# Influence of deep learning on precision improvement in predictive models of Wind Power Generation

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***Abstract*— This paper, proposes the use of Deep Learning in predictive nonparametric models that use artificial intelligence tools to approximate power curves of wind farms. Three different tools are evaluated: artificial neural networks, fuzzy inference systems and Auto Encoders, an initial model of deep learning networks. The tools are inserted in a non-parametric model of power prediction, where they are compared. The results show that the autoencoder-based power curve performs well above other proposed tools. This significantly improves the performance of the predictive power model.**

***Keywords—Wind Power Prediction, Power Curves, wind Farms, Artificial Intelligence, Deep learning***

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## I. Introduction

Due to the growth of the energy demand in Brazil, the wind power source has been a very plausible solution, but this one has a basic characteristic, the variability of wind, which generates the possibility of new heuristics focused on the wind power forecast. Investigating new possibilities, the predictive power models, can be linked to parks or wind turbines, whose type can be parametric or non-parametric. In the case of non-parametric models, the highlight go to the predictive models that tend to adjust the power curve. For the adjustment of power curve in the predictive model, artificial intelligence tools are used, as: Artificial neural networks, Fuzzy inference systems, and new study tendencies such as the Deep Learning models. These tools have an essential role to aggregate accuracy of the response of predictive models.

## II. Objective

The main goal of this paper is to show how artificial intelligence tools are effective in the approximation of predictive models, in particular, new techniques that use deep learning concepts to attest the accuracy of wind power predictions. Analyzes were performed for two wind farms titled X and Y located in the northeast of Brazil, cited in [1]. Then, a comparison is made between the efficiency of the tools used in the predictive model, at the end are exposed the conclusions and settings.

## III. Non-parametric models of power curves

### A. Non-parametric model of the power curve using Artificial Neural Networks.

In this paper, two non-parametric models of power curves are created and evaluated in [1] and later published in [1]. The network models have two architectures, one with one input and one output and the other with two inputs and one output. The inputs are the wind speed (m/s) and wind direction (º) and the outputs the Power (MW). The parameters of these networks are described in [1] and [2]. They are named PCANN1 and PCANN2.

Figures 1 to 4 show the respective architectures of the non-parametric models of the power curves using neural networks for Park X and Park Y.

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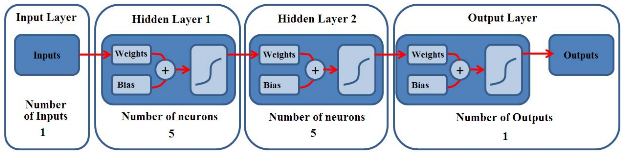


Fig. 1. PC1ANN Architecture for Park X chosen in the learning period (Source: [1]).

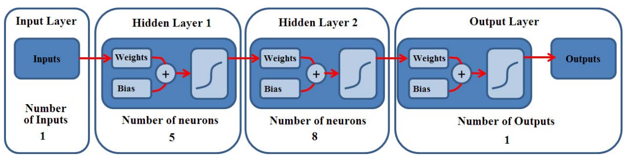


Fig. 2. PC1ANN Architecture for Park Y chosen in the learning period (Source: [1]).

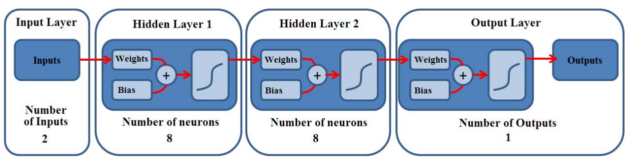


Fig. 3. PC2ANN architecture for Park X chosen during the learning period (Source [1]).

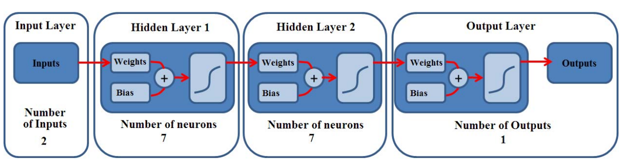


Fig. 4. PC2ANN Architecture for Park Y chosen during the learning period (Source [1]).

*B. Non-parametric model of the power curve using Fuzzy Inference Systems.*

In this paper two models of Fuzzy power curves with the same architecture of the RNA power curves created and evaluated in [2] and later published in [1] are used. Two using the Mamdani inference [3] and two using the TSK inference [4], the same are named PC1Fuzzy and PC2Fuzzy.

Figures 5 and 6 show the respective architectures of non-parametric models of power curves using fuzzy inference systems for Park X and Park Y.

