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Research Article

Use of Wiener-Hammerstein (WH) Model Optimized with Genetic Algorithm in Identification of Photovoltaic System

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Abstract

System identification is a method of identification or measuring a mathematical model of a system by measuring the inputs and outputs of the system. In this paper we apply the Genetic Algorithm (GA) approach to model a photovoltaic (PV) systems with a Wiener-Hammerstein structure. Non-linear dynamic systems have both dynamic elements (energy storage elements) and in these types of systems there are non-linear relationships between some variables. If in such systems it can be assumed that dynamic parts and non-linear parts are separable, they can be modeled with the structures of block-oriented models. These types of models are composed of a combination of linear dynamic block(s) and static nonlinear block(s). This approach is concerned with the estimation of a photovoltaic (PV) system based on observed data. The nonlinear input and output are taken from the irradiance and DC output current data of the real system, respectively. The simulation results revealed the effectiveness and robustness of the proposed model using a genetic algorithm. The simulation results show an MSE value of 0.000774 for normal operation of the PV system and 0.009863 for the shading effect between the estimated and reference information rates.

Keywords: System Identification, Wiener-Hammerstein Model, Photovoltaic (PV) System, Genetic Algorithm.

Highlights

- Identifying the photovoltaic system in normal and shadow operating conditions.
- Using the block-oriented model.
- Using Wiener-Hammerstein model optimized with genetic algorithm.

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1- Introduction

The purpose of system identification is to obtain a mathematical model of a phenomenon (for example, a dynamic system) using laboratory information. This definition indicates the importance of this technique in various engineering fields, such as the identification of biological systems, industrial processes, economic systems, aerospace, and automotive. The purpose of modeling is engineering analysis, simulation, status measurement, forecasting, and control. The following steps we performed to identify the system:

1. Select a model class based on basic knowledge.
2. Input Design, Testing, and Data Collection
3. Parameterizing the model class based on the theory of realization and recognizability
4. Estimation of model parameters
5. Evaluation of the model based on the objective function

Recently, system identification has attracted the attention of many researchers and practitioners because there is difficulty in modeling many systems using physical modeling approaches. Good experimental mathematical models that show a variety of practical applications in various fields of engineering are needed to meet different needs [1]. These needs may include understanding and analyzing the limitations of existing systems, predicting and simulating new experiments, or designing or modifying new ones. Unlike many machine learning methods, system identification gives more insight into system structure and dynamics. A very common approach in identifying systems is to use the model structure methods used in this work. Because the model is an approximation of the real system, a balance must be established between the complexity of the model structure and the accuracy of these predictions. In many cases, linear models can be used to generate accurate predictions of a system's behavior, particularly if its performance is limited to a small area. However, if the model is required to cover a larger work area, a nonlinear model is required. One of the most challenging problems in identifying a nonlinear system is the choice of a suitable model structure. Currently, there are several structures based on neural networks [2], block–oriented models [3-4], Volterra series [5], NARMAX models [5], and fuzzy models [7]. A study on black box methods for nonlinear identification was conducted by [8]. Nonlinear dynamic systems have both dynamic elements (energy storage elements), and nonlinear relationships exist between some variables in these types of systems. In such systems, it can be assumed that the dynamic and nonlinear parts are separable, and they can be modeled using block-oriented models. These models consist of a combination of linear dynamic blocks (s) and static nonlinear blocks (s). Block-oriented models can be divided according to how nonlinear and linear dynamic factors are located:

Wiener model: In this model, the input signal is first filtered by the linear conversion function and then enters the nonlinear factor. This model is a simplified mode of the Wiener series model [9-17].

Hammerstein model: In this model, the input first enters the nonlinear block and then the resulting signal is filtered by the linear conversion function. [18-26],

Hammerstein-Wiener model: This model consists of combining a series of two nonlinear factors with a linear conversion function between them. [27-30],

Wiener-Hammerstein model: Such a model is created by combining the Wiener model series and the Hammerstein model. That is, it consists of two linear conversion functions, between which there is a nonlinear factor. [31-40].

In this paper, we are dealing primarily with Wiener-Hammerstein-type nonlinear systems. These types of systems have simple structures that consist of a series combining a static nonlinear part with two dynamic linear parts. In many cases, the linear section is modeled as a filter, and the terms linear system and filter are used interchangeably. One of the advantages of this model is that it considers nonlinear behavior statically and linear behavior dynamically. These structures are very simple and have been used frequently in many control users. Many identifications have been developed for these structures.

