energies

MDPI

Article

Modeling a High Concentrator Photovoltaic Module Using Fuzzy Rule-Based Systems

Manuel Angel Gadeo-Martos [1,*], Antonio Jesús Yuste-Delgado [1], Florencia Almonacid Cruz [2], Jose-Angel Fernandez-Prieto [1] and Joaquin Canada-Bago [1]

1 Telematic Engineering System Research Group, CEATIC Center of Advanced Studies in Information and Communication Technologies, University of Jaén, Campus Científico-Tecnológico de Linares, C.P. 23700 Linares, Spain; ajyuste@ujaen.es (A.J.Y.-D.); jan@ujaen.es (J.-A.F.-P.); jcbago@ujaen.es (J.C.-B.)

2 IDEA Solar Energy Research Group, Center of Advanced Studies in Energy and Environment, University of Jaén, Campus las Lagunillas, C.P. 23071 Jaén, Spain; facruz@ujaen.es

* Correspondence: gadeo@ujaen.es

Received: 28 November 2018; Accepted: 31 January 2019; Published: 12 February 2019

check for updates

Abstract: Currently, there is growing interest in the modeling of high concentrator photovoltaic modules, due to the importance of achieving an accurate model, to improve the knowledge and understanding of this technology and to promote its expansion. In recent years, some techniques of artificial intelligence, such as the Artificial Neural Network, have been used with the goal of obtaining an electrical model of these modules. However, little attention has been paid to applying Fuzzy Rule-Based Systems for this purpose. This work presents two new models of high concentrator photovoltaics that use two types of Fuzzy Systems: the Takagi-Sugeno-Kang, characterized by the achievement of high accuracy in the model, and the Mamdani, characterized by high accuracy and the ease of interpreting the linguistic rules that control the behavior of the fuzzy system. To obtain a good knowledge base, two learning methods have been proposed: the "Adaptive neuro-fuzzy inference system" and the "Ad Hoc data-driven generation". These combinations of fuzzy systems and learning methods have allowed us to obtain two models of high concentrator photovoltaic modules, which include two improvements over previous models: an increase in the model accuracy and the possibility of deducing the relationship between the main meteorological parameters and the maximum power output of a module.

Keywords: artificial neural network; fuzzy rule-based systems; adaptive neuro-fuzzy inference system; ad hoc data-driven generation; high concentrator photovoltaic modules; maximum power prediction

1. Introduction

Over the past few years, high concentrator photovoltaics (HCPV) have attracted the attention of multiple researchers. HCPV technology is based on the use of an inexpensive optical device to concentrate light in a little solar cell, typically a III-V multi-junction solar cell [1] with the aim of reducing the amount of expensive semiconductor material.

An HCPV module is the smallest unit able to transform non-concentrated solar radiation into electricity. It comprises solar cells, optical devices and peripheral components necessary to generate electricity. In addition, the HPCV module uses passive cooling to dissipate the great amount of heat that is generated when the solar cells are working at high concentration levels, and it also incorporates other components such as bypass diodes to prevent the overheating of cells.

As with any type of energy system, estimating the electrical characteristics of an HCPV module is going to be essential for designing, monitoring, life-cycle assessment and therefore promoting the market expansion of this emerging technology. Moreover, as with the conventional PV technology, the main parameters that influence the output of the HCPV module are solar spectrum, solar irradiance and temperature [1–7]. However, the modeling of an HCPV device, due to its special features, is more complex than the modeling of PV technology [8,9]. This is mainly due to the following factors:

(a) The use of high-efficiency multi-junction (MJ) solar cells, made of several p-n junctions of semiconductor material with different band gap energies, that are more influenced by changes in the solar spectrum than single-junction solar cells [10].
(b) The use of optical elements modifies the impact of the incident irradiance on the solar cells and introduces a strong angular dependence to the system [11,12].
(c) The difficulty of measuring the temperature at which the solar cells are working in an HCPV module; since they are mounted on a substrate surrounded by other peripheral elements, the direct measurement of this temperature is not possible without deleterious the module or the components of the assembly that surround the cells [13–15].
(d) The HCPV modules only react to the direct component of the solar radiation (DNI) due to the use of point-focus optical elements. This component of the solar radiation is more variable and difficult to predict than the global irradiance since it is more affected by the existence of clouds and aerosols in the atmosphere [10,16].

Consequently, the modeling of HCPV systems is complex and still challenging from a fundamental point of view in many cases. As of today, several models of HCPV modules have been developed [9,17–30]. Most of these models try to determine the relations that exist among the electrical parameters of an HCPV module (i.e., open-circuit voltage, short-circuit current and maximum power) and the main atmospheric parameters that have influence on them. One of the researched approaches to address this issue is based on the use of artificial intelligence techniques, mainly artificial neural networks (ANN) [31]. This is due to the advantages offered by the ANNs to solve non-linear and complex problems and the great level of complexity of electrical modeling of HCPV devices, as discussed above. The use of ANNs has the benefit of offering alternative solutions to complex problems that are still challenging from a fundamental physical approach due to the complexity of the different physical event involved in the performance of these systems.

Taking into account that, in recent years, the Fuzzy Rule-Based Systems (FRBS) [32] have been successfully used to model a large number of systems [33–35], in this paper we propose the use of FRBS with the goal of modeling HCPV systems. For that purpose, two types of FRBS have been proposed: a) the Takagi-Sugeno-Kang (TSK) systems [36], which are characterized by the achievement of high accuracy in the model, and b) the Mamdani systems [37,38], which is characterized by high accuracy and the ease of interpreting the linguistic rules that control the behavior of the fuzzy system.

To generate a good model based on an FRBS, it is necessary to have a good knowledge base. To obtain such a model, in this paper we propose two methods: a) "Adaptive neuro-fuzzy inference system" (ANFIS) [39] and b) "Ad Hoc data-driven generation method" [40–42]. These methods have been used in the process of linguistic rule learning, in TSK and Mamdani FRBS, respectively. Finally, the experimental results show that the new HCPV models proposed in this paper improve the accuracy of the best published model [8].

The remainder of the article is organized as follows: In Section 2, we introduce the related work, and in Section 2.1, a review of the models for the electrical characterization of HCPV is presented. In Section 2.2, a short description of the architecture and reasoning method of the ANN is given. In Section 2.3, a summary of the applications of ANNs in the field of HPCV is presented. Section 2.4 describes an HCPV model based on ANN. Section 3 demonstrates the utility of the FRBS for modeling an HCPV module. In Section 3.1, we give a description of the FRBS concept, the main types and their characteristics with respect to the structure of the fuzzy rules, as well as an introduction to the design process. Sections 3.1.1 and 3.1.2 describe the types of fuzzy systems proposed in this paper to model the HCPV modules: Mamdani FRBS and TSK FRBS. In Section 3.2, the learning methods used to define the fuzzy rules that control the behavior of the FRBS are introduced. Section 3.2.1 presents the ANFIS method. Section 3.2.2 shows the Ad Hoc data-driven generation method. Section 4 describes the new methods proposed in this paper to improve the model of the HCPV module, and in Section 4.1, we discuss the particularization of the methodology presented in Section 3.2.1 to obtain a good HCPV model based on a TSK FRBS, and in Section 4.2, we discuss the particularization of the methodology proposed in Section 3.2.2 to obtain a good HCPV model based on a Mamdani FRBS. In Section 5, we show the results obtained by applying the methodologies presented in Sections 4.1 and 4.2. In Section 6, we extend the results of Section 5.

2. Related Work

2.1. Models for the Electrical Characterization of HCPV

In [43] a critical review of the models for the electrical characterization of HCPV has been made. In this paper, it shows that the model accuracy it is related with the number of "physical sensor", thus the ATSM [18] and the King [20] models, that only take in count three atmospheric parameters, presents a medium accuracy level. On the other hand there are others models as Chan [28] and Steiner [30] characterized by an advanced level of accuracy but which use a complex physical model and whose parametrization require advanced module information and indoor measurements as well as require specific software.

In [19] Peharz et al. proposed a model that provides better accuracy than the previous ones but it requires a more expensive experimental set-up. In [9] Fernandez et al. proposed a simple model, with an optimum balance between simplicity and accuracy, based on simple mathematical relationships between atmospheric parameters, but this model is focused for sites with climates characterized by high-medium turbidity levels.

In [29] Almonacid et al. proposed a model that use of the ability of artificial neural networks in order to obtain the complex relations between the electrical behavior of HCPV module and their inputs variables, with a high level of accuracy. However, its difficulty to be applied is that a deep knowledge on ANN architectures and its training algorithms is necessary to determine the parameters of this model, and this is not always available to be applied.

Energy prediction is a key factor in the market integration and growth of any type of energy production system. However, due to their special features, the modeling of HCPV devices is quite complex and still challenging. As commented, one of the more important lines of research to try to address some of the issues related to this technology is based on the use of artificial intelligence techniques, mainly ANNs. Therefore the next subsections present a brief summary of ANN and its application in the field of HCPV.

2.2. Artificial Neural Networks

Artificial neural networks (ANN) are a widely used tool for approximating nonlinear functions that have multiple entries [44]. An artificial neural network simulates the behavior of the dendrites and axons of nerve cells. In particular, the system inputs are related to the outputs through different neurons grouped in layers that are joined together by arcs. These arcs are denoted mathematically by a number or weight. The type of neural network that is often used in the literature is called the multilayer perceptron. Neurons are grouped into three types of layers: input, output and intermediate layers (called hidden layers). The number of neurons in each layer and the number of hidden layers determine the complexity of the artificial neural network.

2.3. HCPV and ANNs

ANNs have been used for modeling some issues related to MJ solar cells; for instance in [45–47] several ANN-based models have been proposed for estimating the tunneling effects, the the I-V characteristic and External Quantum Efficiency (EQE), both under one sun and in darkness, for dual-junction (DJ) GaInP/GaAs solar cells. In [48] the authors used an ANN-based model to estimate the performance of triple-junction (TJ) InGaP/GaAs/Ge solar cells and the EQE under the influence of an ample range of charged particles. Finally, in [49] Fernández et al. presented three ANN-based models of the main electrical parameters of a TJ solar cell: open-circuit voltage (V_{oc}), short-circuit current (I_{sc}) and maximum power (P_{max}).

