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Intelligent system for a remote diagnosis of a photovoltaic solar power plant

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Abstract. Usually small and mid-sized photovoltaic solar power plants are located in rural areas and typically they operate unattended. Some technicians are in charge of the supervision of these plants and, if an alarm is automatically issued, they try to investigate the problem and correct it. Sometimes these anomalies are detected some hours or days after they begin. Also the analysis of the causes once the anomaly is detected can take some additional time. All these factors motivated the development of a methodology able to perform continuous and automatic monitoring of the basic parameters of a photovoltaic solar power plant in order to detect anomalies as soon as possible, to diagnose their causes, and to immediately inform the personnel in charge of the plant. The methodology proposed starts from the study of the most significant failure modes of a photovoltaic plant through a FMEA and using this information, its typical performance is characterized by the creation of its normal behaviour models. They are used to detect the presence of a failure in an incipient or current form. Once an anomaly is detected, an automatic and intelligent diagnosis process is started in order to investigate the possible causes. The paper will describe the main features of a software tool able to detect anomalies and to diagnose them in a photovoltaic solar power plant.

1. Introduction

Usually small and mid-sized photovoltaic plants are located in rural areas and typically they operate unattended. Some technicians are in charge of the supervision of these plants including their usual maintenance and, if an alarm is automatically issued, they try to investigate the problem and correct it. These technicians tend to live close to the geographical area of the plant but they need some time to attend an alarm. In this context it is necessary to have the appropriate tools available that can continuously and remotely monitor the normal behaviour of the plant and diagnose the causes of possible anomalies resulting in losses of production or damaging some components of the plant. Current monitoring systems in solar power plants are based on alarms triggered when a threshold is over passed in some measured variable [1], [2]. However, in some cases the behaviour of the plant can be slowly degrading over important periods of time without over passing any threshold and without issuing any warning of this situation. In this context there are various studies and publications trying to characterize the performance of the solar plant and the degradation of some of its functional parts using several procedures and algorithms [3], [4], [5], [6] and [7]. In many cases in order to detect anomalies either some specific expert knowledge is required to analyze the behaviour of the solar plant, or some knowledge is desired to be automatically extracted from its operation, or both. In order to cover theses aspects several Artificial Intelligent techniques have been tested with promising results [8], [9] and [10]. Along this research line, this paper presents a prototype of an intelligent system

designed to work in real-time whose main contribution in this field is an architecture that integrates in a unique framework the capability of data acquisition, anomaly detection and diagnosis of an unattended solar power plant.

The paper is organized as follows: Section 2 describes the objectives and architecture of the intelligent system named ISDIPV (**I**ntelligent **S**ystem for **DI**agnosis of a **P**hoto**V**oltaic solar power plant). Section 3 describes the detection of anomalies of ISDIPV based on normal behaviour models. Section 4 describes the diagnostic module and a brief presentation about the interface of the application. Section 5 enumerates the conclusion of the paper.

2. Objectives, operation and architecture of ISDIPV

This paper presents the main characteristics of an intelligent system, named ISDIPV, of which the objective is the automatic detection and diagnosis of anomalies and faults that can occur in a photovoltaic (PV) solar power plant. The system tries to identify anomalies as soon as possible with respect to the normal behaviour expected in the operation of a photovoltaic plant. Once an anomaly is detected, its possible causes are investigated automatically and diagnosed. The events detected and their diagnoses are issued to the personnel in charge of the plant.

ISDIPV is able to collect information in real-time from different types of sensors installed in a PV solar plant and to pass it through its different modules in order to analyze if this information includes some symptoms of anomalies that must be diagnosed.

The functional architecture of ISDIPV and its main modules are presented in 'figure 1'. They are briefly described in the next paragraphs.
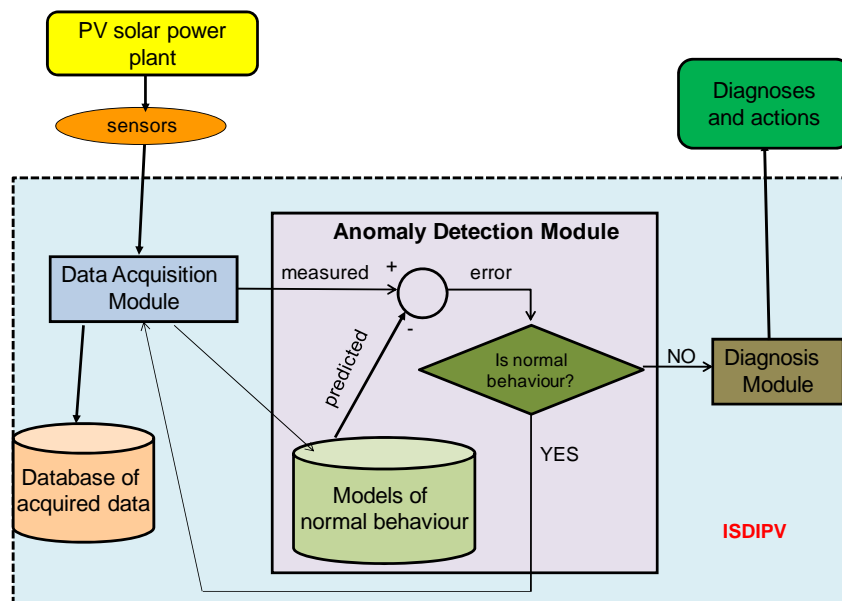

