Wind turbine modeling with the slopes algorithm

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Abstract—In this paper, a fuzzy slopes model is introduced for the modeling of nonlinear systems with sparse data. The proposed method is the combination of the slopes and fuzzy models. The slopes model is used to obtain the missing output data of a nonlinear behavior, later, the fuzzy model is used for its approximation.

I. INTRODUCTION

The fuzzy systems and neural networks have been widely used in prediction, pattern recognition, classification, nonlinear modeling, and control [6].

In [5], [9], [11], [12], [13], [14], [20], the fuzzy systems are used as the structure of evolving intelligent systems. In [2], [3], [15], [19], [22], [23], the neural networks are used as the structure of evolving intelligent systems. New methods for exploring the evolution of social groups are mentioned in [4], [17]. An approach to predict from a data stream of real estate sales transactions is presented in [29].

Despite these above proposals, few researches have been carried out in the past to perform structure selection and parameter identification for sparse data. There is some research about sparse data modeling. In [6], kernel regression method is used for the modeling with sparse data. The story of sparse and redundant representation modeling is introduced in [7]. In [28], the authors propose a new model called sparse hidden Markov model. The authors propose a novel sparse shape composition model in [33]. In [35], a method is introduced for regression and classification problems. The above studies use noise signals considering the design as a stochastic problem, while in this paper, the deterministic problem is focused.

In this research, the slopes algorithm is used to obtain the missing data of the output of some nonlinear behavior.

On the other hand, some authors have proposed the equations to model the dynamic behavior of the wind turbine as are in [8], [16], [27], [31], and [34]. In [24], the authors present a novel dynamic model of a wind turbine, the first dynamic is for the wind turbine, the second is for the tower, and both are related. Because the rotatory tower can turn, it may help the wind turbine to increase the air intake. Some companies propose wind turbines that consider rotatory blades; however, in [24] a rotatory tower is proposed instead of the rotatory blades because the first dynamic model is easier to obtain than the second.

Researchers are often trying to improve the total power of a wind turbine. The modeling of a wind turbine plays an important role on some applications as the control, classification, pattern recognition, or prediction. Consequently, the proposed algorithm could be applied for the modeling of the wind turbine behavior.

The paper is structured as follows. In section 2, the slopes algorithm is mentioned as the first part of the proposed algorithm. In section 3, the fuzzy model is considered as the second part of the proposed algorithm. Finally, in section 4, the conclusion and future research are detailed.

II. SLOPES ALGORITHM FOR A NONLINEAR BEHAVIOR WITH SPARSE DATA

The slopes algorithm is described in this section as the first part of the proposed algorithm. The following subsection describe the algorithm proposed by this study used to obtain the missing data of a nonlinear behavior with sparse data.

A. Slopes algorithm

Consider the function $y_r(k) = f(x_k) \in \mathbb{R}$ with $x_k \in \mathbb{R}$, for $k = 1, 2, \ldots, T$, $T$ is the number of iterations, $y_r(k)$ is the output real data of the nonlinear behavior. The approximation consists to find $\hat{y}_k$ such that it approximates $y_r(k)$.

The slope of $y_r(k)$ denoted as $m_k$ using the $x_k$ and $y_r(k)$ data of the nonlinear behavior is obtained as follows [21], [30]:

$$m_k = \frac{y_r(k) - y_r(k-1)}{x_k - x_{k-1}}$$  \hspace{1cm} (1)

The nonlinear behavior is divided in $N$ intervals, each interval is generated by considering the following inequality:

$$|(m_k - m_{k-1})| \geq h$$  \hspace{1cm} (2)

where $h$ is a small selected threshold parameter, consider that the signal taken from $x_k$ for each of the $N$ intervals is denoted by $j$.

The equation (3) describes the approximation of the nonlinear behavior using the proposed slopes algorithm [21], [30]:

$$\hat{y}_k = (1 - \lambda_k) \cdot y_{i,j,k} + \lambda_k \cdot y_{f,j,k}$$  \hspace{1cm} (3)

where $y_{i,j,k}$ is the initial value of $y_r(k)$ in the interval $j$, $y_{f,j,k}$ is the final value of $y_r(k)$ in the interval $j$, $k$ is the variant iteration inside of interval $j$, $\lambda_k$ is a variant-in-time parameter of the interval $j$, $\lambda_k$ is given as [21], [30]:

$$\lambda_k = \frac{k - k_{i,j}}{k_{f,j} - k_{i,j}}$$  \hspace{1cm} (4)
where \( k_{i,j} \) is the initial value of \( \lambda_k \) in the interval \( j \), and \( k_{f,j} \) is the final value of \( \lambda_k \) in the interval \( j \).