Regarding HCPV modules and systems, several ANN-based models have been developed to try to solve some problems related to these devices. In [50] Fernandez et al. presented an ANN-based model for spectrally corrected direct-normal irradiance. This parameter is defined as the part of the incident spectrum that an HCPV module is capable to convert into electricity, so it can be used to quantify the spectral effects on an HCPV device. In [13] and [51] two ANN-based models to estimate the cell temperature of an HCPV module were developed. The direct measurement of this temperature is quite complex since it is not possible to access the inside of the module without damaging it. ANN-based models were developed to try to solve this problem by attempting to characterize the relationship between the main meteorological parameters and the cell temperature that affect the temperature. In [29] and [52] two ANN-based models were developed to estimate the maximum power of an HCPV module: a feed-forward artificial neural network and a cooperative-competitive hybrid algorithm for radial basis-function networks. Finally, in [53,54] two ANNs were used to model the complete I-V characteristic of an HCPV module.

2.4. Application of ANNs to Obtain an HCPV Model

The solar research group of Jaén University has ample experience in the application of ANN in the photovoltaic field [55–59]. Taking into account this knowledge, Almonacid et al. [29] developed an ANN-based model to find the relation between the main parameters that affect its performance: spectrum (S), irradiance (B), wind speed (Ws) and temperature (T) and the output of an HCPV.

The architecture of the proposed ANN was based on a three-layer feed-forward neural network trained with the Levenberg-Marquardt back-propagation algorithm. The input layer had five nodes: the direct-normal irradiance (DNI), the air mass (AM), the precipitable water (PW), the wind speed (Ws) and the air temperature (Tair). The ANN-based model used the precipitable water and air mass to evaluate the spectrum, the direct-normal irradiance to evaluate the irradiance and the wind speed and the air temperature to evaluate the cell temperature. The hidden layer had seven nodes, and there was one node in the output layer (P_{max}). Coefficients of the neural network were obtained from outdoor monitoring. The results show that the ANN-based model could be used to calculate successfully the output of an HCPV module with an RMSE of 2.91%, an MBE of 0.07% and an R^2 of 0.99.

By virtue of this results it may be stated that this model provides one of the best level of accuracy between the models mentioned in Section 2.1. However, as commented, the difficulty in applying this model is focused in the determination of the parameters, which requires a deep knowledge of complex artificial neural networks architectures and their training algorithms. On other hand, once the parameters have been determined, the knowledge remains implicit and the model becomes easy to use, however the complex relations that link the HCPV module behavior and the atmospheric variables have a short degree of interpretability. In order to improve the knowledge over these relations without decrease the level of accuracy in this paper we propose the use of FRBS.

3. Utility of the FRBS for Modeling an HCPV Module

To obtain the maximum annual electric power for an HCPV system, it is advisable to use highly accurate and stable solar trackers. High-accuracy dual-axis solar trackers, which track the Sun's motion across the sky, must be used in HCPV systems because these systems only accept direct solar light with a very small deviation in the acceptance angle [60].

In the literature, we can observe the use of FRBS to implement solar tracker using fuzzy control [61–64]. In [65], the authors explain that fuzzy control could be a good option when an accurate model of the tracking system is absent. Therefore, if we use this type of control for a solar tracker, it is necessary to learn a good knowledge base (KB) for this control system, and to achieve this task it is necessary to have a good model of the HCPV module.

Because of the large quantity of relevant variables, the problem of modeling a HCPV becomes very complex, thus it is advisable to solve it by means of modeling techniques able of obtaining a model representing the non-linear relationships existing in it. Furthermore, the problem-solving goal must be to obtain a user-interpretable model, as well as obtain an accurate model, able of putting some light on the relations that exist among the electrical parameters of an HCPV module and the main atmospheric parameters that have influence on them. Due to all these reasons, in this paper we introduce the use of FRBSs in order to model the HCPV module.

A Fuzzy Rule-Based System is any system, where Fuzzy Logic may be used either to model the relationships and interactions among the system variables, or as the basis for the representation of different forms of knowledge. Fuzzy Systems have proven to be a significant tool for modeling complex systems in which, due to the imprecision or the complexity, conventional tools are unsuccessful [33,34,66,67]. For that reason, they have been successfully used to a wide range of problems from different areas presenting vagueness and uncertainty in different ways [68].

With the general purpose of optimizing the HCPV fuzzy control system, in this paper we introduce two new HCPV module models. Each is a variation of a Fuzzy Rule-Based System and is characterized by their properties. For this reason, the sections below detail the study of Fuzzy Rule-Based Systems, their types and properties.

3.1. Fuzzy Rule-Based System

In 1965, Zadeh [69] suggested a modified set theory, called fuzzy set theory, in which an element could have a degree of membership that takes continuous values, rather than being 0 or 1. One of the most important areas of application of his theory is the FRBSs. An FRBS is a rule-based system in which fuzzy logic (FL) is used as a tool for managing different forms of knowledge about the problem at hand [32]. These systems are a development of the classical rule-based system because they address “IF-THEN” rules whose consequents and antecedents are composed of fuzzy statements (fuzzy rules), instead of classical logical statements. FRBSs incorporate the human knowledge of the expert using the FL. One of the main characteristics of these systems is the ability to incorporate human knowledge by means of uncertainty or imprecision and lack of accuracy.

FRBSs have some advantages over traditional rule-based systems, such as (a) inference methods become more robust with the approximate reasoning methods employed within FL and (b) the key features of knowledge captured by fuzzy sets involve the handling of uncertainty.

In an FRBS, the knowledge is stored in a knowledge base that consists of three elements: membership functions, a set of “*IF-THEN*” rules, and linguistic variables. These rules are defined by their consequents and antecedents. Antecedents and, frequently, consequents, are associated with fuzzy concepts.

Because of these properties, FRBSs have been successfully applied to modeling the interactions and relationships that exist between their input and output variables. In this way, one of the most common application of FRBSs is fuzzy modeling [34]. There are two types of FRBSs for engineering problems:

(a) *Mamdani* FRBSs [37]. In this type of FRBSs, antecedents and consequents are composed of linguistic variables. The rules possess the following form.

IF X_1 is A_1 and ... and X_n is A_n THEN Y is B,

where X_i are input variables, A_i are fuzzy sets associated to input variables, Y is the output variable and B is a fuzzy set associated to the output variable.

(b) *Takagi-Sugeno-Kang* FRBSs [36]. This model of FRBSs is based on rules in which the antecedent is composed of linguistic variables and the consequent is an analytical function of the input variables. In this case, the rules are as follows:

IF X_1 is A_1 and . . . and X_n is A_n THEN Y = f (X_1, . . . , X_n).

In most cases, the function is a linear function:

IF X_1 is A_1 and . . . and X_n is A_n THEN Y = p_0 + p_1* X_1 + . . . + p_n* X_n, with X_i as the input variables, Y as the output variable, A_i as the fuzzy sets related to the input variables, and p = (p_0, p_1, . . . , p_n) as a vector of real parameters. These types of rules are usually called TSK fuzzy rules.

The accuracy of an FRBS directly depends on two aspects: the composition of the fuzzy rule set and the way in which it implements the fuzzy inference process. Therefore, the FRBS design process includes two main tasks [32]:

(a) The choice of the type of FRBS (Mamdani or Takagi-Sugeno-Kant), and the different fuzzy operators that are employed by the inference process.
(b) The generation of the fuzzy rule set. That requires some design tasks, such as

    1. Selection of the relevant input and output variables.
    2. Definition of the scale factor, the number of term sets and the membership function for each linguistic variable.
    3. Derivation of the linguistic rules that will form part of the rule set.

With the intention of use the best properties and facilities provided by the FRBSs, in this paper we propose the generation of two HCPV models based on a Mamdani FRBS and a Takagi-Sugeno-Kant (TSK) FRBS. This systems are explained in more detail below, as well as the adaptations made in our proposal.

3.1.1. Mamdani Fuzzy Rule-Based Systems

In 1974, Mamdani [37] proposed an FRBS that addresses real inputs and outputs. He augmented Zadeh´s formulation to apply an FS to a control problem. Later, in 1975, he proposed the Fuzzy Logic Controllers (FLCs) [38] as a type of FS, which are referred to as FRBSs with fuzzifier and defuzzifier. Hence, FLCs may be considered knowledge-based systems, that incorporate human knowledge into their Knowledge Base through fuzzy membership functions and fuzzy rules. As can be observed (see Figure 1), a Mamdani FRBS consists of the following components [32]:

(a) A Knowledge Base (KB), which stores the knowledge about the problem. The KB comprises a Database (DB) and a fuzzy Rule Base (RB). The DB contains the definitions of the fuzzy rules and linguistic labels, and the RB comprises the collection of linguistic rules representing the expert knowledge.
(b) A fuzzy inference engine, that presents the following structure:

    1. A fuzzification interface, which converts the values of input variables into fuzzy information, for this it assigns grades of membership to each fuzzy set defined for that variable.
    2. An inference system, which infers fuzzy outputs by employing fuzzy implications and the rules of inference of FL.
    3. A defuzzification interface, which produces a non-fuzzy output from an inferred fuzzy output. This interface has to aggregate the information provided by the output fuzzy sets and to obtain an output value from them. There are two basic techniques for doing this: Mode B-FITA (first infer, then aggregate) and Mode A-FATI (first aggregate, then infer). The FRBS proposed in this paper uses mode B-FITA because it reduces the computational burden compared to mode A-FATI.