Figure 1. ISDIPV architecture.

- *Data acquisition module*. This allows for the collection of all information coming from the different sensors installed at key points of the PV solar power plant. The information collected in real-time includes the following items: date, solar irradiation, ambient temperature and generated electrical power energy. This data is saved in a historical database.
- *Anomaly detection module*. This module analyses all the data collected in real-time and tries to discover if they include some symptoms of anomalies. In order to do this, a set of models

named "models of normal behaviour" are used to predict the evolution expected for key variables representative of performance of the PV plant monitored. The models are fitted before they can be used as references of normal behaviour. The models allow for the characterisation of the typical relationships between a set of input variables and one or several output variables for all the possible working conditions considered as normal performance at the plant being monitored. Once the models are fitted, they can be used in real-time to compare their estimation to the real values of the variables predicted and, if a relevant deviation is observed, the normal performance expected is violated and an anomaly is discovered. The models used by ISDIPV are of two types: one is based on dynamic regression techniques [11], [12] and the other one is based on neural networks techniques [13], [14]. Both types of models are redundant in order to facilitate the reliability of the anomalies detected.

- *Diagnosis module*. In the case that an anomaly is detected by the anomaly detection module, the diagnosis module will try to investigate its root cause and if possible, to suggest corrective actions. This module is based on a small expert system which processes the information about the anomaly detected and its symptoms. The expert knowledge is represented by common production rules with the format: **If** conditions **Then** conclusions and **Also** actions. The uncertainty is based on certainty factors associated to each production rule according to the results of the models and a previous FMEA (Failure Mode and Effects Analysis) [15]. The expert system reasons, as is usual in the diagnostic field, in a forward-chaining mode from symptoms to diagnoses.

3. Anomaly detection module and normal behaviour models

The anomaly detection module of ISDIPV has as its main goal the detection of anomalies as soon as possible in a PV solar power plant using the results given by the normal behaviour models. Thus, the comparison between the normal behaviour expected for the PV plant with its real behaviour, will suggest the presence or not of abnormal behaviour symptoms whose causes must be immediately investigated and diagnosed [16], [17].

The normal behaviour models in this context have to be considered as a reference of the normal behaviour observed in the PV solar power plant for any working condition. Any deviation with respect to this behaviour can suppose an anomaly that can progress resulting in a catastrophic fault, or it can be a simple stress condition with little or no consequences in the life of the plant components or it can be a fault that is taking place. In any case, a deviation with respect to the normal behaviour expected in the plant is not desirable and has to be corrected as soon as possible, because if it is not corrected, economic and production losses will impact the normal life of the plant. For this reason it is extremely important to have a good reference available about the normal behaviour, but due to the dynamic working conditions of the plant, it is not possible to prefix a particular value. A model is required that uses as inputs the changing environmental conditions of the plant, as independent variables, and as output the resulting generated electrical energy from the plant.

There are many alternative techniques and options for building a model that can reach the desired objective. In ISDIPV two types of techniques were finally used in order to obtain the normal behaviour models: dynamic regression modelling based on Linear Transfer Functions (LTF) [11] and neural networks models based on multi-layer perceptrons (MLP) [13]. Two types of redundant models where built in order to make the process of anomaly detection more reliable than when using only one type of model. As was mentioned, other modelling techniques can also be good candidates to be used, but the experience of the authors and the results obtained sufficiently covered the need to characterize the normal behaviour of the PV solar power plant. The reason for the selection of the mentioned techniques was based on the fact that, in general, the behaviour of the plant is reasonably linear with respect to the environmental variables, however in some cases a more non-linear relationship appears. Taking into account these considerations, dynamic regression and neural networks models were selected to cover them adequately due to their good ability to model these types of dynamic relationships.

