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# Short-term wind power prediction with harmony search algorithm: Belen region

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**Keywords**
Renewable Energy
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**ABSTRACT**

Wind power is the fastest-growing technology among alternative energy production sources. Reliable forecasting of short-term wind power plays a critical role in the acquisition of most of the generated energy. In this study, short-term wind power forecast is performed using radial-based artificial neural networks, forecast error and cost to be minimized with the harmony search algorithm. Experimented results show that, we can predict wind power with fewer features and less error by using harmony search algorithm. A %7 percent improvement in RMSE rate has been achieved with the proposed method for short-term wind power prediction.

## 1. INTRODUCTION

The required energy of the world raises nearly 4-5% every year meanwhile the fossil fuel reserve that accommodated the world's need is decreasing day by day. It is predicted that the oil, coal and natural gas reserves, which are among the basic energy resources, will be depleted in the next 30-40 years at best. The increase in the use of fossil fuels has also increased the world average temperature. Increasing temperature caused material and moral damages and loss of life by triggering various natural events such as floods and storms. Evacuations have begun with the melting of glaciers and the rise of the water level on many islands located at sea level. Without action, life in cities at sea level will not be possible. Clean energy sources have now become an obligation, not an alternative. It is essential to turn to clean resources without waiting for the depletion of energy reserves. Using renewable energy sources is advantageous in many ways. The most important of these advantages are reducing foreign dependency, providing cheap energy, no fuel expense, and being environmentally friendly. Due to these advantages, its use is increasing day by day. Wind power, one of the popular renewable energy alternatives, is of great importance in terms of the wind potential in our country. Among the European countries, Germany is the country that benefits from wind power the best. Spain follows Germany in second place. According to the German Wind power Institute DEWI, Spain's wind potential and Turkey's wind potential are equivalent. According to the wind map of our country, electricity can be produced from wind power in four seasons a year. In order to produce energy without the need for any other energy support, a storage area of 6 times the hourly production is required. Despite this high potential, wind power is the least utilized resource in energy generation.

Turkey's Wind Power Potential Atlas (REPA), prepared by the Ministry of Energy and Natural Resources and prepared by the Electrical Works Survey Administration (EIE), determines Turkey's wind power potential and guides investors. According to REPA, wind power of our country is 67 MW. Again, according to the same report, our country has a wind power potential of 50000 MW. The installation of wind power plants is also ongoing in Turkey.

There are some operational challenges for both electrical systems and electricity markets when the

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large-scale integration of wind power (Exizidis et al., 2017). Wind power prediction takes an important role in the reliable and economical process of power systems with wind leakage (Cui et al., 2017). Long-term predictions of wind energy are necessary for capacity planning and maintenance planning (Kanna and Singh, 2016). Medium term forecasts are used for maintenance planning (Alberdi et al., 2017; Bae et al., 2017), fuel planning (Guangyu et al., 2017) and hydro pool management (Meng et al., 2015). Short-term load prediction is a fundamental and vital factor for daily operations, unit commitment and timing functions, assessment of net change and system security analysis (Zhou et al., 2016a; Zhou et al., 2016b). Very short-term predictions are used for optimizing the process of wind energy reserves (Wang et al.; 2017). When the literature is reviewed, there are many studies on wind prediction in recent years (Zhuo and Savkin, 2017). Long-term wind prediction has been performed using the adaptive wavelet neural network method (Kanna and Singh, 2016). In the literature, support vector machine regression model (Ahmed et al., 2017), nonlinear autoregressive network model with extroverted inputs (Baby et al., 2017), double-tier hierarchical genetic algorithm trained artificial neural network model (Li et al.; 2017), deep learning network architecture model with stacked automatic encoders (Khodayar et al., 2017), particle swarm optimization-based adaptive neuron fuzzy inference model (Eseye et al., 2017), particle swarm optimization model integrated with mutation operator (Quan et al., 2013), K-clustering-based artificial sine network model (Xu et al., 2015) and advanced Markov model (Yang et al., 2015) are used for short-term wind prediction. Very short-term wind estimation has been performed using the spatial-temporal method (Dowell and Pinson, 2015), neural fuzzy networks method (Paixao et al., 2017), and autoregressive model and Hilbert-Huang transform method (Shi et al., 2016).