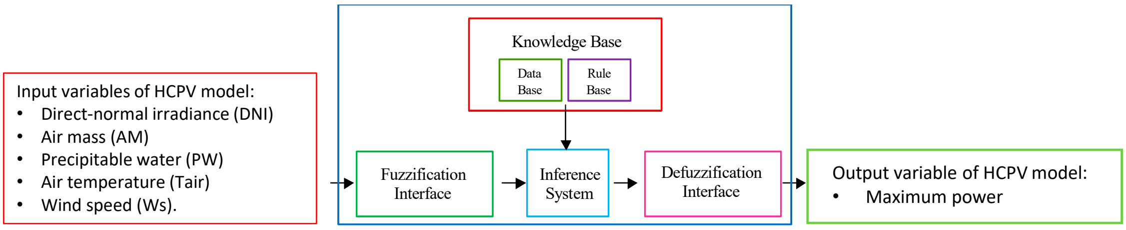

Figure 1. Structure of a HCPV model based on a Mamdani FRBS.

In the same way as the ANN-based model, the input variables of the proposed HCPV models based on a FRBS are: the direct-normal irradiance (DNI), the air mass (AM), the precipitable water (PW), the air temperature (Tair) and the wind speed (Ws), as well as the output variable is the maximum power.

In this model based of a Mamdani FRBS we have chosen a uniform partition of the membership functions into the fuzzy sets of output and input variables. Figure 1 shows the structure of a HCPV model based on a Mamdani FRBS.

3.1.2. Takagi-Sugeno-Kang Fuzzy Rule-Based Systems

The output of a TSK FRBS is the sum of the individual outputs provided by each rule, Yi (i = 1, ..., m, where m is the number of rules of the TSK KB), weighted by the values of the parameters hi, where hi = T(Ai1(x1), . . . ,(Ain(xn)) is the matching degree between the current inputs to the system, x0 = (x1, . . . xn) and the antecedent part of the i-th rule. T stands for a conjunctive operator modeled by a t-norm. To design the inference engine of a TSK FRBS, the designer only must select this connective operator T. The most common choices are the algebraic product and the minimum [36] (In this paper the algebraic product have been used as an operator T). Figure 2 shows the structure of a HCPV model based on a TSK FRBS.

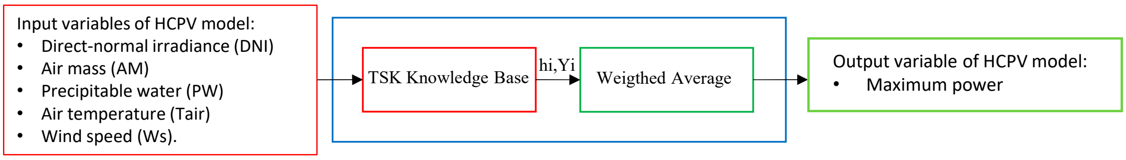

Figure 2. Structure of a HCPV model based on a TSK FRBS.

To help achieve the goals of both Mamdani FRBSs and TSK FRBSs they must have a complete and consistent knowledge base, therefore it is necessary to use learning methods to define the fuzzy rules.

These models are capable of estimate the HCPV maximum power from outdoor measurements over atmospheric variables, but they are not suitable to model the I-V curve and no to evaluate algorithms to obtain maximum power point tracking (MPPT), because they are complex processes, that require modelling the HCPV module with a number of curves sufficiently representative, in which each one of their parameters will be influenced by each one of the atmospheric parameters.

3.2. Learning Methods to Define the Fuzzy Rule Set

To define the fuzzy rule set in modeling applications of FRBSs, two types of information are available to the designer: linguistic and numerical. Related to this information, there are two main ways of deriving the fuzzy sets:

Derivation from the experts. In this case, the human expert specifies the linguistic labels, the structure of the rules and the meaning of each label. This method is useful only if the expert is capable to express his knowledge in the form of linguistic rules.

Derivation from automated learning methods based on the existing numerical information. To overcome the difficulties related with the derivation of the knowledge from the expert, in recent years, numerous inductive methods have been developed. Such methods include ad hoc data-driven generation methods [40–42], neural networks [44], clustering techniques [70,71], and evolutionary algorithms [72,73].

For modeling a system with very high complexity (such as HCPV), it is very difficult to obtain the linguistic rules that define the behavior, and therefore in this paper we propose the use of two learning methods to define the fuzzy rule set: (a) ANFIS and (b) the Ad Hoc data-driven method.

3.2.1. ANFIS

ANFIS is capable of providing in a single tool the advantages of systems based on neural networks and fuzzy systems. Thus, the expert knowledge provided by the fuzzy rules is complemented by the training and validation of neural networks. Researchers have frequently used ANFIS since it was first presented by Jang et al. in [39] for different problems such as pattern classification or adjustment of non-linear functions. This method has been used for discriminating voice/music [74], for modeling solar radiation [75], to predict air pollution [76], in solar PV [77], and in treating water qlity [78], to cite just a few current examples.

ANFIS uses a set of data (input/output) to build a TSK fuzzy system [39] in which the parameters of member functions and the relations with the output are adjusted using neural networks. For this purpose, a fuzzy system is identified with a neural network, as shown in Figures 3 and 4.

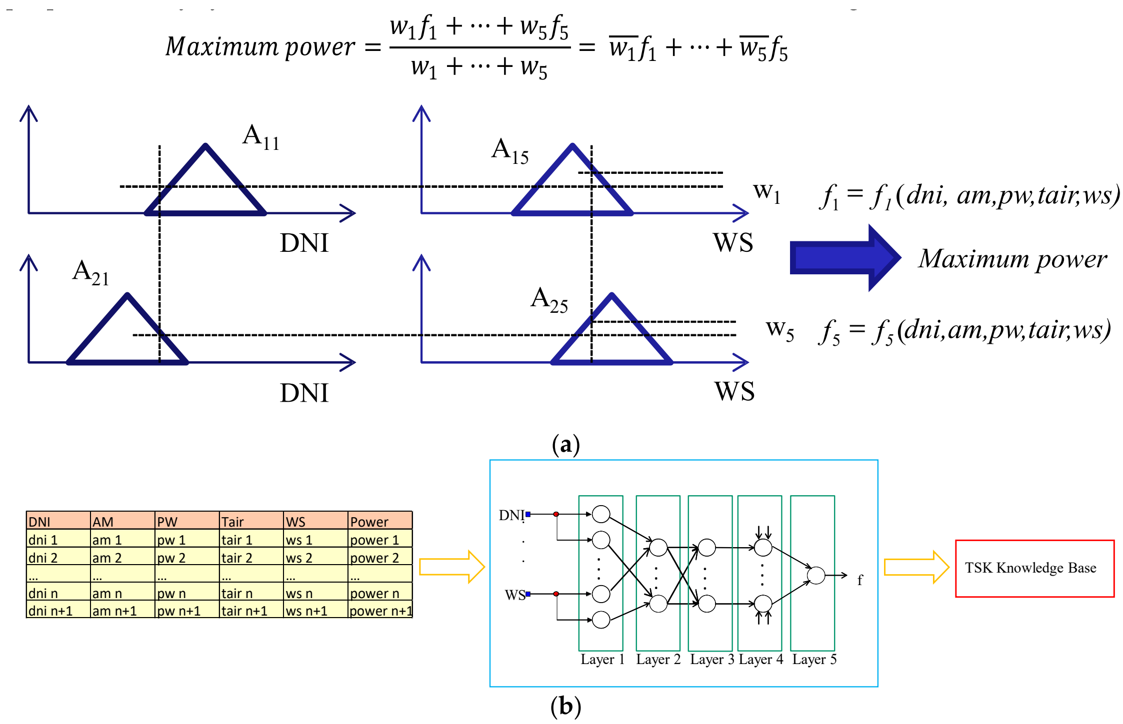

Figure 3. ANFIS versus ANN: relationship. (**a**) Antecedent and consequent part of fuzzy rule; (**b**) Inputs, ANN and KB of ANFIS structure.

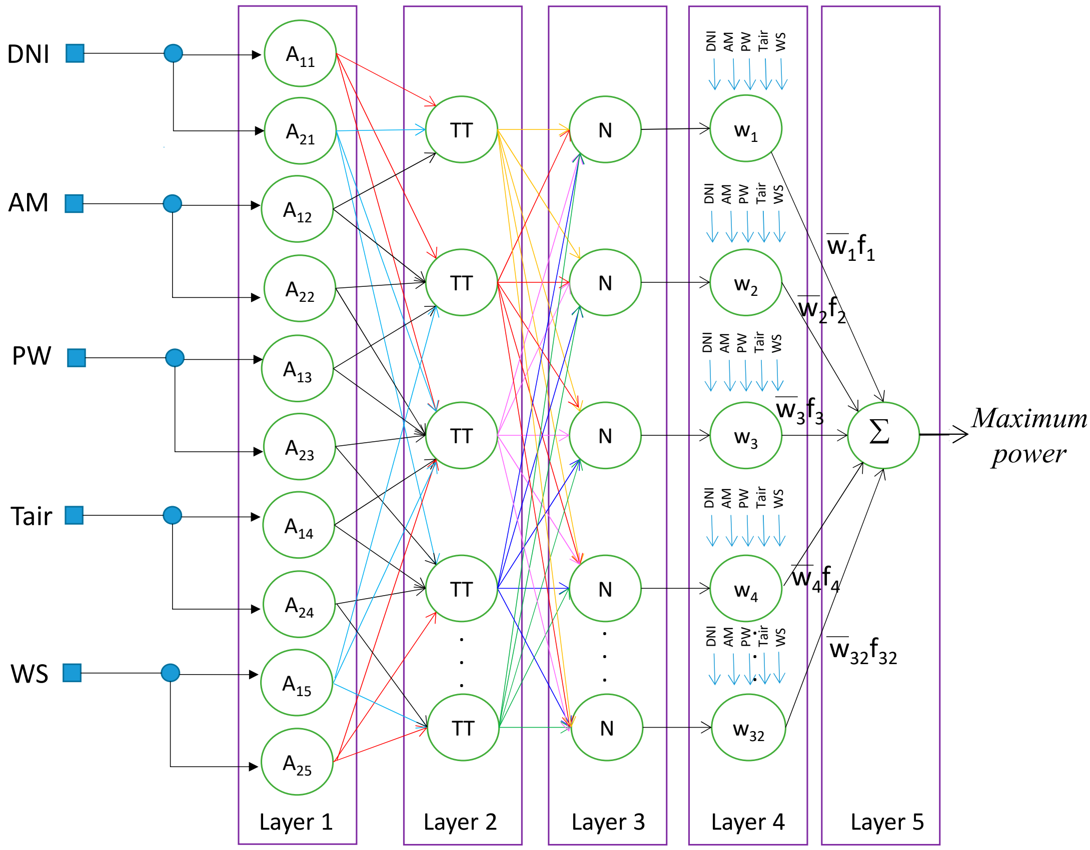

Figure 4. Detail of ANN used in the ANFIS method.