ISDIPV includes 2x10 models of normal behaviour inside its anomaly detection module, half of which are based on LTF techniques and another half based on MLP. 'Figure 2' shows a functional scheme of the anomaly detection module and its main components. The next subsections describe the process followed to build the normal behaviour models and how they are used by the anomaly detection module.
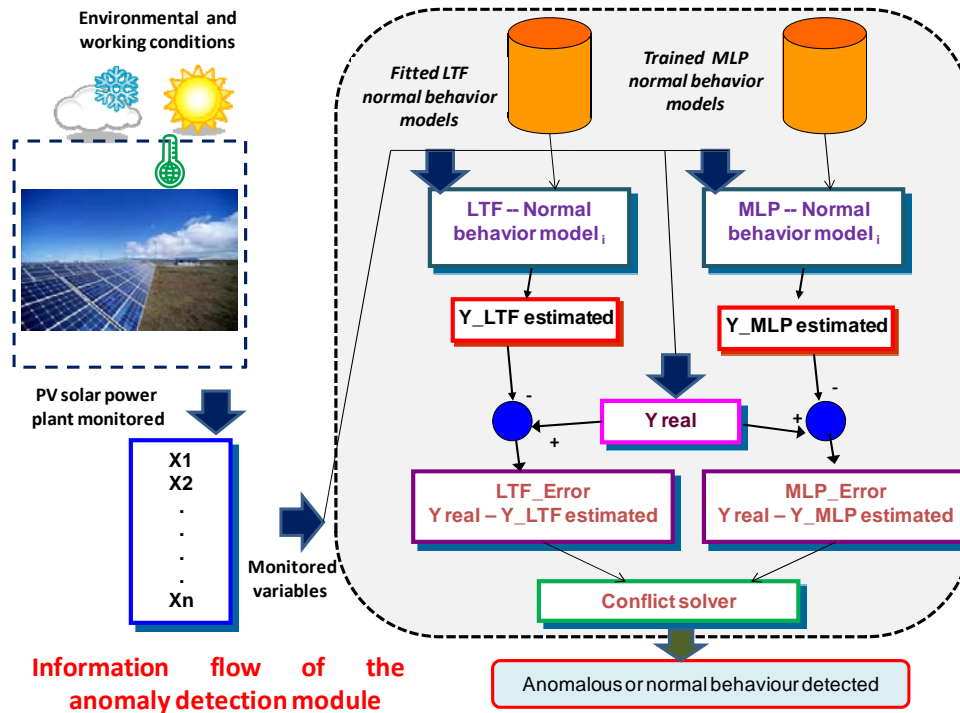

Figure 2. ISDIPV anomaly detection module.

3.1. Data used and its preprocessing

The data used for the creation of the normal behaviour models come from two PV solar power plants in the same location. These data are those mentioned in section 2 for the data acquisition module: date, solar irradiation (W/m^2), ambient temperature (°C) and generated electrical energy (kWh). The measured variables for both plants are the same.

In order to develop both the LTF and MLP normal behaviour models, a period of time without any detected malfunction in both plants was selected, and the data corresponding to this period was used for fitting/training the models. This period of time covers eight months between June 2009 and January 2010. During this period both summer and winter working conditions are included and the data are available every 15 minutes. Before using the data for building the models, a preprocessing analysis was done in order to remove a few outliers and to better know the relationships among the measured variables. As an example, 'figure 3' presents the profiles of produced electrical energy and solar irradiation during the period of time analyzed in one of the two PV solar power plants, and from this figure it is easy to infer that an obvious relationship between solar irradiation and produced energy exists. Also it can be observed in 'figure 3' that the night time hours have been removed.
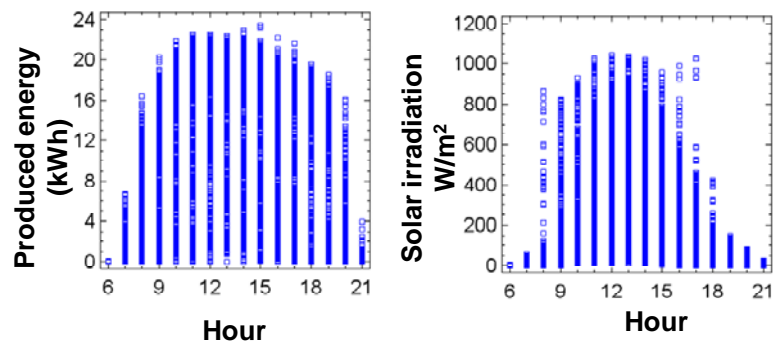
Figure 3. Profiles of generated electrical energy and solar irradiation during the period of time analyzed.