The aim of this study is to show the effects of feature selection on the performance of short-term wind power prediction. In the literature, there is no such study to our knowledge, and the results presented here will be helpful to researchers.

The rest of the paper is organized as follows: in the second section, a detailed overview of the dataset and methods are presented. Experimental results are discussed in the third section.

## 2. METHOD and DATASET

In this study, the wind power dataset produced by the Belen region wind power plant is used to predict short-term wind power using the radial-based artificial neural networks and the harmony search feature selection algorithm. Details about the dataset and methods used are given in the next subsections.

### 2.1. Dataset

The yearly data which is obtained from wind turbines in Belen region and recorded on a daily was used in this study. Wind turbine model is seen in Figure 1.

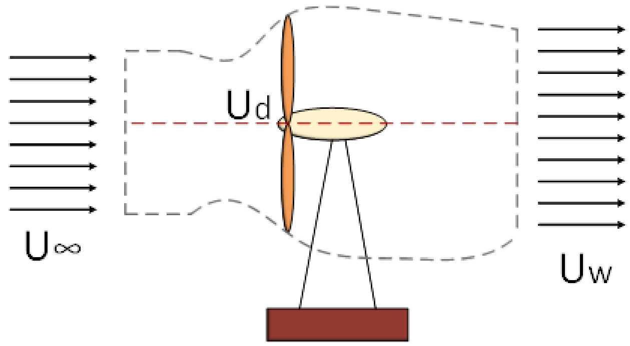


**Figure 1**. Wind Turbine Model

The dataset contains 365 different sample data with 10 numeric features; *day*, *ud*, *m*, *a*, *uw*, *U∞*, *cp*, *ct*, *trust*, *kn* and finally the *class* value representing the amount of electricity generated, which represents the output value of the modeled network.

### 2.2. Radial Based Artificial Neural Networks

Radial-based regressor was used to train the regression model in proposed study. Radial-based neural network model is shown in figure 2. While modeling the radial-based regressor, which is a supervised learning method, unlike traditional radial-based neural networks, the BFGS (Broyden-Fletcher-Goldfarb-Shanno algorithm) method, which is suitable for the optimization of nonlinear problems, has been used to minimize the quadratic error (Buhman, 2003). All attributes in the dataset used were normalized in the range of [0,1]. The model learned by the designed artificial neural network is given by equation 1.

$$f(x_1, x_2, \dots, x_m) = g(w_0 + \sum_{i=1}^{b} w_i \exp\left(-\sum_{j=1}^{m} \frac{a_j^2 (x_j - c_{i,j})^2}{2\sigma_{i,j}^2}\right)) \qquad (1)$$

Such that; $x_1, x_2, \dots, x_m$ denote the attributes used, *g(.)* denoting the activation function, *b* denoting the number of basic functions, $w_i$is the weight value of each function, $a_j^2$ represents the weight of the $j^{th}$ attribute, $c_i$ and $\sigma_i^2$ are the central and variance values of the basic functions, respectively. Attribute weights were not used during the modeling. All $a_j^2$ values are taken as 1 as a constant. The value of *b*, which is the basic function number, was chosen as 5 empirically. The Least Squared Simulated Errors function used is given in equation 2.

$$LSSE = \frac{1}{2}\sum_{i=1}^{n}(y_i - f(\underset{x_i}{\rightarrow}))^2 + (\lambda \sum_{i=1}^{b} w_i^2) \qquad (2)$$

If the $y_i$ value in the given function is the predicted value$x_i$, it is the real value. *n* is the total number of training samples. λ is the penalty coefficient used to prevent over fitting and was taken as 0.01.