In Figure 3, at the top, the inputs are fuzzified into the system by means of membership functions. Then, the output from the combination of the IF-THEN rules is obtained. A five-layer neural network, as illustrated in Figure 4, can model this process. Each layer of the ANFIS model handles a task:

(a) Layer 1: Responsible for determining the degree of membership of each input to each of the fuzzy sets (fuzzification of inputs).
(b) Layer 2: The output of this layer is the products obtained by the rules that are activated. Each node symbolizes the firing strength of the rule (wi).
(c) Layer 3: Outputs of this layer are denominated normalized firing strengths (wi). The ith node obtains the ratio of the ith rule´s firing strength to the addition of all rule´s firing strengths.
(d) Layer 4: Outputs are obtained from the consequent parameters of the rules (fi).
(e) Layer 5: Calculates the overall output as the sum of all incoming data.

Through a process of training, you can obtain all the values of the different layers and then create the fuzzy knowledge base.

3.2.2. Ad Hoc Data-Driven Generation Method

A family of simple and efficient methods, called ad hoc data-driven methods, which generate new rules from the training database, guided by the covering criteria of the data in the example set, have been proposed in the literature [40–42]. The ad hoc data-driven linguistic rule-learning methods are identified by four main features:

(a) They are based on working with an input-output data set.
(b) They consider a previous definition of the database, composed of the output and input primary fuzzy partitions.

(c) The generation of the linguistic rules is guided by the covering criteria of the data in the example set.
(d) The learning mechanism is not based on search techniques or any well-known optimization; it is specifically developed for this purpose.

In this paper, we propose the use of the simpler type, the "ad hoc data-driven linguistic rule-learning methods guided by examples", to obtain the linguistic rules in the Mamdani FRBS. This method obtains each rule from a specific example in the data set. These rules belong to a candidate rule set because after this generation stage, a selection process is performed to derive the final RB.

One of the most widely used and well-known example-based methods is Wang and Mendel's method [41]. This method implements the RB generation by means of the following steps (see Figure 5):

(a) Consider a fuzzy partition of the variable space.
(b) Generate a candidate linguistic rule set. This set will be composed by the rules best covering each example included in the input-output data set.
(c) Assign an importance degree to each rule. This will be obtained by computing the covering value of the rule.
(d) Obtain a final RB from the candidate linguistic rule set, by selecting the rule with the highest importance degree in each group.

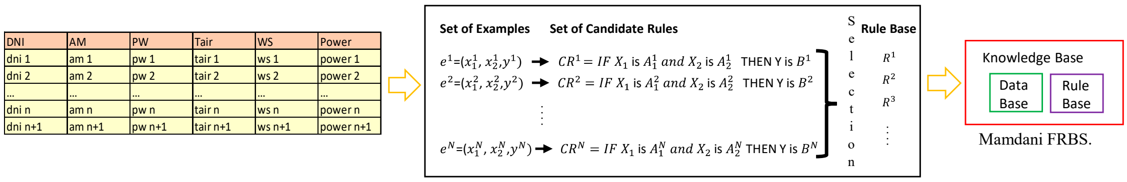

Figure 5. Graphical illustration of the rule-generation process.

4. Proposed Methods to Obtain an HCPV Model

4.1. Application of ANFIS to Train a TSK FRBS to Obtain an HCPV Model

The proposed ANFIS model has the following characteristics:

(a) The five variables mentioned above as inputs: direct-normal irradiance (DNI), wind speed (Ws), air temperature (Tair), precipitable water (PW), and air mass (AM), each with two Gaussian fuzzy sets.
(b) The output variables as linear functions: maximum power.
(c) A training algorithm based on back-propagation.

4.2. *Application of* Ad Hoc *Data-Driven Methodology to Obtain an HCPV Model*

In this case, we use a Mamdani FRBS to provide a highly flexible method to formulate knowledge, while at the same time remaining interpretable. In these systems, each rule is a description of a relation between one condition and one action, which allows for easy interpretation by a human. This property makes these systems useful for application in problems that require high model interpretability, such as fuzzy control [79], and linguistic modeling [34,35].

To obtain a model of the HCPV module behavior, we select the following input variables: DNI, AM, PW, Tair, and Ws. These variables have been normalized using a linear transformation that was applied between their minimum and maximum values. The output will be the estimated maximum power delivered by the HCPV module. Taking into account the steps described in Section 3.2.2, we implement the following steps:

(a) A fuzzy partition of the input and output variable space is created. Over all of the five input variables, we have applied a uniform partition composed of 19 fuzzy sets, and over the output variable we have applied a uniform partition with 495 fuzzy sets. Based on these values, we have generated a partition of the five-dimensional space that is composed of 19^5 subspaces or regions.
(b) Candidate rules are generated in each fuzzy input subspace. For each example of the training set (which is composed of 8926 examples) contained in each subspace, a fuzzy rule is proposed. All of these rules have the same antecedent and differ in their consequents.
(c) Each rule is assigned an importance degree, which is obtained by computing the covering value of the rule in its subspace [42].
(d) Select the rule with the highest importance degree in each group or subspace. The algorithm generated a KB with 6216 different rules.

In this learning algorithm, the accuracy of the modeled output variable is related to the number of subspaces into which the original five-dimensional space was divided. In the same way, the complexity of the model increases with the number of subspaces and their dimension. On the other hand, the number of rules, which is related to the number of subspaces, determines the accuracy of this model.

5. Experimental Results

As commented, the ANN model provides one of the best level of accuracy between the models mentioned in the related work. For that reason, in this paper, the developed models are evaluated and compared to the ANN model.

As a result of executing these proposed modeling methods (see Sections 4.1 and 4.2), we have obtained two models of an HCPV:

(a) TSK FRBS training with ANFIS.
(b) Mamdani FRBS obtained with the Ad Hoc data-driven method.

To conduct this study, the electrical performance of a HCPV module mounted on a two-axis solar tracker (Figure 6 left) together with the main atmospheric parameters that have influence in its output, have been measured at the Centro de Estudios Avanzados en Energía y Medio Ambiente (CEAEMA) of the University of Jaén.

Figure 6. Experimental set-up used to conduct this study at the Centro de Estudios Avanzados en Energía y Medio Ambiente at the University of Jaén. (**left**) HCPV module; (**right**) atmospheric station.

The module is made up of 20 triple-junctions lattice-matched GaInP/GaInAs/Ge solar cells interconnected in series. The module uses silicon-on-glass (SOG) Fresnel lenses as primary optical element. The secondary optical element consists of reflexive truncated pyramids made up of an aluminium film layer to enhance the reflectivity. The module has an optical efficiency of 80%, a geometric concentration of 700 and uses passive cooling to ensure that MJ solar cells operate on their optimal operation range [49]. Table 1 shows the main electrical characteristics of the HCPV module under Concentrator Standard Operating Conditions, CSOC, (i.e., AM1.5D, DNI = 900 W/m^2, ambient temperature, T = 20 °C and wind speed, WS = 2 m/s).

Table 1. Electrical characteristics of the HCPV module under Concentrator Standard Operating Conditions, CSOC, (i.e., AM1.5D, DNI = 900 W/m^2, ambient temperature, T = 20 °C and wind speed, WS = 2 m/s).

Electrical Characteristics	Value
Short-circuit Current (I_{sc})	5.30 A
Open-circuit Voltage (V_{oc})	57.28 V
Maximum Current (I_{ppm})	4.85 A
Maximum Voltage (V_{ppm})	47.62 V
Maximum Power (P_{max})	230.85 W

In order to measure the electrical parameters of the HCPV module a four-wire electronic load located was used. In addition, the centre is equipped with an atmospheric station MTD 3000 from Geonica S.A. (Figure 6 right) to record the main atmospheric parameters such as direct normal irradiance, air temperature, wind speed or humidity. The values of aerosol optical depth not provided by the atmospheric station were obtained from MODIS Daily Level-3 data source [80].

To obtain the knowledge base that characterizes each model, in this paper, we have considered a set of input and output variable values, recorded by the experimental setup, that it is composed of 11155 examples that were recorded every 5 minutes from January 2011 to December 2012.

In the case of ANFIS, to prevent the learning method from memorizing the training examples, the available data are separated into three subsets:

(a) A training set: the learning method is trained with this set in the classical way. It includes 33% of the examples.
(b) A validation set: each time you complete a training iteration, this set is used to determine whether you can stop training. The goal is to avoid overtraining. This set contains 33% of the examples.
(c) A test set to discern the goodness of the process. This set contains 33% of the examples.

After this, the following procedure was used. The system trains on the first set for 10 iterations. Then the validation set is used, and if a result with low enough error is obtained, the process is finished; otherwise another 10 iterations are performed. Finally, the third set is used to check the degree of fitness of the system. The three sets each contain 33% of the samples.

In the case of the Ad Hoc data-driven method, to prevent biasing the learning process, the available data are divided into two subsets:

(a) A training set, which includes 80% of the examples.
(b) A test set, which contains 20% of the examples.

This training set has been used to generate the linguistic rules that constitute the KB. Then the test set was employed to evaluate the performance of this learning method.