'Figure 4' shows the relationships between produced energy, solar irradiation and temperature respectively. This suggests that a possible model can be developed among these variables. In order to enhance these relationships a new analysis was performed dividing the data of the period analyzed into two groups corresponding to environmental conditions close to winter and summer respectively. This made it possible to narrow the areas observed in 'figure 4' and to create a more robust modelling of the existing relationships.
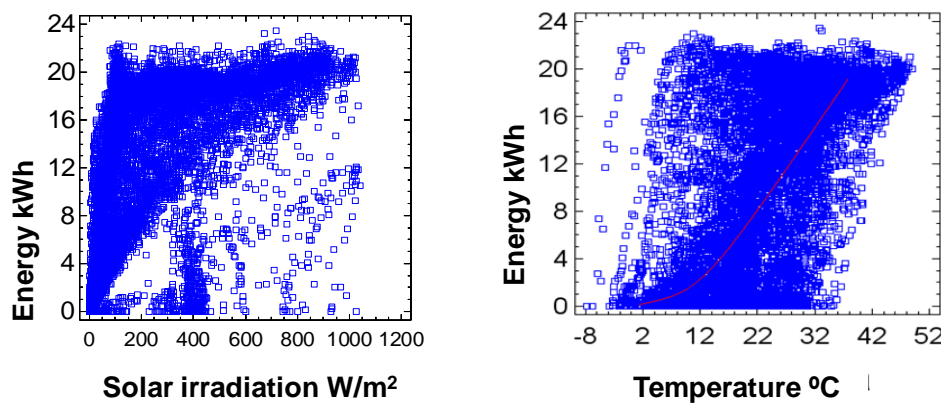

Figure 4. Generated electrical energy versus solar irradiation and temperature during the period of time analyzed.

3.2. Normal behaviour models

The relationships found in the measured variables suggest the creation of models able to predict certain variables as a function of other ones. This will make it possible to predict the value of a variable using the value of others due to the relationship existing among them. In order to create such models, the data previously selected were used. In the case that significant residual are discovered due to that the predicted value does not correspond to the real value measured, the typical relationship existing in normal behaviour is broken.

After the analysis of the data of the two PV solar power plants, referred to from now on as PV_1 and PV_2, the models developed for characterization of their normal behaviour were the following:

a. Estimation of produced energy as a function of solar irradiation and ambient temperature. Four models were developed, two for each photovoltaic plant monitored for winter and summer periods. The objective of these models is to verify that the produced energy for particular environmental conditions is the same along time. In the case of detection of a deviation, a possible fault in the photovoltaic panels or in the sensors has to be investigated.

b. Estimation of produced energy in PV_2 as a function of the produced energy in PV_1. Two models were developed, one for winter and another one for summer. Due to the fact that both solar power plants are in the same location and under similar environmental conditions, an obvious relationship between the productions of both plants must exist. If this is broken, there is a fault in one of the plants and this has to be investigated.

c. Estimation of solar irradiation in PV_2 as a function of that in PV_1. Similar to case b, two models (winter and summer) were developed for monitoring the measured solar irradiations which have a typical similar evolution. In this case if the relationship between solar irradiations is broken, one of the sensors measuring the solar irradiation should be reviewed.

d. Estimation of ambient temperature in PV2 as a function of the ambient temperature in PV_1. Similar to case c, two models (winter and summer) developed for monitoring the measured temperatures agree following a similar evolution. In this case if the relationship between temperatures is broken, one of the sensors measuring the ambient temperature should be reviewed.

A total of ten models were proposed for each one of the two modelling methods LTF and MLP used. Therefore, the anomaly detector module of ISDIPV consists of 20 models characterizing particular and different aspects of PV_1 and PV_2.

3.2.1. *Linear Transfer Functions models (LTF).* The LTF models were developed according to the method of dynamic regression proposed in [11]. A LTF model has the general expression shown in equation (1).