Many approaches to identifying parameter Wiener-Hammerstein systems have been proposed by academics and engineers.

In [31], a new approach to identifying Wiener-Hammerstein model structures has been developed. In the first step, the system is triggered by a set of fixed inputs to capture the nonlinearity of the system. In the second stage, an identification approach based on spectral analysis is developed using periodic input signals to determine the parameters of linear elements. In the present method, very interesting concepts such as Fourier analysis, frequency approach and spectrum analysis have been used. In [32], nonlinear dynamic systems are approximated by a series of Volterra. To use the Volterra representation While the purpose of a blockchain model can be interpreted, a link is established between the Volterra representation and the Wiener-Hammerstein parallel model, based on the separation of multivariate polynomials. Then the problem of modified separation of the parameters of the Wiener-Hammerstein parallel model of the system is solved. In [33], the identification of the Wiener-Hammerstein model is expressed as a multi-objective optimization (MOP) problem. The accuracy is calculated by the absolute mean error (MAE) between the actual output and the quantitative estimate. Using WH-MOEA, a method for analyzing different linear structures with various poles and zeros (known as design concepts) is proposed. Comparison of Pareto fronts in any design concept allows for in-depth analysis to select the most appropriate model according to the user's needs. In [34], it proposes an iterative random forest (RF) as an alternative to hybrid dynamic selection. This is like re-choosing holiday destinations based on random traveler recommendations. The proposed technique supports a relatively high noise level and requires optimization of a model. Therefore, the increase in processing time is achieved without any prior knowledge of model configuration on both simulated samples and standard data.

In this study, we show that it is possible to obtain a good Wiener-Hammerstein model with a genetic algorithm by solving a single optimization problem, where user interaction is only required at the beginning, simply configuring simple parameters of a genetic algorithm. With regard to the nonlinear nature of the system and the mathematical complexity of classical methods, or the high estimation error of these methods in the identification of nonlinear systems, in this study, the genetic algorithm, which is in the category of modern methods, is used.

In this study, we used a validation data sequence to determine model quality. The validation dataset was obtained from the system to be modeled. This was not used in the estimation step. Based on the error between the measured and simulated data using this data sequence as an excitation, we can assess whether the model satisfies the quality requirements.

The rest of this paper is organized as follows. In Section 2, the method for the identification of Wiener-Hammerstein systems is introduced. The optimization problem statement is presented in Section 3 to demonstrate the good results and practical applicability of the proposed identification methods. Section 4 presents the simulation results. Finally, in Section 5, conclusions are presented.

2. Innovation and contributions

In this study, the mean square error for the genetic algorithm designed for the input and output data is the criterion for network evaluation. In this paper, the execution time of the genetic algorithm for the photovoltaic (PV) system under Normal Operating is 85.52 seconds and the photovoltaic (PV) system under Shading Operating is 94.16 seconds. Among the innovations of this paper, the following can be stated:

1- The identification of a Weiner Hammerstein model for photovoltaic (PV) systems under normal and shading operating conditions using a genetic algorithm was studied.

2-This approach is concerned with the estimation of a photovoltaic (PV) system based on observed data.

3-The Wiener-Hammerstein model consists of two linear dynamic blocks, with a nonlinear static block between them.

4-The simulation results revealed the effectiveness and robustness of the proposed model using a genetic algorithm.

3. Materials and Methods

In this study, we show that it is possible to obtain a good Wiener-Hammerstein model with a genetic algorithm by solving a single optimization problem, where user interaction is only required at the beginning, simply configuring simple parameters of a genetic algorithm. With regard to the nonlinear nature of the system and the mathematical complexity of classical methods, or the high estimation error of these methods in the identification of nonlinear systems, in this study, the genetic algorithm, which is in the category of modern methods, is used.

In this study, we used a validation data sequence to determine model quality. The validation dataset was obtained from the system to be modeled. This was not used in the estimation step. Based on the error between the measured and simulated data using this data sequence as an excitation, we can assess whether the model satisfies the quality requirements.