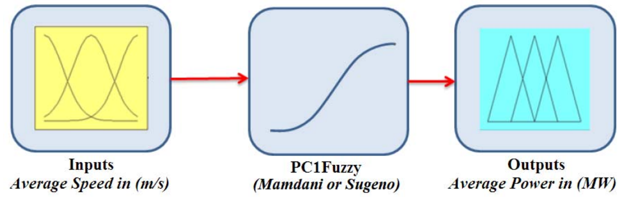


Fig. 5. PC1Fuzzy Architecture (Source: [1]).

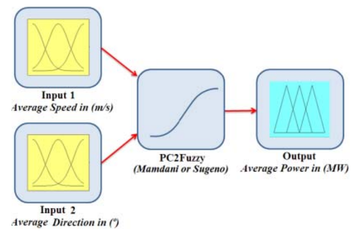


Fig. 6. PC2Fuzzy architecture.

*C. Auto Encoders*

Autoencoders or "Diabolo networks" [5] belong to a specific set of neural networks, called encryptors. These networks are a type of deep learning network of initial conjuncture; where, according to the complexity of the problem can constitute chains of encryptors, resulting in a "stacked autoencoder" [6] and [7].

In this article only simple autoencoders are treated, i.e., with a single input and output layer. In general, the formation of a self-encoder is not a difficult task, its training is intended to encode an input *(a)* into a counter-domain representation *g(a)*, so that the input *(a)* can be reconstituted through its codified representation function.

The decode function, *f (g (a))* produces the reconstruction of the network, being generally a vector of values obtained through a transfer function, this being: sigmoid logistic *"logsig"*, pure linear "*purelin"* or saturated linear *"satlin"*. The main duty of self-enrichment training is the creation of a function *g (a)* whose distributed representation of the data captures the major factors of its variations.

For the self-encoder training a pair of related inputs was used as shown by Equation 1, where the pair is assembled as the input vector, with half of its elements composed of mean speed values and half composed of mean values of power rating. In this way a single input with two coding functions established.

$$[v_{input}\ P_{output}] \tag{1}$$

Each variable is approximated by a different coding function, as shown by Equations 2 and 3:

$$v_{input} \to g_v(v_{input}) \tag{2}$$

$$P_{output} \to g_P(P_{output}) \tag{3}$$

Thus, internally the auto encoder suit $v_{input}$ to an $P_{output}$ as shown by Equation 4.

$$[v_{input}\ P_{output}] \tag{4}$$

Figure 7 shows the respective non-parametric model of the power curve using the autoencoder for Parks X and Y.

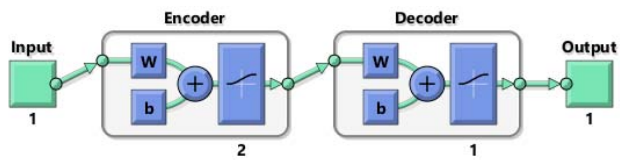


Fig. 7. PCAutoencoder Architecture for Park X and Y chosen during the learning period.

## IV. FORECASTING MODEL

The predictive model can have two different architectures according to the chosen power curve model, such architectures will depend on the number of analysis variables, these being (average speed (m/s)) or (average speed (m/s) and average direction (º)).

To deliver predicted values for approximate power curves depending on the architecture, the predictive model will have, its analysis horizon within the next 24 hours. Thus, it will use two forward-looking neural networks, according to previously mentioned architectures, where the parameters of these networks are described in [1] and [2], they are named ANN1 and ANN2.

Figures 8 and 9, show the ANN1 and ANN2 network architectures. Figure 10 show the architecture of predictive model.

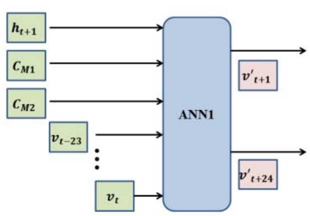


Fig. 8. Architecture of the ANN1 for Park X and Y (Source [1]).

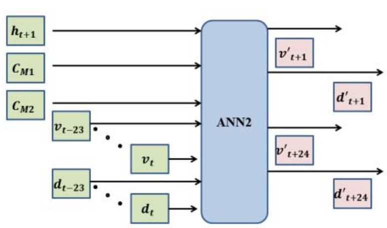


Fig. 9. Architecture of the ANN2 for Park X and Y (Source [1]).

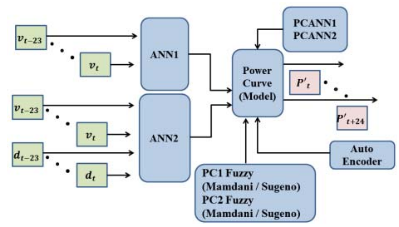


Fig. 10. Architecture of the Previsor Power Model for Park X and Y.