$$P_t = C + v_1(B)X_{1t} + ... + v_n(B)X_{nt} + \frac{\theta_{q_0}(B)\theta_{q_1}(B^{S_1})...\theta_{q_m}(B^{S_m})}{\nabla^d\nabla_{S_1}^{D_1}...\nabla_{S_m}^{D_m}\phi_{p_0}(B)\phi_{p_1}(B^{S_1})...\phi_{p_m}(B^{S_m})}\varepsilon_t \tag{1}$$

where P_t is the output variable to be predicted, C is a constant term, $X_{1t}, ..., X_{nt}$ are exogenous variables such as solar irradiation and ambient temperature, and ε_t is an independent random noise. The integer values $S_1,...,S_m$ stand for the seasonal periods, e.g, 24 and 168 for hourly time series. B is a backshift operator ($BX_t=X_{t-1}$), and $\phi_{p_0}(B), \phi_{p_1}(B^{S_1}),..., \phi_{p_m}(B^{S_m})$ and $\theta_{q_0}(B), \theta_{q_1}(B^{S_1}),..., \theta_{q_m}(B^{S_m})$ are backshift operator polynomials modelling the regular and seasonal autoregressive and mean average effects, respectively, of the output variable. $\nabla^d, \nabla_{S_1}^{D_1},..., \nabla_{S_m}^{D_m}$ are difference operators meaning for example $\nabla^d X_t = (1-B)^d X_t$ and $\nabla_{S_1}^{D_1} X_t = (1-B^{S_1})^{D_1} X_t$. These operators describe the differences applied to input and output variables of the model to transform in stationary the analyzed process. $v_1 ... v_n$ represent a family of linear transfer functions able to capture a wide number of impulse responses with few parameters. They can be expressed by equation (2).

$$v(B) = \frac{(w_0 + w_1B + w_2B^2 + ... + w_sB^s)B^b}{1 + \delta_0 + \delta_1B + \delta_2B^2 + ... + \delta_rB^r} \tag{2}$$

Predictions are therefore obtained as linear combinations of past and present values of actual and predicted prices and, if available, of other exogenous variables. Note also that these models are able to

deal with the daily and weekly seasonal cycles. The success of these models lays in a well-established identification and diagnostic checking methodology [12], [11], a reduced number of parameters that can be easily interpreted and their representation capabilities (accurate forecasts are obtained in a wide range of processes). ARIMA, ARMAX and Dynamic Regression models fit within the general formulation of LTF models.

As an example, the main characteristics of the LTF winter model for predicting the generated electrical energy by PV_1 (E_PV_1) are described in the following lines. This model has as inputs the solar irradiation received by PV_1 and the ambient temperature.

First the main parameters of the dynamic regression model were fitted after several iterations finding their best values. These parameters correspond to the regression coefficients for the exogenous variables solar irradiation (SI) and ambient temperature (AT). After this analysis and according to equation (1), the model can be formulated as in equation (3).

$$E\_PV\_1(t) = (0.2162 - 0.1781B^{-1})\ SI(t) + (0.01604 + 0.001577B^{-1})AT(t) + N(t) \quad (3)$$

Then an ARIMA model was studied for the component $N(t)$ in equation (3) corresponding to the error of this model. After a previous analysis of this error using autocorrelation and partial autocorrelation functions, a regular component was determined along with a seasonal component of order 52 corresponding to the number of samples collected each day. Also difference operations were required for both regular and seasonal components of the time series. Finally for the regression error, the ARIMA structure $(2,1,1)x(0,1,1)_{52}$ was selected whose coefficients where fitted. The behaviour of the complete LTF model and its main characteristics are presented in 'figure 5'. As can be observed, a fitting accuracy of 95.8% was obtained along with a reasonable final residual error.
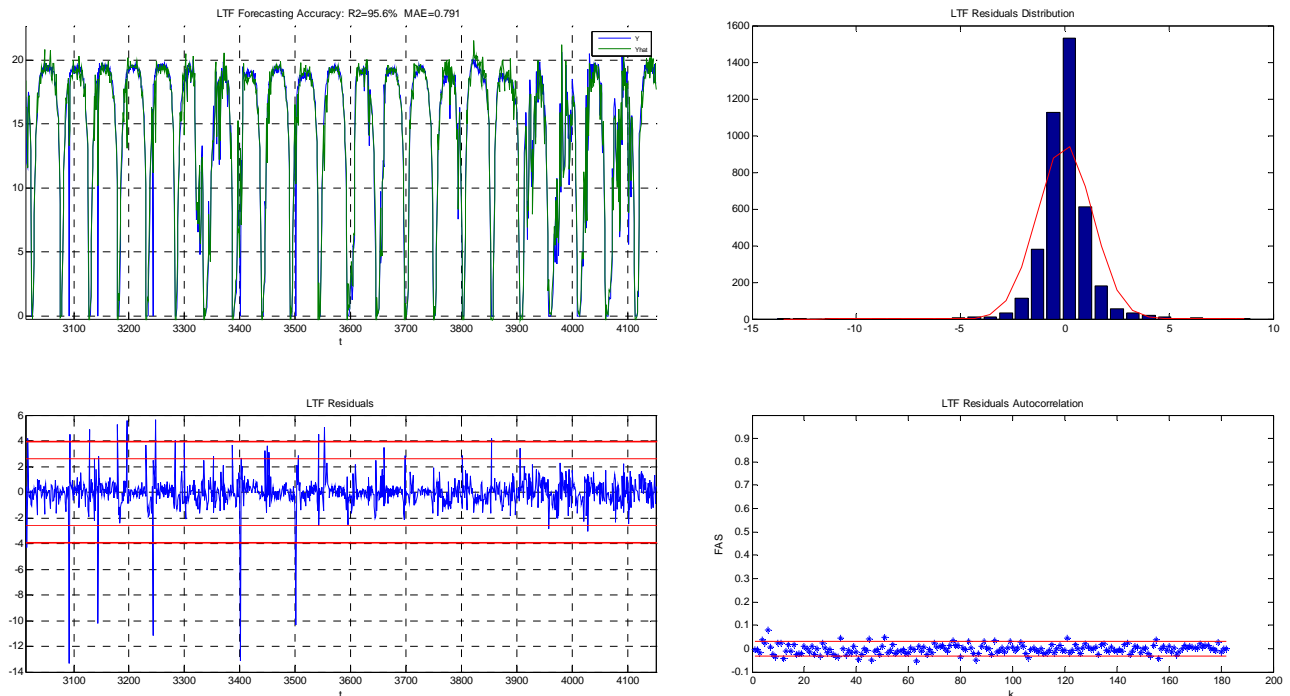