All the earlier sets have been obtained based on all data sets and were formed by carrying out a random and uniform selection of the subspaces, and then a random selection of an example contained in each subspace.

As a result of executing the proposed modeling methods, the characteristics of the obtained knowledge bases are as follows:

(a) For TSK, FRBS training with ANFIS:

    1. Number of rules: 32.

2. Number of fuzzy sets for each input variable: 2.
3. The partition of the membership functions into the fuzzy sets of input variables is shown in Figure 7. From the observation of the captured data and the membership functions of the two fuzzy sets, for each of the atmospheric variables represented in Figure 7, the conclusion can be drawn that the crossing point of the two fuzzy sets has been chosen so that the number of samples is approximately equal to right and left of said point. Therefore, the high and low fuzzy sets will cover approximately the same number of samples, half of the total number of samples captured. This distribution of the membership functions, which responds to the density of the samples captured, as well as the choice of the initial and final values of the height of the fuzzy sets and the slope of the curve that defines them, allows to have a number of very reduced rules, without a decrease in model accuracy.

(b) For Mamdani, FRBS obtained with the Ad Hoc data-driven method:

1. Number of rules: 6216.
2. Number of fuzzy sets for each input variable: 19.
3. Number of fuzzy sets for each output variable: 495.
4. Uniform partition of the membership functions into the fuzzy sets of output and input variables.

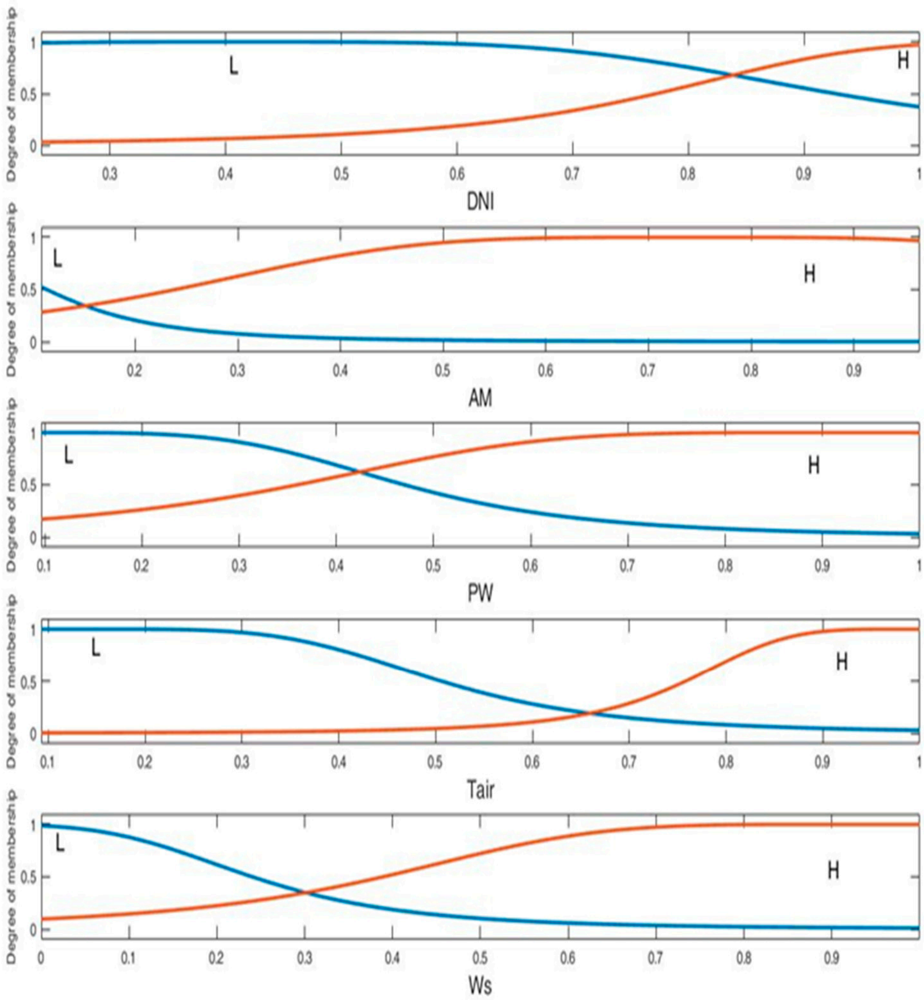

Figure 7. Membership functions of the input variables for the HCPV model based on the TSK FRBS training with the ANFIS method.

After the KBs have been obtained, in order to evaluate the level of accuracy of these models, for each element of the test set (five values of atmospheric variables) it is made the simulation of each model to obtain the predicted maximum output power. To study the behavior of these models, we have to calculate the normalized root mean square error (*NRMSE*) between the measured (*Pm*) and the predicted (*Pp*) maximum output power. The equations of the *RMSE* (in watts) and *NRMSE* (in %) are:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(P_p - P_m\right)^2}{n}} NRMSE = \frac{RMSE}{\overline{P_m}} \tag{1}$$

The values of *NRMSE* (in %), obtained with the three models of HCPV (including the ANN model introduced in [29]) are shown in Table 2. A comparison of the values of the *NRMSE* gain for the models of HCPV presented in this paper versus the ANN model, is shown in Table 3. The equations of the gain in *NRMSE* are:

$$Gain_{NRMSE\ TSK\ FRBS\ vs\ ANN} = \frac{|NRMSE_{TSK\ FRBS} - NRMSE_{ANN}|}{NRMSE_{ANN}} \tag{2}$$

$$Gain_{NRMSE\ Mamdani\ FRBS\ vs\ ANN} = \frac{|NRMSE_{Mamdani\ FRBS} - NRMSE_{ANN}|}{NRMSE_{ANN}} \tag{3}$$

Table 2. *NRMSE* for the three models: ANN, TSK FRBS training with ANFIS and Mamdani FRBS obtained with Ad Hoc data-driven method.

***NRMSE* (%)**	**Train**	**Validation**	**Test**	**Overall**
ANN	2.11	2.1	2.45	2.16
TSK FRBS training with ANFIS	1.85	1.99	2.21	1.93
Mamdani FRBS training with Ad Hoc data-driven	2.04		2.25	2.07

Table 3. Comparison of the gain in *NRMSE*, for the model TSK FRBS training with ANFIS versus ANN and for Mamdani FRBS obtained with the Ad Hoc data-driven method versus ANN.

Gain in *NRMSE*	**Train**	**Validation**	**Test**	**Overall**
ANN	0	0	0	0
TSK FRBS training with ANFIS	12.32	5.24	9.80	10.65
Mamdani FRBS training with Ad Hoc data-driven	3.32		8.16	4.17

In addition to the *NRMSE* analysis between the measured and predicted output maximum power, the linear regression analysis have also been calculated to study the results of the compared methods (ANN, Mamdani, TSK) in more detail, as shown in Figures 8–10.

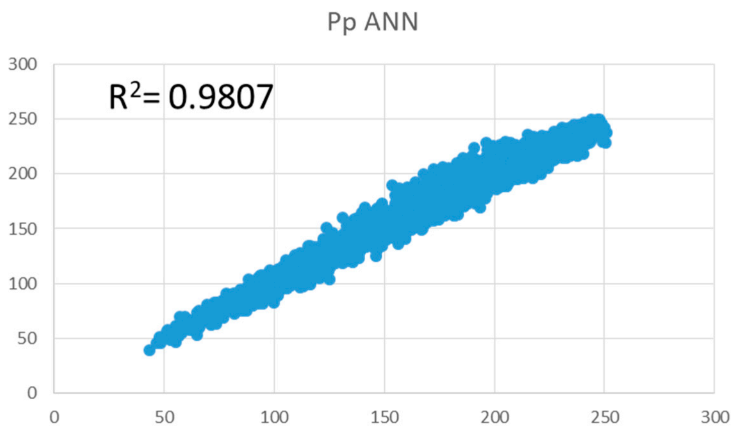

Figure 8. A regression analysis between the predicted output maximum power in the ANN model and the measured output maximum power for the total set of data.

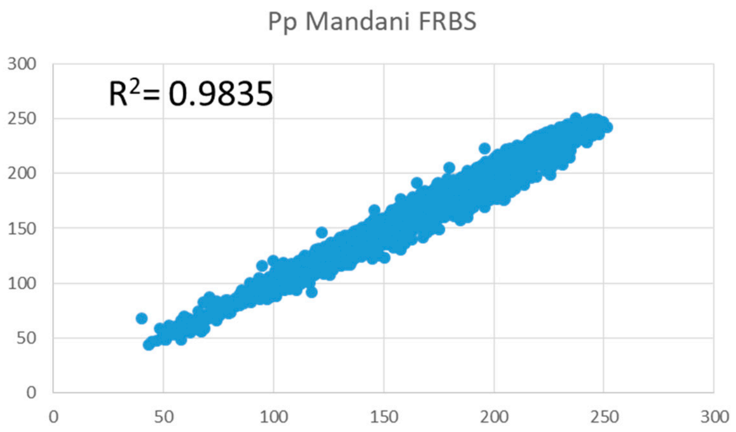

Figure 9. A regression analysis between the predicted output maximum power in the Mamdani FRBS model and the measured output maximum power for the total set of data.

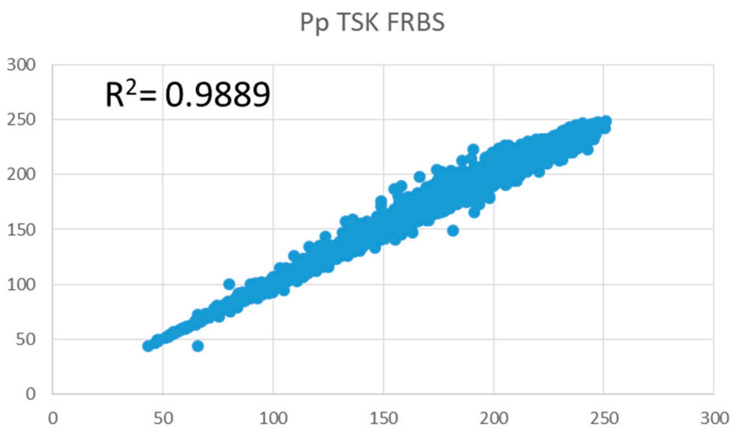

Figure 10. A regression analysis between the predicted output maximum power in the TSK FRBS model and the measured output maximum power for the total set of data.