For the analysis and comparison between the proposed models with respect to the expected generation (MW), prediction error indices of [8] are used, such as: the MAE and the NMAE arranged according to equations 5, 6 and 7.

$$e_P(k) = P(k) - \overline{P}(k), \tag{5}$$

$$MAE_P(k) = mean(|e_P(k)|), \tag{6}$$

$$NMAE_P(k) = \frac{1}{P_{Max_{Instal}}} mean(|e_P(k)|), \tag{7}$$

## V. ANALYSIS AND RESULTS

For the analyses of the proposed models, were used the same periods of learning and simulation considered in [2], expressed in Table (I). In the same, the respective training and simulation periods are arranged.

TABLE I. DIVISION OF THE MODELS FEED PATTERNS.

| ***Sets*** | ***Learning - (Nº of Patterns)*** | ***Simulation - (Nº of Patterns )*** |
|---|---|---|
| Park 01 | (14h) 02/04/2010 - (22h) 30/12/2011 (2064 Patterns) | (23h) 01/01/2012 – (9h) 10/11/2012 (3664 Patterns) |
| Park 02 | (10h) 05/10/2010 - (23h) 29/03/2013 (3950 Patterns) | (23h) 01/04/2013 - (0h) 08/04/2014 (1390 Patterns) |

In an objective way, the results of the comparison between the predictions performed by the predictor using the non-parametric models of the respective power curves are shown. Table II shows the coding for each power curve model used in this paper:

TABLE II. CODIFICATION ABOUT THE PAPER MODELS

| ***Model*** | ***Code*** | ***Model*** | Code |
|---|---|---|---|
| PC1ANN | ( A ) | PC1Fuzzy (Sugeno) | ( E ) |
| PC2ANN | ( B ) | PC2Fuzzy (Sugeno) | ( F ) |
| PC1Fuzzy (Mamdani) | ( C ) | PC Autoencoder | ( G ) |
| PC2Fuzzy (Mamdani) | ( D ) | - | |

Table III shows the comparison between the values of the indices according to the power curve model used and the park under analysis.

TABLE III. MAE [MW] FOR THE MODELS OF PARK X

| Code | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1h | 5.498 | 5.900 | 5.468 | 5.996 | 5.766 | 5.970 | 1.007 |
| 2h | 7.431 | 7.793 | 7.435 | 7.726 | 7.704 | 7.667 | 1.009 |
| 3h | 8.786 | 8.785 | 8.765 | 8.609 | 9.106 | 8.559 | 1.014 |
| 4h | 8.906 | 9.318 | 8.932 | 9.241 | 9.111 | 9.161 | 1.019 |
| 5h | 9.495 | 9.271 | 9.500 | 9.203 | 9.774 | 9.113 | 1.026 |
| 6h | 9.689 | 9.694 | 9.713 | 9.620 | 9.958 | 9.527 | 1.033 |
| 7h | 10.273 | 10.024 | 10.290 | 9.912 | 10.605 | 9.823 | 1.039 |
| 8h | 10.458 | 9.842 | 10.448 | 9.721 | 10.786 | 9.675 | 1.045 |
| 9h | 10.829 | 9.732 | 10.802 | 9.629 | 11.137 | 9.589 | 1.050 |
| 10h | 10.587 | 9.980 | 10.554 | 9.877 | 10.864 | 9.833 | 1.049 |
| 11h | 10.359 | 10.238 | 10.349 | 10.008 | 10.578 | 9.949 | 1.046 |
| 12h | 10.367 | 10.207 | 10.355 | 10.158 | 10.605 | 10.050 | 1.047 |
| 13h | 10.520 | 10.164 | 10.464 | 10.082 | 10.803 | 10.011 | 1.045 |
| 14h | 10.673 | 10.282 | 10.658 | 10.162 | 10.939 | 10.076 | 1.043 |
| 15h | 10.632 | 10.426 | 10.615 | 10.376 | 10.948 | 10.237 | 1.040 |
| 16h | 10.735 | 10.419 | 10.707 | 10.182 | 11.020 | 10.084 | 1.035 |
| 17h | 10.507 | 10.882 | 10.481 | 10.587 | 10.773 | 10.468 | 1.035 |
| 18h | 10.563 | 10.879 | 10.534 | 10.667 | 10.868 | 10.530 | 1.035 |
| 19h | 10.275 | 10.139 | 10.254 | 10.066 | 10.591 | 9.966 | 1.035 |
| 20h | 10.359 | 10.324 | 10.323 | 10.198 | 10.713 | 10.104 | 1.040 |
| 21h | 10.602 | 10.259 | 10.590 | 10.314 | 10.983 | 10.218 | 1.044 |
| 22h | 10.400 | 10.616 | 10.383 | 10.555 | 10.717 | 10.497 | 1.046 |
| 23h | 10.553 | 11.061 | 10.557 | 10.934 | 10.819 | 10.868 | 1.047 |
| 24h | 10.626 | 10.738 | 10.617 | 10.666 | 10.919 | 10.638 | 1.049 |
| Mean | 9.963 | 9.874 | 9.950 | 9.770 | 10.254 | 9.692 | 1.037 |
| Std. | 1.235 | 1.110 | 1.232 | 1.068 | 1.246 | 1.055 | 0.013 |