Figure 5. LTF model of normal behaviour for predicting the energy generated by PV_1 in function of the solar irradiation and the ambient temperature.

3.2.2. Multi-Layer perceptron models (MLP). The MLP neural networks are well-known Artificial Intelligence techniques [13], [14] and [18] that can approximate non-linear relationships among

variables. In particular, in the context of this paper, MLP models are used as multivariate non-linear regression models with universal function approximation capabilities [19]. Their main drawbacks are the risk of overfitting and their lack of interpretability.

A MLP model was developed for each LTF model. This expected redundancy between both types of models permits a better reliability in the anomaly detection process by complementing their advantages and disadvantages.

A first decision to take, when a MLP model is trained, is its architecture. In this process and for each model, different architectures were tested and finally the one with best results for fitting the training and validation sets of data was selected. During the same testing process, several options of delays for the inputs variables were tried because the output predicted by the model could be sensitive to delayed samples of an input variable.

As an example, the main characteristics of the MLP winter model for predicting the generated electrical energy by PV_1 (E_PV_1) are described in the following lines. After the mentioned process of selection for inputs variables and neurons of the ML architecture, this model has as inputs the solar irradiation received by PV_1, the irradiation received by PV_1 in the previous sample and the ambient temperature. This model can be expressed by equation (4).