The governing equations for the nonlinear Wiener-Hammerstein model are as follows:

$$x = a_1 u^2 + a_2 u + a_3 \tag{1}$$

$$F[x] = \frac{b_1 z + b_2}{c_1 z^2 + c_2 z + c_3} \tag{2}$$

$$y_{estimated} = d_1 r^2 + d_2 r + d_3 \tag{3}$$

The cost function, called the mean square error (MSE), is usually expressed as a time- averaged function defined by Equation (10). In this study, a quite different search approach, based on evolutionary computation theory, is developed by genetic algorithm. Finally, the uniqueness of the cost function defined by Equation (4) is guaranteed.

$$\text{cost}_{\text{ function } = \min}(J(\theta_{estimated})) = \min((\frac{1}{N_e}\sum_{t=1}^{N_e}(y(t) - y_{estimated}(t/\theta_{estimated}))^2))$$
$$\theta = [b_0 \ b_1 \ b_2 \ldots b_{nb} \ a_0 \ a_1 \ a_2 \ldots a_{na} \ d_0 \ d_1 \ d_2 \ldots d_{nd} \ c_0 \ c_1 \ c_2 \ldots c_{nc}]^T \tag{4}$$

where N_e is the number of data points in the measured input-output record. Where $y_{estimated}/\theta_{estimated}$ denotes the best prediction of the system output $y_0(t)$ using the model induced by the parameter vector estimate $\theta_{estimated}$.

4. Results and Discussion

It is well known that the parameter update law can be obtained by minimizing the cost function. Based on the favorable motives mentioned above, a novel cost function is constructed to obtain the parameter update law for the considered systems using expanded estimation error information and initial estimate information. The unknown parameter vector θ to be estimated using the genetic algorithm for the PV system under normal operating conditions and PV systems under shading operating. In this study, the mean square error for the genetic algorithm designed for the input and output data is the criterion for network evaluation. In this paper, the execution time of the genetic algorithm for the photovoltaic (PV) system under Normal Operating is 85.52 seconds and the photovoltaic (PV) system under Shading Operating is 94.16 seconds.

5. Conclusion

In this paper, the identification of a Photovoltaic (PV) system under normal and shading operating conditions using a Weiner-Hammerstein model based on a genetic algorithm is presented. Wiener and Hammerstein systems are nonlinear models that are used in many domains owing to their simplicity and physical meaning. Different nonlinear systems with different nonlinearities use different Wiener and Hammerstein structures. In this study, owing to the nonlinearity of the system and the mathematical complexity of classical methods or the estimation error, a genetic algorithm is used in the category of modern methods. The step response results from the system identification tool for both conditions showed a good reaction to the final steady value. The simulation results showed the MSE value of 0.000774 for the normal operation of the PV system and 0.009863 for the shadow effect. Simulation results demonstrate the high accuracy of the proposed method in identifying the photovoltaic (PV) system. Suggestion for further work:

1- The use of the presented method to identify the system online can be investigated both in terms of accuracy and speed.

2- It has been shown in new articles that the real-world systems all have a degree of fractionality, so it is suggested to use the fractional order conversion function to increase accuracy.

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Appendix

Table 1: Parameters of model (under normal operating).

Parameters	Values	Equations for the nonlinear Wiener-Hammerstein model
$\mathbf{a_1}$	-1.11	$x = -1.11u^2 - 1.12u + 0.59$
$\mathbf{a_2}$	-1.12	
$\mathbf{a_3}$	0.59	
$\mathbf{b_1}$	-0.31	
$\mathbf{b_2}$	-0.22	$F[x] = \dfrac{-0.31z - 0.22}{0.02z^2 + 3.57z + 2.36}$
$\mathbf{c_1}$	0.02	
$\mathbf{c_2}$	3.57	
$\mathbf{c_3}$	2.36	
$\mathbf{d_1}$	3.51	$y_{estimated} = 3.51r^2 + 4.26r - 0.86$
$\mathbf{d_2}$	4.26	
$\mathbf{d_3}$	-0.86	
Mean Square Error (MSE)	**0.000774**	

Table 2: Parameters of model (under shading operating).

Parameters	Values	Equations for the nonlinear Wiener-Hammerstein model
$\mathbf{a_1}$	-0.37	$x = -0.37u^2 - 3.74u + 0.086$
$\mathbf{a_2}$	3.74	
$\mathbf{a_3}$	0.086	
$\mathbf{b_1}$	1.126	
$\mathbf{b_2}$	1.545	$F[x] = \dfrac{1.126z + 1.545}{0.44z^2 + 4.43z + 4.18}$
$\mathbf{c_1}$	0.44	
$\mathbf{c_2}$	4.43	
$\mathbf{c_3}$	4.18	
$\mathbf{d_1}$	-0.751	$y_{estimated} = -0.7511r^2 + 2.22r - 0.81$
$\mathbf{d_2}$	2.22	
$\mathbf{d_3}$	-0.81	
Mean Square Error (MSE)	**0.009863**	

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