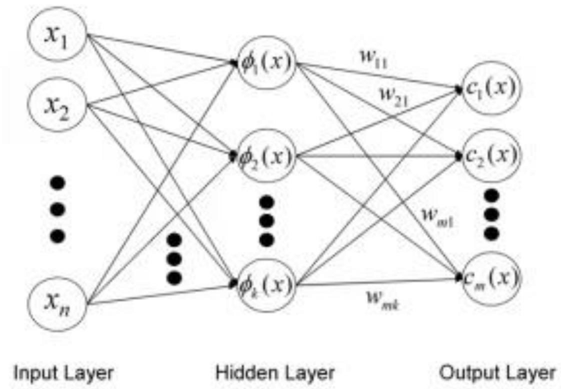


**Figure 2.** Radial-based Neural Network Model

### 2.3. Harmony Search Algorithm

Harmony search (Woo et al., 2001) is inspired by the music orchestra. It is one of the popular population-based algorithms. Like a music orchestra, which tends to create the most harmonious melody, this algorithm mimics the behavior of a music orchestra. In an orchestra, musicians repeatedly improve the melody; the HS algorithm, like the process in real orchestras, iteratively improves the fitness value of the candidate solutions. The candidate solutions are kept in the Harmony Memory. A new harmony vector is produced by applying optimization parameters to Harmony Memory.

First of all, HS start with the initialization of the HM, and then a new harmony is generated. If there is an improvement with newly generated harmony, this new harmony is included in the HM. Algorithm continues to generate the new harmony until a termination criterion is satisfied.

HS uses two different probabilistic operators to control the new harmony generation procedure, which are Harmony Memory Considering Rate (HMCR), and Pitch Adjusting Rate (PAR).

HMCR ∈[0,1], HMCR ∈[0,1], is used to define the probability of drawing a new note uniformly from the values of this same note. Without this probability value, algorithm can choose note values randomly.

PAR ∈[0,1], is similar to mutation operation in genetic algorithms, and it is used for to avoid local optima in the HS algorithm.

Pseudo code of Harmony Search Algorithm is given in Figure 3.

Nature inspired based Harmony search algorithm is used to select optimum features over wind power dataset to predict wind power with low error rates in the proposed study.

```
begin
Define fitness function f(a), a = (a_1, a_2, ..., a_N)^T
Define (HMCR),(PAR),(HMS),(EOR)
Define Maximum number of iterations (NI).
HM ← GenerateInitialPoplution()
min = minimum visible value.
max = maximum visible value.
while (iter ≤ NI) do
  while (a_i ≤ number of variables) do
    if (rand ∈ (0,1) ≤ HMCR) then
      choose a value from HM for i
      if (rand ∈ (0,1) ≤ PAR) then
        adjust the value of i by:
        a_{i_new} = a_{i_old} + rand ∈ (0,1) × bw
      end if
    else
      choose a random variable:
      a_i = min + rand ∈ (0,1) × (max − min)
    end if
  end while
  if (FitFun(new harmony solution) ≤ worst(FitFun(HM)) then
    accept the new harmony and replace the worst in HM with it.
  end if
end while
best=find the current best solution
end
```

**Figure 3.** Pseudo Code of Harmony Search Algorithm

## 3. RESULTS

In this study, the yearly data which is obtained from wind turbines in Belen region and recorded on a daily was used. So, the dataset contains 365 different sample data with 10 numeric features. The amount of electricity produced has been tried to be estimated so that other values in the data will be inputs. Radial based regressor method is used to perform the regression between the input set and the output set. Harmony search algorithm is used as feature selector. In Figure 3, Belen region and the power plant where data is taken are shown. Figure 4 shows the Turkey wind speed map.