$$E\_PV\_1(t) = f(SI(t), SI(t-1), AT(t)) \quad (4)$$

Therefore the architecture of the MLP selected consists of three input neurons, one output neuron and 15 neurons in a hidden layer between inputs and output. The activation functions in the ouput and hidden layers were the linear and the tanh-sigmoid functions respectively. The behaviour of the MLP model for this case and its main characteristics are presented in 'figure 6'. As can be observed a fitting accuracy of 93.6% was obtained along with a reasonable final residual error.
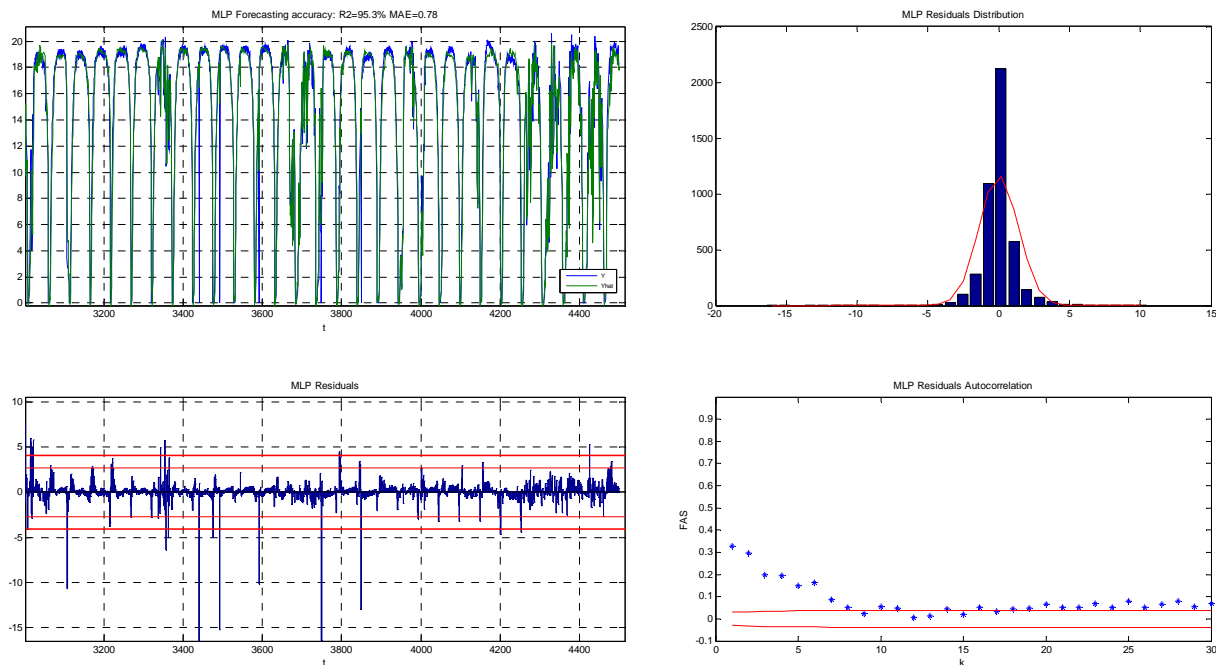

Figure 6. MLP model of normal behaviour for predicting the energy generated by PV_1 in the instant t as a function of the solar irradiation in t and t-1 and the ambient temperature in t.

3.3. Anomaly detection procedure

Once the normal behaviour models have been developed it is necessary to define the requirements to assert that an anomaly is present. First, it is necessary to define when an abnormal behaviour is detected. This is done when the difference between real and predicted values for an output variable of a model overpasses three times or more the standard typical deviation of the used model which was obtained after training/fitting its parameters. This is based on a well-known statistical rule about the distribution of a gaussian white noise. As can be observed in the examples shown in 'figures 5 and 6', the remaining errors after fitting the model parameters are similar to distributions of white noise (see the "normalization test" section in the mentioned figures).

In order to guarantee the reliability of the presence of an abnormal behaviour, an anomaly is detected and issued when in a time frame of five consecutive samples of data, three or more of them have been detected as being abnormal behaviours. This is based on typical control quality criteria [20] and attempts to reduce the risk of false alarms.

Once an anomaly is detected, a certainty factor is associated to this detection based on the number of abnormal behaviours detected in the time frame of the last consecutive five samples of data and in the quality of the model defined by its degree of explanation of the data used in its fitting. As an example, if a LTF or MLP model has detected 4 abnormal behaviours in the last five samples of data and the model has an accuracy of 95% obtained in the training/fitting process, its associated certainty factor would be: (4/5)*0.95= 0.76

Each time that an anomaly is detected and due to the fact that each model has two versions: LFT and MLP, the final certainty factor of the anomaly detected is the mean value of the certainty factors of both models. This will reinforce the reliability and robustness of the anomaly detected. The final certainty factor of a discovered anomaly will be obtained using equation (5).

$$FC = (FC\_LFT \times A\_LFT + FC\_MLP \times A\_MLP) / (A\_LFT + A\_MLP) \qquad (5)$$

Where FC_LFT and A_LFT are the certainty factors and the accuracy of the LFT model respectively, and FC_MLP and A_MLP are the certainty factor and the accuracy of the MLP model respectively.

The severity of an anomaly detected can be catalogued according to the value of its certainty factor FC in the following categories: *important* $0.5 \leq FC$, *medium* if its certainty factor is $0.25 \leq FC < 0.5$ and low being $FC < 0.25$.

4. Diagnosis module and ISDIPV interface

The main goal of the diagnosis module of ISDIPV is the investigation of the root causes of the detected anomalies. The diagnosis module has the typical structure of an expert system [21], [22] including a facts database with static information about the main characteristics of the PV solar plant and dynamic information corresponding to on-line detected events and measured variables. These events correspond to the outputs from the anomaly detection module with their associated certainty factors. Also, the diagnosis module has a knowledge base where the knowledge required to investigate the possible causes of the detected anomalies is stored. The knowledge is represented by production rules using the typical schema **if** *conditions* **then** *conclusions*. These rules were obtained from an FMEA (Failure Mode and Effects Analysis) of the main malfunctions of the PV solar power plant and experience of the plant. The failures considered were: energy generation system failure, solar irradiation sensor failure, ambient temperature sensor failure and DC/AC power converter failure.

