historical data of wind power is used, i.e., no exogenous data are taken into account.

Figures 4 and 5 show the numerical wind power results for spring and fall days, respectively. In both results is possible to observe how the HPM model accurately predict the sudden and heavy changes of wind power profiles, i.e., its uncertainty behavior in the whole day of prediction in analysis day.

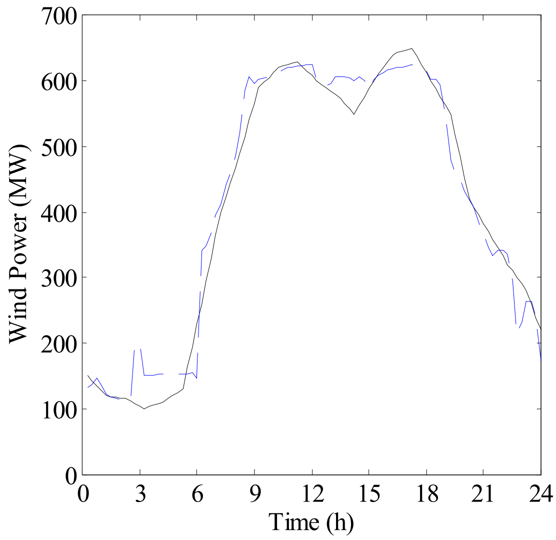

Fig. 4. Real (black), and predicted (dashed blue line) of wind power results for spring day in Portugal.

Additionally, Tables II, III and IV, show a comparison between HPM model with other previous model published in specialized literature, regarding MAPE, daily error variance and NMAE criterion respectively.

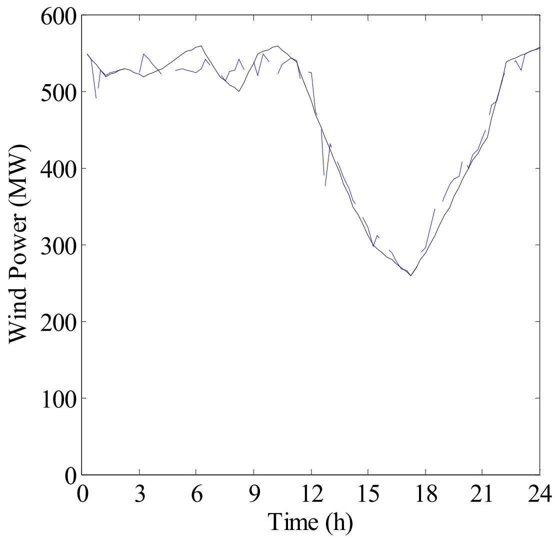

Fig. 5. Real (black), and predicted (dashed blue line) of wind power results for fall day in Portugal.

TABLE II
COMPARATIVE MAPE OUTCOMES FOR WIND POWER

	Winter	Spring	Summer	Fall	Average
NN [12]	9.51	9.92	6.34	3.26	7.26
NF [12]	8.85	8.96	5.63	3.11	6.64
WNF [12]	8.34	7.71	4.81	3.08	5.99
WPA [12]	6.47	6.08	4.31	3.07	4.98
EPA [23]	6.13	6.68	4.45	2.85	5.03
Proposed HPM	5.35	5.72	4.08	2.58	4.43

TABLE III
COMPARATIVE DAILY ERROR VARIANCE OUTCOMES FOR WIND POWER

	Winter	Spring	Summer	Fall	Average
NN [12]	0.0044	0.0106	0.0043	0.0010	0.0051
NF [12]	0.0041	0.0086	0.0038	0.0008	0.0043
WNF [12]	0.0046	0.0051	0.0021	0.0011	0.0032
WPA [12]	0.0021	0.0035	0.0016	0.0011	0.0021
EPA [23]	0.0022	0.0032	0.0017	0.0011	0.0021
Proposed HPM	0.0026	0.0030	0.0013	0.0007	0.0019