TABLE IV. MAE [MW] FOR THE MODELS OF PARK Y.

| Code | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| 1h | 7.231 | 7.042 | 7.223 | 7.133 | 7.146 | 7.256 | 3.937 |
| 2h | 9.205 | 9.289 | 9.000 | 9.124 | 8.975 | 9.116 | 3.920 |
| 3h | 10.158 | 9.946 | 9.910 | 9.868 | 9.930 | 9.937 | 3.895 |
| 4h | 10.389 | 10.371 | 10.368 | 10.197 | 10.339 | 10.259 | 3.920 |
| 5h | 10.570 | 10.426 | 10.571 | 10.335 | 10.552 | 10.466 | 3.924 |
| 6h | 10.606 | 10.989 | 10.610 | 10.867 | 10.571 | 10.880 | 3.920 |
| 7h | 10.809 | 11.076 | 10.807 | 10.944 | 10.770 | 11.058 | 3.948 |
| 8h | 11.041 | 11.388 | 11.065 | 11.256 | 11.007 | 11.324 | 3.965 |
| 9h | 11.154 | 10.976 | 11.275 | 11.012 | 11.184 | 11.111 | 3.959 |
| 10h | 11.185 | 11.360 | 11.308 | 11.353 | 11.235 | 11.391 | 3.952 |
| 11h | 11.192 | 11.689 | 11.459 | 11.776 | 11.328 | 11.865 | 3.952 |
| 12h | 11.245 | 11.739 | 11.389 | 11.866 | 11.285 | 11.808 | 3.926 |
| 13h | 11.085 | 11.472 | 11.247 | 11.529 | 11.151 | 11.547 | 3.870 |
| 14h | 11.065 | 11.453 | 11.270 | 11.520 | 11.168 | 11.483 | 3.809 |
| 15h | 11.290 | 11.493 | 11.515 | 11.541 | 11.402 | 11.517 | 3.794 |
| 16h | 10.916 | 10.956 | 11.247 | 11.130 | 11.136 | 11.222 | 3.766 |
| 17h | 10.649 | 10.956 | 11.041 | 11.091 | 10.919 | 11.100 | 3.769 |
| 18h | 10.690 | 10.846 | 11.063 | 10.952 | 10.932 | 11.041 | 3.776 |
| 19h | 10.717 | 10.882 | 10.959 | 11.041 | 10.823 | 11.192 | 3.778 |
| 20h | 11.020 | 11.207 | 11.126 | 11.208 | 11.041 | 11.232 | 3.781 |
| 21h | 11.023 | 11.433 | 11.293 | 11.517 | 11.186 | 11.559 | 3.778 |
| 22h | 10.998 | 11.419 | 11.315 | 11.492 | 11.198 | 11.466 | 3.752 |
| 23h | 11.178 | 11.521 | 11.305 | 11.655 | 11.201 | 11.699 | 3.745 |
| 24h | 11.429 | 11.486 | 11.664 | 11.573 | 11.512 | 11.580 | 3.739 |
| Mean | 10.702 | 10.892 | 10.835 | 10.916 | 10.750 | 10.963 | 3.857 |
| Std. | 0.873 | 1.002 | 0.963 | 1.030 | 0.942 | 1.011 | 0.084 |

TABLE V. NMAE FOR THE MODELS [% OF WIND CAPACITYT] OF PARKS X AND Y .

| Pk.X | A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|---|
| Mean | 14.120 | 13.968 | 14.126 | 13.846 | ***14.531*** | 13.736 | **1.469** |
| Pk.Y | A | B | C | D | E | F | G |
| Mean | 8.493 | 8.598 | 8.598 | 8.663 | 10.484 | 8.701 | **3.061** |

## CONCLUSION

The results show a marked advantage of the power curve model of the autoencoder over the other models. One can notice a constancy of precision over the forecast horizon. This is due to the functional connection by decoding range that the autoencoder establishes, as commented in equations 2 and 3.

In this way, the techniques of this type are very useful for the application in predictive models of variable energy generation as is the case of wind generation. Another factor is that the accuracy can still improve greatly with the addition of one more input variable coupled to the [speed, Power] pair. Another approach is the use of cascaded autoencoders with each layer being responsible for a characteristic of the power curve.

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