As an example, an energy production system failure could be diagnosed as present in PV_1 when:

- an anomaly has been detected by the model that predicts the produced energy of PV_1 as a function of solar irradiation and ambient temperature of PV_1.
- an anomaly has been detected by the model that predicts the produced energy in PV_2 as a function of the produced energy in PV_1.

- no anomaly was detected by the model that predicts the produced energy of PV_2 as a function of solar irradiation and ambient temperature of PV_2.
- no anomalies were detected in the sensors of solar irradiation and ambient temperature.
- Similar reasoning can be asserted for the detection of a failure in the energy production system of PV_2.

As another example, the diagnosis of a failure in the solar irradiation sensor can be formulated as:

- an anomaly has been detected by the model that predicts the solar irradiation received in PV_1 as a function of the received in PV_2.
- an anomaly has been detected by the model that predicts the produced energy of PV_1 as a function of solar irradiation and ambient temperature of PV_1.
- no anomaly was detected by the model that predicts the produced energy of PV_2 as a function of solar irradiation and ambient temperature of PV_2.
- no anomaly was detected for the PV_1 ambient temperature sensor

The ISDIPV knowledge base includes the mentioned cases translated into production rules and others obtained using a similar method for all the rest of the considered failure modes.

The main interface of the ISDIPV is presented in 'figure 7'. It includes information about the variables measured in the solar power plants, the detected anomalies and the issued diagnostics with its explanation. The ISDIPV application was developed in JAVA as a prototype able to demonstrate the main features of an automatic and intelligent remote diagnostic of a PV solar power plant.
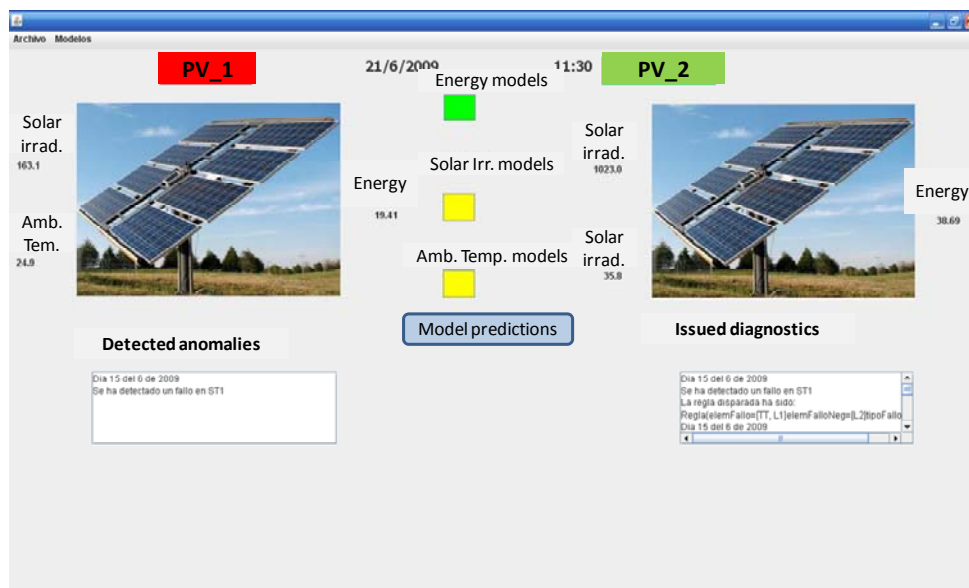

Figure 7. Main ISDIPV interface.

5. Conclusions

This paper describes a prototype of a tool called ISDIPV which is able to diagnose the causes of anomalies in an unattended PV solar power plant. It consists of three main functional components for data acquisition, anomaly detection and diagnosis of causes of the detected deviations with respect to the normal behaviour. The detection of anomalies is based on models able to characterize the normal behaviour observed in the PV plant. Two types of modelling techniques were used for the characterization of the normal behaviour expected: LFT and MLP. The redundancy between both types of models guarantees a better robustness in the reliability of the anomaly detection. An expert system was used for analyzing the causes of the abnormal behaviours detected. Its knowledge base

was based on experience and an FMEA analysis. A software tool was developed for integrating all these functional modules and for communication to the user.

The ISDIPV tool is useful in unattended PV solar power plants because it continuously analyzes the information received like an operator working in the plant and, in the case that some important event occurs, this is communicated to the person in charge of the plant.

Acknowledgements

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