TABLE IV
COMPARATIVE NMAE OUTCOMES FOR WIND POWER

	Winter	Spring	Summer	Fall	Average
NN [12]	5.22	3.72	2.35	2.15	3.36
NF [12]	4.86	3.36	2.09	2.05	3.09
WNF [12]	4.58	2.89	1.78	2.03	2.82
WPA [12]	3.56	2.28	1.60	2.02	2.37
Proposed HPM	1.02	0.89	0.39	0.44	0.69

B. *Electricity Market Prices Prediction*

The HPM model was used also to predict the Spanish EMP for the next 168 hours with a time-step of 1 hour considering the previous 6 weeks. More details are available in [17]. As previous case study, to allow a fair and clean comparison, no exogenous data are taken into account, and the whole 4 seasons were considered for comparison. Figures 6 and 7 show the numerical results for summer and winter weeks considering EMP study, respectively. In both results is again possible to observe how the HPM model accurately predict the behavior in the whole week of prediction in each analysis week. Furthermore, Tables V and VI, show a comparison between HPM model with other previous model published in specialized literature, regarding MAPE, and weakly error variance and criterion respectively. The CPU time was less than 2 minutes, on average, in all cases studied, running in standard PC with 2GHz CPU and 4GB of RAM.

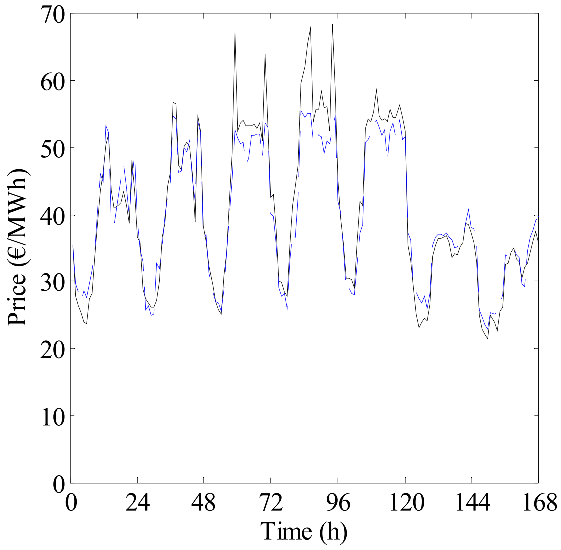

Fig. 6. Real (black), and predicted (dashed blue line) of EMP results for summer week in mainland Spanish market.

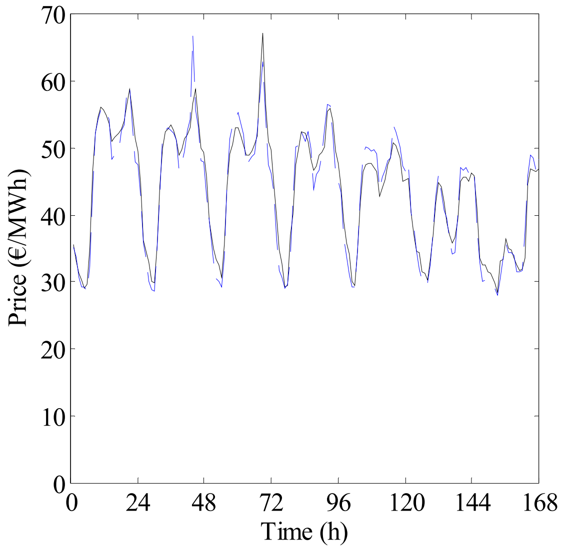

Fig. 6. Real (black), and predicted (dashed blue line) of EMP results for winter week in mainland Spanish market.

TABLE V
COMPARATIVE MAPE OUTCOMES FOR EMP

	Winter	Spring	Summer	Fall	Average
FNN [17]	4.62	5.30	9.84	10.32	7.52
HIS [17]	6.06	7.07	7.47	7.30	6.97
AWNN [17]	3.43	4.67	9.64	9.29	6.75
NNWT [17]	3.61	4.22	9.50	9.28	6.65
CNEA [17]	4.88	4.65	5.79	5.96	5.32
EPA [24]	3.59	4.10	6.39	6.40	5.12
Proposed HPM	3.55	3.70	6.16	6.28	4.92