**Figure 4.** Belen Wind Power Plant from Real Data

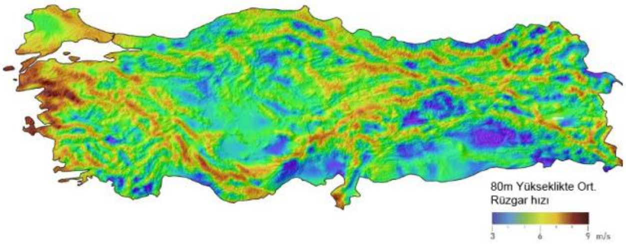


**Figure 5**. Turkey wind speed map

The dataset containing 365 samples was randomly separated as 70% training, 10% validation, and 20% testing. After the training process with radial based regressor is completed, the model is verified and tested on test data. The results obtained from the test data were evaluated according to the Root Mean Square Error (RMSE, Equation 3), Mean Absolute Error (MAE, Equation 4), and Correlation Coefficient (R, Equation 5) error measurement criteria.

$$\mathrm{RMSE} = \frac{1}{n}\left[\sum_{i=1}^{n}(O_i - P_i)^2\right] \tag{3}$$

$$MAE = \frac{1}{n}\left[\sum_{i=1}^{n}|O_i - P_i|\right] \tag{4}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_m)^2}} \tag{5}$$

For the given equations;
n: number of data in test data,
$P_i$: predicted value
$O_i$: observed value
$O_m$: is the average of the observed values.

With the error equation, the squares of the errors are taken. In this way, the effect of higher error values in the predicted values on the average is higher, and the effect of these higher error values on the entire prediction can be determined. MAE considers the absolute error between actual values and model predictions. The model can be predicted more accurately if the RMSE and MAE values are close to zero. R value is used to define the relationship between the true value and the predicted value. The R values can be in the range of [+1, -1]. If the value of R is equal to +1, which is the biggest value it can take; there is a positive and fully linear relationship between variables.

According to HS algorithm, these 7 features were chosen; *day*, *ud*, *m*, *uw*, $U_\infty$, *cp* and *trust*. Comparison of selected features on wind power prediction with all 10 features is given in Table 2.

**Table 2.** Performance comparison of the proposed system with all features

| | MAE | RMSE | R |
|---|---|---|---|
| All features | 12.92 | 17.92 | 0.9997 |
| HS Feature Selection | 4.95 | 10.80 | 0.9998 |

Experimented results show that, wind power can be predicted with fewer features and less error by using harmony search algorithm. A %7 percent improvement in RMSE rate has been achieved with the proposed method for short-term wind power prediction.

Prediction of wind power with HS selected features is given in Figure 6.

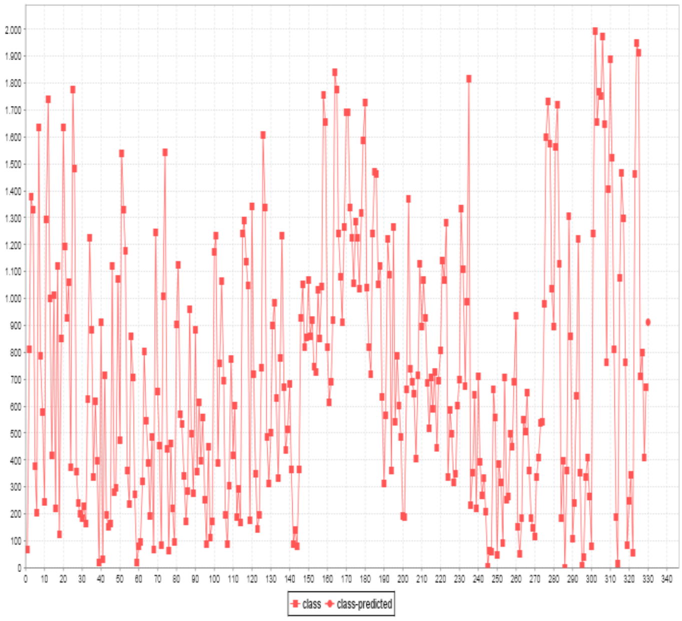


**Figure 6.** Prediction Result with Selected Features

With this study, daily wind power production was estimated and the most accurate information was tried to be given in order to adjust the storage capacities. The lower the error of the estimates, the more efficient use of the energy produced will be.

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