It is known that \( k_{i,j} \leq k \leq k_{f,j} \) for each interval \( j \); consequently, \( 0 \leq \lambda_k \leq 1 \), and \( \lambda_k \) always increases.

The variant parameter \( \lambda_k \) is important in the proposed slopes algorithm because lets \( \hat{y}_k \) to approximate \( y_r(k) \) from the initial point to the final point for each interval \( j \).

### III. Fuzzy slopes model of a nonlinear system with sparse data

The fuzzy algorithm is described in this section as the second part of the proposed algorithm. The following subsection describe the algorithm proposed by this study used for the modeling of a nonlinear behavior with sparse data.

#### A. Fuzzy slopes model

In this study, sparse data is considered, consequently, the fuzzy system of this paper is used to approximate a nonlinear behavior using only the output of the slopes model, not the real data output, that is, the output of the slopes algorithm \( \hat{y}_k \) is used instead of the real data output of the nonlinear behavior \( y_r(k) \). The fuzzy model learns the behavior considering real data of the inputs and states, the eight inputs for the nonlinear behavior are denoted as \( z_1(k) = u_{1r}, z_2(k) = u_{2r}, z_3(k) = x_{1r}, z_4(k) = x_{2r}, z_5(k) = x_{3r}, z_6(k) = x_{4r}, z_7(k) = x_{5r}, \) and \( z_8(k) = x_{6r} \). The output for the learning of the fuzzy slopes model is \( y(k) = \hat{y}_k \) where \( \hat{y}_k \) denotes the output of the slopes algorithm.

The fuzzy slopes model which approximates the real data output of the nonlinear behavior \( y_r(k) \) is as follows:

\[
FS(k) = \frac{\sum_{j=1}^{m} v_j(k) \alpha_j(x_j(k))}{\sum_{j=1}^{m} \alpha_j(x_j(k))} \tag{5}
\]

where \( z_1(k), z_2(k), z_3(k), z_4(k), z_5(k), z_6(k), z_7(k), \) and \( z_8(k) \) are the eight behavior inputs, \( c_{i,j}(k) \) and \( \sigma_{i,j}(k) \) are the centers and widths of the input membership functions and \( v_j(k) \) are the centers of the output membership functions. \( m \) is the rules number. \( \alpha_j \) is the Gaussian function given as follows:

\[
\alpha_j(x_j(k)) = \exp(x_j(k)) \tag{6}
\]

where \( x_j(k) = -\prod_{i=1}^{8} \frac{|x_i(k)-c_{i,j}(k)|^2}{\sigma_{i,j}^2(k)} \). The updating of the centers and widths of the input membership functions and the centers of the output membership functions for the training is given as follows:

\[
v_j(k+1) = v_j(k) - \eta_{c3} \frac{\alpha_j(x_j(k))}{\sum_{j=1}^{m} \alpha_j(x_j(k))} e_{FS}(k) \tag{7}
\]

\[
c_{i,j}(k+1) = c_{i,j}(k) - \eta_{c3} \beta_{c}(e_{FS}(k)) \tag{8}
\]

\[
\sigma_{i,j}(k+1) = \sigma_{i,j}(k) - \eta_{\sigma3} \beta_{\sigma}(e_{FS}(k)) \tag{9}
\]

\[
\beta_{c}(k) = \frac{2\alpha_j(x_j(k))[c_{i,j}(k)-c_{i,j}(k)z_{i,j}(k)]}{\sum_{j=1}^{m} \alpha_j(x_j(k))} \tag{10}
\]

\[
\beta_{\sigma}(k) = \frac{2\alpha_j(x_j(k))[c_{i,j}(k)-c_{i,j}(k)z_{i,j}(k)]}{\sum_{j=1}^{m} \alpha_j(x_j(k))} \tag{11}
\]

where \( 0 < \eta_{c3} < 1, 0 < \eta_{c3} < 1 \) and \( 0 < \eta_{\sigma3} < 1 \) are the constant learning speeds, the initial weights \( v_j(1), c_{i,j}(1), \) and \( \sigma_{i,j}(1) \) are the fuzzy error defined as follows:

\[
e_{FS}(k) = FS(k) - \hat{y}_k \tag{12}
\]

where \( FS(k) \) is the output of the fuzzy slopes model and \( \hat{y}_k \) is the output of the slopes algorithm.

Note that the eight inputs of the fuzzy slopes algorithm because they are the real data of the inputs and states of the analytic model of [24].

### IV. Conclusion

In this paper, a fuzzy slopes model is proposed for the modeling of the wind turbine behavior. Important experiments to show how a fuzzy slopes model can improves an analytic model are shown in [25]. The proposed technique could be used in control, prediction, or classification. As a future research, the modeling will be used in the design of interesting applications as are the control [1], [18].

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### REFERENCES