TABLE VI
COMPARATIVE WEAKLY ERROR VARIANCE OUTCOMES FOR EMP

	Winter	Spring	Summer	Fall	Average
FNN [17]	0.0018	0.0019	0.0092	0.0088	0.0054
AWNN [17]	0.0012	0.0031	0.0074	0.0075	0.0048
NNWT [17]	0.0009	0.0017	0.0074	0.0049	0.0037
HIS [17]	0.0034	0.0049	0.0029	0.0031	0.0036
CNEA [17]	0.0036	0.0027	0.0043	0.0039	0.0036
EPA [24]	0.0012	0.0016	0.0048	0.0032	0.0027
Proposed HPM	0.0008	0.0013	0.0037	0.0017	0.0019

V. CONCLUSIONS

A novel hybrid model, called HPM, was proposed for short-term wind power and EMP prediction. An innovative combination of relevant models (DEEPSO and ANFIS) was proposed for the first time to predict wind power and EMP behavior, considering only historical data within each field of prediction. The comparison carried out shows an interesting improvement, where the MAPE criterion reached 4.43% in case of wind power and 4.92% in case of EMP. The error variance reached 0.0019 and 0.0019, respectively, showing the enhanced precision of the proposed model without considering exogenous data, working only with historical data available from public domain, providing also a tractable trade-off between computational time and MAPE, which is important for real-life applications.

ACKNOWLEDGEMENTS

This work was supported by FEDER funds through COMPETE and by Portuguese funds through FCT, under FCOMP-01-0124-FEDER-020282 (Ref. PTDC/EEA-EEL/118519/2010), UID/CEC/50021/2013 and SFRH/BPD/103079/2014, and also by funds from the EU 7th Framework Programme FP7/2007-2013 under GA no. 309048.

REFERENCES

[1] R. Dufo-López, J. L. Bernal-Agustín, and C. Monteiro, "New Methodology for the Optimization of the Management of Wind Farms, Including Energy Storage," *Appl. Mechanics Materials*, vol. 330, pp. 183-187, 2013.

[2] E. M. G. Rodrigues, G. J. Osório, R. Godina, A. W. Bizuayehu, J. M. Lujano-Rojas, J. C. O. Matias, and J. P. S. Catalão, “Modelling and Sizing of NaS (sodium sulfur) Battery Energy Storage System for Extending Wind Power Performance in Crete Island,” *Energy*, vol. 90, pp. 1606-1617, 2015.

[3] L. Li, and J. Wang, “Sustainable energy development scenario forecasting and energy saving policy analysis of China,” *Renew. Sust. Energy Rev.*, vol. 58, pp. 718-724, 2016.

[4] W. -Y. Chang, “A Literature Review of Wind Forecasting Methods,” *J. Power Energy Eng.*, vol. 2, pp. 161-168, 2014.

[5] R. Weron, “Electricity Price forecasting: A Review of the State-of-the-Art with a Look into the Future,” *Int. J. Forecasting*, vol. 30, pp. 1030-1081, 2014.

[6] D. C. Rakesh, M. K. Sailaja, and M. Sydulu, “A Detailed Literature Review on Wind Forecasting,” *in Proc. International Conf. Power, Energy and Control – ICPEC*, Tamilnadu, India, pp. 630-634, 2013.

[7] Y. Ren, P. N. Suganthan, and N. Srikanth, “Ensemble methods for Wind and Solar Power Forecasting – A State-of-the-Art Review,” *Renew. Sust. Energy Rev.*, vol. 50, pp. 82-91, 2015.

[8] P. Mandal, A. U Haque, J. Meng, A. K. Srivastava, and R. Martinez, “A Novel Hybrid Approach Using Wavelet, Firefly Algorithm, and Fuzzy ARTMAP for Day-Ahead Electricity Price Forecasting,” *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1041-1051, 2013.

[9] J. P. S. Catalão, H. M. I. Pousinho and V. M. F. Mendes, “Hybrid Wavelet-PSO-ANFIS Approach for Short-Term Electricity Prices Forecasting,” *IEEE Trans. Power Syst.*, vol. 26, pp. 137-144, 2011.