From the analysis of the experimental results, we note the following observations:

(a) An improvement in the *RMSE* and R^2 of results obtained with TSK FRBS training with ANFIS and with Mamdani FRBS using the Ad Hoc data-driven method compared with the results obtained using ANN.

(b) An improvement in the *RMSE* and R^2 of the results obtained with TSK FRBS training with ANFIS compared with the results obtained using Mamdani FRBS with the Ad Hoc data-driven method.
(c) A strong decrease in the number of rules in the knowledge base obtained for TSK FRBS compared with that obtained for Mamdani FRBS. This simplicity results in an increase in the speed of the inference process.

Nevertheless, the use of a Mamdani FRBS has several advantages, among which we can highlight the fact that each rule is a description of a condition-action statement that has a clear interpretation to a human. In this section, we emphasize the meanings of several rules.

The rule that infers the scene in which the HCPV module generates the least amount of power is:

If DIN is A1, Tair is A17, Ws is A6, PW is A12 and AM is A9, then Power is B1.

By analyzing this linguistic rule, and taking into account the proposed uniform partition of the membership functions, composed by 19 fuzzy sets for each meteorological variables and 495 fuzzy sets in the maximum output power variable, we can say that:

The fuzzy set A1 covers values of the variable DNI very close to its minimum measured value (between 0 and 5% of its range of values). The fuzzy set A17 covers values of the variable Tair close to its maximum measured value (between 87 and 92% of its range of values). The fuzzy set A6 cover values of the variable Ws around 1/3 of its range of measured values (between 29 and 34%). The fuzzy set A12 cover values of the variable PW between 60 and 66% of the range of its measured values. The fuzzy set A9 cover values of the variable AM close to the medium value of its range of measured values (between 45 and 50%). The fuzzy set B1 covers values of the variable Power very close to its minimum value measured (between 0 and 0.2% of its range of values). Therefore we can interpret this rule as follows:

If the value taken by the variable DNI is within the set A1 and if the value taken by the variable Tair is within the set A17 and if the value taken by the variable Ws is within the set A6 and if the value taken by the variable PW is within the set A9 and if the value taken by the variable AM is within the set A9 then the value taken by the variable Power will be within the set B1.

In a simplified way, the conditions that generate the least amount of maximum power are:

A very low DNI, very high Tair, medium-low Ws, medium-high PW and medium AM.

The rule that infers the scene in which the HCPV module generates the largest amount of maximum power is:

If DIN is A16 and Tair is A11 and Ws is A8 and PW is A9 and AM is 1, then Power is B495.

As can see by observing this rule, the maximum amount of maximum power will be supplied under the following conditions:

A very high DNI, medium-high Tair, medium Ws, medium PW, and very low AM.

One of the advantages of Mamdani FRBS is that we can deduce the relationships between the input and output variables. If we consider these rules, we realize that there is a clear connection between the DNI input variable and the amount of electric power supplied by the HCPV module.

The relationships between other variables can be deduced by analyzing other rules in the knowledge base. For example:

If DIN is CB17 and Tair is CB17 and Ws is CB3 and PW is CB8 and AM is CB1, then Power is CB441.

If DIN is CB17 and Tair is CB15 and Ws is CB3 and PW is CB8 and AM is CB1, then Power is CB443.

If DIN is CB17 and Tair is CB14 and Ws is CB3 and PW is CB8 and AM is CB1, then Power is CB454.

If DIN is CB17 and Tair is CB13 and Ws is CB3 and PW is CB8 and AM is CB1, then Power is CB457.

Analyzing these linguistic rules, we realize that under these conditions of the DNI, Ws, PW and AM variables (which are the same in the five rules), the maximum power supplied by this HPCV model will increase if the value of the Tair variable decreases.

Throughout the knowledge base, we can find several sets of rules with the same values for four of the five conditions in their antecedents. Then the values taken by the fuzzy sets for the condition that differs and for the consequent allow for the determination of the relationship between the output maximum power and this input variable.

Although the knowledge base obtained for the HCPV model based on TSK FRBS has only 32 linguistics rules, the analysis of these rules does not allow for the interpretation of the relationships between the input and output variables; thus we cannot deduce human knowledge from the examination of the knowledge base.

In the HCPV modules, the input variables are mutually dependent, for this reason it is difficult to find a proper fuzzy partition of the input variables. To increase the precision of the HCPV model based on Mamdani FRBS, we have been proposed a uniform partition of the space of the input variables and their division into a large number of fuzzy sets. This results in a great increase in the number of linguistic rules.

To decrease the number of rules in the knowledge base without decreasing the accuracy of the model, in the future we can propose a non-uniform partition of the space of input variables, which will decrease the complexity of the input-output mapping and therefore allow for increasing the speed of the inference process and the human interpretability of the linguistic rules in the knowledge bases. This new partition must take into account the density of the examples contained in the input-output data set. This solution must increase the granularity of the fuzzy partition in the areas in which there is a higher density of examples for each one of the input variables.

Another aspect to take in account is the execution time in the process of obtaining the model (the KB). As can see by observing the Table 4, the process of training for Mamdani FRBS model is more expensive in terms of CPU time, than the TSK FRBS and the ANN. However this process is off-line and it is done once.

Table 4. Comparison of the execution time (training, validation and test) for the model TSK FRBS training with ANFIS versus Mamdani FRBS obtained with the Ad Hoc data-driven.

Execution Time (units)	Training (h)	Validation (s)	Test (s)
ANN	1/60	2	2
TSK FRBS training with ANFIS	4	2	2
Mamdani FRBS training with Ad Hoc data-driven	216		2

6. Conclusions

In this paper we have proposed the use of two types of FRBS (Mamdani and Takagi-Sugeno-Kant), with the goal of modelling HCPV systems. With the intention of obtaining the best performances of each fuzzy systems we have proposed a learning method: the ANFIS one, for training a TSK FRBS, in order to obtain its KB, and the Ad Hoc data-driven methodology to obtain the KB of the Mamdani FRBS.

From the analysis of the experimental setup and the description of these methods, it is noticed that the proposed modelling method:

(a) They only need simple outdoor measurements.
(b) They do not need an expensive experimental system.
(c) They are valid for any climatic conditions.
(d) They do not need any specific simulation software.
(e) They can be applied to the modelling of any model of HCPV module.

These characteristics, which they share with the ANN-based method, allow the building of HCPV models without complex requirements. In addition they allow to obtain the complex relationships that link the electrical behaviour of an HCPV module and its inputs variables, with a high level of accuracy.

On the other hand, from the analysis of the experimental results, it is noticed that:

(a) The use of an HCPV model obtained using TSK FRBS trained with ANFIS produced an improvement in the model accuracy compared to the use of the model obtained using ANN.
(b) The use of an HCPV model obtained using Mamdani FRBS with an Ad Hoc data-driven method produced an improvement in the model accuracy compared to the use of the model obtained using ANN.
(c) The use of an HCPV model obtained using TSK FRBS trained with ANFIS produced an improvement in the model accuracy compared to the use of the model obtained using Mamdani FRBS with an Ad Hoc data-driven method.
(d) The use of an HCPV model obtained using Mamdani FRBS with an Ad Hoc data-driven method allowed for the deduction of the relationship between the input and output variables. However, the other HCPV models did not provide information on the modeled system that was interpretable by a human.

For the future work we propose the following lines:

(a) In Mamdani FRBS modelling:
    1. To build a non-uniform partition of the membership functions in the input variables, in order to minimize the number of linguistics rules in the KB obtained by applying Ad Hoc data-driven method.
    2. To use other learning methods, as genetic algorithms, in order to obtain good KB.
(b) In TSK FRBS trained with ANFIS modelling: to increase the number of fuzzy sets in the partition of the membership functions of the input variables, in order to increase its accuracy.
(c) In FRBS (Mamdani and TSK) modelling: to increase the number of input variables, with new atmospheric variables, in order to obtain HCPV models with higher accuracy.

Author Contributions: M.A.G-M., A.J.Y.D and F.A.C. collected the related work, M.A.G-M. and A.J.Y.D. proposed the methods used to model the HCPV modules. M.A.G-M., A.J.Y.D and F.A.C. conceived and designed the experiments; J.C-B. and J-A.F-P. performed the experiments; J.C-B. and J-A.F-P. analyzed the data; M.A.G-M., J.C-B. and J-A.F-P. wrote the paper.

Funding: This work forms part of the project "Nuevos conceptos basados en tecnología de concentración fotovoltaica: desarrollo de sistemas de muy alta concentración fotovoltaica" (ENE2013-45242-R) supported by the Spanish Economy Ministry and the European Regional Development Fund/Fondo Europeo de Desarrollo Regional (ERDF/FEDER).

Acknowledgments: The authors would like to thank the support given by the IDEA Solar Energy Research Group of the University of Jaén, for the cession of the data captured by the experimental set-up, which have been used for the elaboration of this paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Eduardo, F.; Pérez-Higueras, P.; Garcia Loureiro, A.J.; Vidal, P.G. Outdoor evaluation of concentrator photovoltaic systems modules from different manufacturers: First results and steps. *Prog. Photovolt. Res. Appl.* **2013**, *21*, 693–701. [CrossRef]
2. Siefer, G.; Abbot, P.; Baur, C.; Schleg, T. Determination of the temperature coefficients of various IIIeV solar cells. In Proceedings of the 20th European Photovoltaic Solar Energy Conference, Barcelona, Spain, 6–10 June 2005.
3. Siefer, G.; Baur, C.; Meusel, M.; Dimroth, F.; Bett, A.W.; Warta, W. Influence of the simulator spectrum on the calibration of multi-junction solar cells under concentration. In Proceedings of the Conference Record of the Twenty-Ninth IEEE Photovoltaic Specialists Conference, New Orleans, LA, USA, 19–24 May 2002; pp. 836–839.
4. Fernández, E.F.; Loureiro, A.J.G.; Higueras, P.J.P.; Siefer, G. Monolithic III–V triple-junction solar cells under different temperatures and spectra. In Proceedings of the 8th Spanish Conference on Electron Devices, Palma de Mallorca, Spain, 8–11 February 2011.