[10] L. Hui, T. Hong-qi, P. Di-fu, and L. Yan-fei, “Forecasting Models for Wind Speed Using Wavelet, Wavelet Packet, Time Series and Artificial Neural Networks,” *Appl. Energy*, vol. 107, pp. 191-208, 2013.

[11] Y. Wi-Chang, Y. Yuan-Ming, C. Po-Chun, K. Yun-Chin, V. Chung, “Forecasting Wind Power in the Mai Liao Wind Farm Based on the Multi-Layer Perceptron Artificial Neural Network Model with Improved Simplified Swarm Optimization,” *Elect. Power Energy Syst.*, vol. 55, pp. 741-748, 2014.

[12] G. J. Osório, J. C. O. Matias, and J. P. S. Catalão, “Short-Term Wind Power Forecasting Using Adaptive Neuro-Fuzzy Inference System Combined with Evolutionary Particle Swarm Optimization, Wavelet Transform and Mutual Information,” *Renew. Energy*, vol. 75, pp. 301-307, 2015.

[13] L. Xiao, J. Wang, X. Yang, and L. Xiao, “A Hybrid Model Based on Data Preprocessing for Electrical Power Forecasting,” *Elect. Power Energy Syst.*, vol. 64, pp. 311-327, 2015.

[14] H. Chitsaz, N. Amjady, and H. Zareipour, “Wind Power Forecast Using Wavelet Neural Network Trained by Improved Clonal Selection Algorithm,” *Energy Conv. Manag.*, vol. 89, pp. 588-598, 2015.

[15] V. González, J. Contreras, and D. W. Bunn, “Forecasting Power Prices Using a Hybrid Fundamental Econometric Model,” *IEEE Trans. Power Syst.*, vol. 27, pp. 363-372, 2012.

[16] S. Anbazhagan, and N. Kumarappan, “Day-Ahead Deregulated Electricity Market Price Forecasting Using Recurrent Neural Network,” *IEEE Syst. J.*, vol. 7, pp. 866-872, 2013.

[17] G. J. Osório, J. C. O. Matias, and J. P. S. Catalão, “Electricity Prices Forecasting by a Hybrid Evolutionary-Adaptive Methodology,” *Energy Conv. Manag.*, vol. 80, pp. 363-373, 2014.

[18] M. K. Kim, “Short-Term Price Forecasting of Nordic Power Market by Combination Levenberg–Marquardt and Cuckoo Search Algorithms,” *IET Gen. Transm. Distrib.*, vol. 9, pp. 1553-1563, 2015.

[19] M. Alamaniotis, D. Bargiotas, N. G. Bourbakis, and L. H. Tsoulalas, “Genetic Optimal Regression of Relevance Vector Machines for Electricity Pricing Signal Forecasting in Smart Grids,” *IEEE Trans. Smart Grid*, vol. 6, pp. 2997-3005, 2015

[20] V. Miranda, L. M. Carvalho, M. A. Rosa, A. M. L. Silva, and C. Singh, “Improving power system reliability calculation efficiency with EPSO variants,” *IEEE Trans. Power Syst*., vol. 24, pp.1772-1779, Nov. 2009.

[21] V. Miranda, and R. Alves, “Differential Evolutionary Particle Swarm Optimization (DEEPSO): A Successful Hybrid,” *in Proc. 11th IEEE Brazilian Congress on Computational Intelligence – BRICS2013*, Recife, Brazil, pp. 368-374, 2013

[22] Differential Evolutionary Particle Swarm Optimization – DEEPSO. (2016). [Online]. available: http://epso.inescporto.pt/deepso/deepso-basics

[23] J. P. S. Catalão, C. J. Osório, and H. M. I. Pousinho, “Short-Term Wind Power Forecasting Using a Hybrid Evolutionary Intelligent Approach,” *in Proc. 16th International Intelligent System Application to Power Systems – ISAP2011*, Hersonissos, Greece, pp. 1-5, 2011.

[24] J. P. S. Catalão, G. J. Osório, and H. M. I. Pousinho, “Application of an Intelligent System Based on EPSO and ANFIS to Price Forecasting,” *in Proc. 16th International Intelligent System Application to Power Systems – ISAP2011*, Hersonissos, Greece, pp. 1-5, 2011.