5. Siefer, G.; Almonacid, F.; Garcı, A.J.; Ferna, E.F. A two subcell equivalent solar cell model for III–V triple junction solar cells under spectrum and temperature variations. *Sol. Energy* **2013**, *92*, 221–229. [CrossRef]
6. Siefer, G.; Bett, A. Analysis of temperature coefficients for III–V multi-junction concentrator cells. *Prog. Photovolt. Res.* **2014**. [CrossRef]
7. Fernández, E.F.; Siefer, G.; Schachtner, M.; García Loureiro, A.J.; Pérez-Higueras, P. Temperature coefficients of monolithic III–V triple-junction solar cells under different spectra and irradiance levels. *AIP Conf. Proc.* **2012**, *1477*, 189–193.
8. Soria-moya, A.; Cruz, F.A.; Fern, E.F.; Rodrigo, P.; Mallick, T.K.; Pedro, P. Performance Analysis of Models for Calculating the Maximum Power of High Concentrator Photovoltaic Modules. *IEEE J.* **2015**, *5*, 947–955. [CrossRef]
9. Fernández, E.F.; Almonacid, F.; Mallick, T.K.; Pérez-Higueras, P. Analytical modelling of high concentrator photovoltaic modules based on atmospheric parameters. *Int. J. Photoenergy* **2015**, *2015*. [CrossRef]
10. Fernández, E.F.; Soria-Moya, A.; Almonacid, F.; Aguilera, J. Comparative assessment of the spectral impact on the energy yield of high concentrator and conventional photovoltaic technology. *Sol. Energy Mater. Sol. Cells* **2016**, *147*, 185–197. [CrossRef]
11. Fernández, E.F.; Almonacid, F.; Ruiz-Arias, J.A.; Soria-Moya, A. Analysis of the spectral variations on the performance of high concentrator photovoltaic modules operating under different real climate conditions. *Sol. Energy Mater. Sol. Cells* **2014**, *127*, 179–187. [CrossRef]
12. Shanks, K.; Senthilarasu, S.; Mallick, T.K. Optics for concentrating photovoltaics: Trends, limits and opportunities for materials and design. *Renew. Sustain. Energy Rev.* **2016**, *60*, 394–407. [CrossRef]
13. Fernández, E.F.; Almonacid, F.; Rodrigo, P.; Pérez-Higueras, P. Calculation of the cell temperature of a high concentrator photovoltaic (HCPV) module: A study and comparison of different methods. *Sol. Energy Mater. Sol. Cells* **2014**, *121*, 144–151. [CrossRef]
14. Rodrigo, P.; Fernández, E.; Almonacid, F.; Pérez-Higueras, P.J. Review of methods for the calculation of cell temperature in high concentration photovoltaic modules for electrical characterization. *Renew. Sustain. Energy Rev.* **2014**, *38*, 478–488. [CrossRef]
15. Almonacid, F.; Pérez-Higueras, P.J.; Fernández, E.F.; Rodrigo, P. Relation between the cell temperature of a HCPV module and atmospheric parameters. *Sol. Energy Mater. Sol. Cells* **2012**, *105*, 322–327. [CrossRef]
16. Ruiz-Arias, J.A.; Quesada-Ruiz, S.; Fernández, E.F.; Gueymard, C.A. Optimal combination of gridded and ground-observed solar radiation data for regional solar resource assessment. *Sol. Energy* **2015**, *112*, 411–424. [CrossRef]
17. Rodrigo, P.; Fernández, E.; Almonacid, F.; Pérez-Higueras, P.J. Models for the electrical characterization of high concentration photovoltaic cells and modules: A review. *Renew. Sustain. Energy Rev.* **2013**, *26*, 752–760. [CrossRef]
18. ASTM International. *Standard Test Method for Rating Electrical Performance of Concentrator Terrestrial Photovoltaic Modules and Systems Under Natural Sunlight*; E2527-09; ASTM International: West Conshohocken, PA, USA, 2009.
19. Peharz, G.; Ferrer Rodríguez, J.P.; Siefer, G.; Bett, A.W. A method for using CPV modules as temperature sensors and its application to rating procedures. *Sol. Energy Mater. Sol. Cells* **2011**, *95*, 2734–2744. [CrossRef]
20. King, D.L.; Boyson, W.E.; Kratochvil, J.A. *Photovoltaic Array Performance Model*; Paper nr. SAND2004-3844; Sandia National Laboratories: Albuquerque, NM, USA; Livermore, CA, USA, 2004.
21. Whitaker, C.M.; Townsend, T.U.; Newmiller, J.D.; King, D.L.; Boyson, W.E.; Kratochvil, J.A.; Collier, D.E.; Osborn, D.E. Application and validation of a new PV performance characterization method. In Proceedings of the Conference Record of the Twenty Sixth IEEE Photovoltaic Specialists Conference, Anaheim, CA, USA, 29 September–3 October 1997; pp. 1253–1256. [CrossRef]
22. Gerstmaier, T.; Van Riesen, S.; Gombert, A.; Mermoud, A.; Lejeune, T.; Duminil, E. Software modeling of FLATCON© CPV systems. *AIP Conf. Proc.* **2010**, *1277*, 183–186.
23. Nishioka, K.; Takamoto, T.; Agui, T.; Kaneiwa, M. Annual output estimation of concentrator photovoltaic systems using high-efficiency InGaP/InGaAs/Ge triple-junction solar cells based on experimental solar cell's. *Sol. Energy Mater.* **2006**, *90*, 57–67. [CrossRef]
24. Aronova, E.S.; Grilikhes, V.A.; Shvarts, M.Z.; Timoshina, N.H. On correct estimation of hourly power output of solar photovoltaic installations with MJ SCs and sunlight concentrators. In Proceedings of the Conference Record of the IEEE Photovoltaic Specialists Conference, San Diego, CA, USA, 11–16 May 2008.

25. Kinsey, G.S.; Stone, K.; Garboushian, V. Energy prediction of Amonix solar power plants. *Proc. SPIE* **2010**, *7769*, 77690B. [CrossRef]
26. Verlinden, P.J.; Lasich, J.B. Energy rating of Concentrator PV systems using multi-junction III–V solar cells. In Proceedings of the 2008 33rd IEEE Photovoltaic Specialists Conference, San Diego, CA, USA, 11–16 May 2018; pp. 1–6. [CrossRef]
27. Martínez, M.; Antón, I.S. Prediction of PV concentrators energy production: Influence of wind in the cooling mechanisms. First steps. In Proceedings of the 4th International Conference on Solar Concentrators for the Generation of Electricity or Hydrogen, Scottsdale, AR, USA, 1–5 May 2007.
28. Chan, N.L.A.; Young, T.B.; Brindley, H.E.; Ekins-Daukes, N.J.; Araki, K.; Kemmoku, Y.; Yamaguchi, M. Validation of energy prediction method for a concentrator photovoltaic module in Toyohashi Japan. *Prog. Photovolt. Res. Appl.* **2013**, *21*, 1598–1610. [CrossRef]
29. Almonacid, F.; Fernández, E.F.; Rodrigo, P.; Pérez-Higueras, P.J.; Rus-Casas, C. Estimating the maximum power of a High Concentrator Photovoltaic (HCPV) module using an Artificial Neural Network. *Energy* **2013**, *53*, 165–172. [CrossRef]
30. Steiner, M.; Siefer, G.; Hornung, T.; Peharz, G.; Bett, A.W. YieldOpt, a model to predict the power output and energy yield for concentrating photovoltaic modules. *Prog. Photovolt. Res. Appl.* **2015**, *23*, 385–397. [CrossRef]
31. Almonacid, F.; Mellit, A.; Kalogirou, S. Applications of Anns in the Field of the Hcpv Technology. *High Conc. Photovolt.* **2015**, *190*, 333–351.
32. Cordón, Ó.; Herrera, F.; Hoffmann, F.; MAgdalena, L. *Genetic Fuzzy Systems: Evolutionary Tunning and Learning of Fuzzy Knowledge Bases*; World Scientific: Singapore, 2001; Volume 141, ISBN 9810240163.
33. Duckstein, L.; Bardossy, A. *Fuzzy Rule-Based Modeling with Applications to Geophysical, Biological, and Engineering Systems*; CRC Press: Boca Raton, FL, USA, 1995; Volume 8.
34. Pedrycz, W. *Fuzzy Modelling: Paradigms and Practice*; Springer: Berlin/Heidelberg, Germany, 1996; ISBN-13 978-1-4612-8589-2.
35. Sugeno, M.; Yasukawa, T. A Fuzzy-Logic-Based Approach to Qualitative Modeling. *IEEE Trans. Fuzzy Syst.* **1993**, *1*, 7–31. [CrossRef]
36. Takagi, T.; Sugeno, M. Fuzzy Identification of Systems and Its Applications to Modeling and Control. *IEEE Trans. Syst. Man Cybern.* **1985**, *15*, 116–132. [CrossRef]
37. Mamdani, E. Application of fuzzy algorithms for control of simple dynamic plant. *Proc. Inst. Electr. Eng.* **1974**, *121*, 1585. [CrossRef]
38. Mamdani, E.; Assilian, S. An experiment in linguistic synthesis with a fuzzy logic controller. *Int. J. Man Mach. Stud.* **1975**, *7*, 1–13. [CrossRef]
39. Jang, J.S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
40. Cordón, O.; Herrera, F. A proposal for improving the accuracy of linguistic modeling. *IEEE Trans. Fuzzy Syst.* **2000**, *8*, 335–344. [CrossRef]
41. Wang, L.; Mendel, J. Generating fuzzy rules by learning from examples. *IEEE Trans. Syst. Man* **1992**, *22*, 1414–1427. [CrossRef]
42. Casillas, J.; Cordón, O.; Herrera, F. COR: A methodology to improve ad hoc data-driven linguistic rule learning methods by inducing cooperation among rules. *IEEE Trans. Syst. Man Cybern. Part B Cybern.* **2002**, *32*, 526–537. [CrossRef]
43. Pérez-Higueras, P.; Fernández, E.F. *High Concentrator Photovoltaics: Fundamentals, Engineering and Power Plants*; Green Energy and Technology; Springer International Publishing: Berlin/Heidelberg, Germany, 2015; ISBN 9783319150390.
44. Hunt, K.; Sbarbaro, D.; Żbikowski, R.; Gawthrop, P. Neural networks for control systems—A survey. *Automatica* **1992**, *28*, 1083–1112. [CrossRef]
45. Patra, J.C.; Maskell, D.L. Estimation of dual-junction solar cell characteristics using neural networks. In Proceedings of the 2010 35th IEEE Photovoltaic Specialists Conference, Honolulu, HI, USA, 20–25 June 2010; pp. 002709–002713. [CrossRef]
46. Patra, J. Neural network-based model for dual-junction solar cells. *Prog. Photovolt. Res.* **2011**, *19*, 33–44. [CrossRef]
47. Patra, J. Chebyshev neural network-based model for dual-junction solar cells. *IEEE Trans. Energy Convers.* **2011**. [CrossRef]

48. Patra, J.C.; Maskell, D.L. Modeling of multi-junction solar cells for estimation of EQE under influence of charged particles using artificial neural networks. *Renew. Energy* **2012**, *44*, 7–16. [CrossRef]
49. Fernández, E.F.; Almonacid, F.; Garcia-Loureiro, A.J. Multi-junction solar cells electrical characterization by neuronal networks under different irradiance, spectrum and cell temperature. *Energy* **2015**, *90*, 846–856. [CrossRef]
50. Fernández, E.F.; Almonacid, F. Spectrally corrected direct normal irradiance based on artificial neural networks for high concentrator photovoltaic applications. *Energy* **2014**, *74*, 941–949. [CrossRef]
51. Fernández, E.F.; Almonacid, F. A new procedure for estimating the cell temperature of a high concentrator photovoltaic grid connected system based on atmospheric parameters. *Energy Convers. Manag.* **2015**, *103*, 1031–1039. [CrossRef]
52. Rivera, A.J.J.; García-domingo, B.; del Jesus, M.J.; Aguilera, J.; Jesus, M.J.; Aguilera, J.; del Jesus, M.J.; Aguilera, J. Characterization of Concentrating Photovoltaic modules by cooperative competitive Radial Basis Function Networks. *Expert Syst. Appl.* **2013**, *40*, 1599–1608. [CrossRef]
53. Almonacid, F.; Fernández, E.F.; Mallick, T.K.; Pérez-Higueras, P.J. High concentrator photovoltaic module simulation by neuronal networks using spectrally corrected direct normal irradiance and cell temperature. *Energy* **2015**, *84*, 336–343. [CrossRef]
54. García-Domingo, B.; Piliougine, M.; Elizondo, D.; Aguilera, J. CPV module electric characterisation by artificial neural networks. *Renew. Energy* **2015**, *78*, 173–181. [CrossRef]
55. Almonacid, F.; Rus, C.; Hontoria, L.; Fuentes, M.; Nofuentes, G. Characterisation of Si-crystalline PV modules by artificial neural networks. *Renew. Energy* **2009**, *34*, 941–949. [CrossRef]
56. Almonacid, F.; Rus, C.; Pérez, P.; Hontoria, L. Estimation of the energy of a PV generator using artificial neural network. *Renew. Energy* **2009**, *34*, 2743–2750. [CrossRef]
57. Almonacid, F.; Rus, C.; Hontoria, L.; Muñoz, F. Characterisation of PV CIS module by artificial neural networks. A comparative study with other methods. *Renew. Energy* **2010**, *35*, 973–980. [CrossRef]
58. Almonacid, F.; Rus, C.; Pérez-Higueras, P.; Hontoria, L. Calculation of the energy provided by a PV generator. Comparative study: Conventional methods vs. artificial neural networks. *Energy* **2011**, *36*, 375–384. [CrossRef]
59. Almonacid, F.; Rodrigo, P.; Hontoria, L. Generation of ambient temperature hourly time series for some Spanish locations by artificial neural networks. *Renew. Energy* **2013**, *51*, 285–291. [CrossRef]
60. Lee, C.D.; Huang, H.C.; Yeh, H.Y. The development of sun-tracking system using image processing. *Sensors (Switzerland)* **2013**, *13*, 5448–5459. [CrossRef] [PubMed]
61. Alata, M.; Al-Nimr, M.; Qaroush, Y. Developing a multipurpose sun tracking system using fuzzy control. *Energy Convers. Manag.* **2005**, *46*, 1229–1245. [CrossRef]
62. Choi, J.S.; Kim, D.Y.; Park, K.T.; Choi, C.H.; Chung, D.H. Design of fuzzy controller based on PC for solar tracking system. In Proceedings of the ICSMA 2008—International Conference on Smart Manufacturing Application, Gyeonggi-do, Korea, 9–11 April 2008; pp. 508–513.
63. Taherbaneh, M.; Fard, H.G.; Rezaie, A.H.; Karbasian, S. Combination of fuzzy-based maximum power point tracker and sun tracker for deployable solar panels in photovoltaic systems. In Proceedings of the IEEE International Conference on Fuzzy Systems, London, UK, 23–26 July 2007; pp. 1–6.
64. Yousef, H. Design and implementation of a fuzzy logic computer-controlled sun tracking system. In Proceedings of the IEEE International Symposium on Industrial Electronics (Cat. No.99TH8465), Bled, Slovenia, 12–16 July 1999; Volume 3, pp. 1030–1034. [CrossRef]
65. Yeh, H.-Y.; Lee, C.-D. The Logic-Based Supervisor Control for Sun-Tracking System of 1 MW HCPV Demo Plant: Study Case. *Appl. Sci.* **2012**, *2*, 100–113. [CrossRef]
66. Chi, Z.; Yan, H.; Pham, T. *Fuzzy Algorithms: With Applications to Image Processing and Pattern Recognition*; World Scientific: Singapore, 1996.
67. Hirota, K. *Industrial Applications of Fuzzy Technology*; Springer: Berlin/Heidelberg, Germany, 1993.
68. Alcalá, R.; Casillas, J.; Cordón, O.; Herrera, F.; Zwir, S.J.I. Techniques for Learning and Tuning Fuzzy Rule-Based Systems for Linguistic Modeling and their Application. Available online: https://www.researchgate.net/publication/239667434_Techniques_for_Learning_and_Tuning_Fuzzy_Rule-Based_Systems_for_Linguistic_Modeling_and_their_Application_E (accessed on 30 January 2019).
69. Zadeh, A.L. Fuzzy Sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]

70. Delgado, M.; Gómez-Skarmeta, A.F.; Martín, F. A fuzzy clustering-based rapid prototyping for fuzzy rule-based modeling. *IEEE Trans. Fuzzy Syst.* **1997**, *5*, 223–233. [CrossRef]
71. Yoshinari, Y.; Pedrycz, W.; Hirota, K. Construction of fuzzy models through clustering techniques. *Fuzzy Sets Syst.* **1993**, *54*, 157–165. [CrossRef]
72. Cordon, O.; Herrera, F. A General Study on Genetic Fuzzy Systems. Available online: https://sci2s.ugr.es/sites/default/files/ficherosPublicaciones/0160_gfs-1995-33-57.pdf (accessed on 30 January 2019).
73. Cordón, O.; Herrera, F.; Lozano, M. A classified review on the combination fuzzy logic-genetic algorithms bibliography: 1989–1995. In *Genetic Algorithms and Fuzzy Logic Systems. Soft Computing Perspectives*; World Scientific: Singapore, 1997; pp. 209–241.
74. Muñoz-Expósito, J.E.; García-Galán, S.; Ruiz-Reyes, N.; Vera-Candeas, P. Adaptive network-based fuzzy inference system vs. other classification algorithms for warped LPC-based speech/music discrimination. *Eng. Appl. Artif. Intell.* **2007**, *20*, 783–793. [CrossRef]
75. Piri, J.; Kisi, O. Modelling solar radiation reached to the Earth using ANFIS, NN-ARX, and empirical models (Case studies: Zahedan and Bojnurd stations). *J. Atmos. Solar-Terrestrial Phys.* **2015**, *123*, 39–47. [CrossRef]
76. Prasad, K.; Gorai, A.K.; Goyal, P. Development of ANFIS models for air quality forecasting and input optimization for reducing the computational cost and time. *Atmos. Environ.* **2016**, *128*, 246–262. [CrossRef]
77. Kharb, R.K.; Shimi, S.; Chatterji, S.; Ansari, M.F. Modeling of solar PV module and maximum power point tracking using ANFIS. *Renew. Sustain. Energy Rev.* **2014**, *33*, 602–612. [CrossRef]
78. Najah, A.; El-Shafie, A.; Karim, O.A.; El-Shafie, A.H. Performance of ANFIS versus MLP-NN dissolved oxygen prediction models in water quality monitoring. *Environ. Sci. Pollut. Res.* **2014**, *21*, 1658–1670. [CrossRef]
79. Driankov, D.; Hellendoorn, H.; Reinfrank, M. *An Introduction to Fuzzy Control*; Springer: Berlin/Heidelberg, Germany, 1993.
80. MODIS Daily Level-3 Data. Available online: http://gdata1.sci.gsfc.nasa.gov/daac-bin/G3/gui.cgi?instance_id=MODIS_DAILY_L3 (accessed on 24 October 2014).