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Failure Classification in High Concentration Photovoltaic System (HCPV) by using Probabilistic Neural Networks

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Abstract

In this paper, we present an expert diagnostic system for the interpretation of four different categories of system's functioning based on an innovative feature extraction tequiniques and a Probabilistic Neural Network for the classification of events identifying failures that can occur during in a high-concentration photovoltaic (HCPV) system located in Fleri, Sicily (Italy). In this paper we have considered four different categories of system's functioning: sun tracking system malfunction, cloudy conditions and temperature sensor malfunction, darkness and night time, normal functioning.

Keywords: photovolatic systems, performance indicators, neural networks, failure analysis.

INTRODUCTION

In the last decades the growing attention significance to environmental issues has induced many country to investigate the renewable energy sources as a concrete alternative for the thermos-mechanical conversion [1, 2]. As a matter of the fact in last years solar energy has played a key role for innovative energy systems [3]. Among all possible technologies involved in the use of solar energy, solar photovoltaic energy is probably considered one of the most diffuse source of electricity [4]. These technology presents several advantages such as: a decreasing cost of installed kWp with consequent shorter payback periods, it can be easily integrated in buildings, no greenhouse gases emissions [5, 6], a good efficiency in comparison with other renewable energy technologies [7]. Moreover, PV technology is still the fastest growing power generation technology [8, 9]. In last decade it has faced an increase of about 55% each year. As an example, the worldwide cumulative installed capacity passed from 2,0 GW in 2006 to about 3,1 GW.

Despite of these considerations the Solar panel manufacturers are still attempting to make solar panels robust in such way as to ensure two decades at least. However, the Real Lifespan of Solar Panels of 20-25 years without maintenance and degradation, is not real, since the panels subjected to solar constant exposition, are affected by aging [10], deterioration of components [11], mechanical and electrical faults such as a short-circuit failure (water can seep through the surface) or interruption [12]. The other types of faults are related to external phenomena such as atmospheric conditions [13], weather and wind, and physical damage (e.g. surface scratches for trees, snow, leaves, twigs and bushes) that cannot be foreseen or predicted or even removed from the entire photovoltaic system. The infrequent event is the risk of the lightning damages to the entire solar system and electronic equipment [14], on this matter, as deterrent, the lightning rods and cages are installed according to European Lightning Protection Standards IEC/EN 62305-1/4. The most important part of the photovoltaic system is the inverter, performing the conversion of the power produced used for the household appliances. This requires constantly to ensure the regular maintenance and cleaning from dust and any deposits, the replacement of broken or burned fuses [15]. For all these reasons a great attention is turned to mathematical models that are able to foresee and treat mechanical, physical or other types of faults [16, 17]. In this paper it was investigated a new method to recognize and treat failures of a new technology with an advanced optical system to focus the sun light onto each cell for maximum efficiency as the Concentrating Photovoltaic (CPV) system. From the analysis of the collected data for HCPV installed different problems are recognized:

– The mechanical arrangement of the sun tracking system such as the stepper motor can no longer control the angle of the panel and the rotation of platform moving the HCPV at different direction of

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solar radiation. In such case the light sensors can malfunction however the temperature is correctly detected by the sensor;

- The PV module temperature sensor remains failure for a certain period of time until the maintenance task;
- Failure of data communication system;
- Any exchanged data for absence of network;
- Others problems.

During the night time or darkness the PV panels are not generally energized and the power generation is not produced. In case of snow, rain, cloudy weather and dark climate the solar panel performance decreases.

The method proposed is based on Probabilistic Neural Network (PNN) for the classification of events that identifying the failures that can occur in the high-concentration photovoltaic (HCPV) system located in Fleri, Sicily (Italy).

THE PROBLEM OF FAULTS PREDICTION

Protection is a critical point in Smart Grid and the various distributed generators connections to distribution feeders require advanced protection devices to improve security and reliability. Communication based relays, automatic fault location, and automatic sensitivity and selectivity changes in the protection devices, are characteristics of smart protective applications to distribution networks [18, 19].

Advanced fault management is also a critical task in Smart Grid, In fact combining communication-based adaptive protection relays, wide area monitoring such as phasor measurement units, and fast acting switching devices with communication capabilities, an advanced fault management can limit the extent of an abnormal condition and rapidly restore large portion of the network, isolating the faulted sections.

The presence of distributed generators in a Smart Grid environment influences the design of the protection system. Conventional distribution networks which have unidirectional current flow employ over-current protection schemes. But, with the inclusion of distributed generators, network power flows may change, making conventional protection schemes unsuitable. Moreover, as the Smart Grid acts as a single entity to the main grid, the protection scheme should include the capability to isolate itself in case of a fault in the main grid. Similarly, the protection scheme should be capable of localizing faults within the Smart Grid. In particular, the sensitivity and selectivity of the protection system needs to be carefully designed to ensure secure and reliable operation of the Smart Grid. Conventional techniques involve complicated calculations and may introduce errors in the estimated fault prediction. These can be overcome by the application of Neural Networks (NN). We feel that NN are suitable for an efficient faults prediction [20-22].

Figure 2: The HCPV system installed in Fleri (Sicily-Italy).

Table I: The HCPV Manufacturer's Specifications

Number of Modules	8 (with a nominal peak power of 440 W)
Geometrical concentration factor	476x
Module's surface	18 m^2
Active collector	16 m^2
area	930 Kg
Weight	8.6 m
Width	8.4 m
Length	25%
Overall efficiency	

The incipient faults in can be detected using diagnostic techniques by observing the degradation in system performance. Due to the nature of observed data and available knowledge, diagnostic methods are often a combination of statistical inference and machine learning methods [23]. NN are a better option for diagnosing faults in electrical equipment for the following reasons:

- They can interpolate from previous learnings and give a more accurate response to unseen data, making them better at handling uncertainty.
- They are fault tolerant, so they handle corrupt or missing data more effectively.
- They are good non-linear function approximators by nature, making them better at equipment diagnostics.
- They are more suitable for extracting the relationship between input and output in fault detection and diagnosis applications.

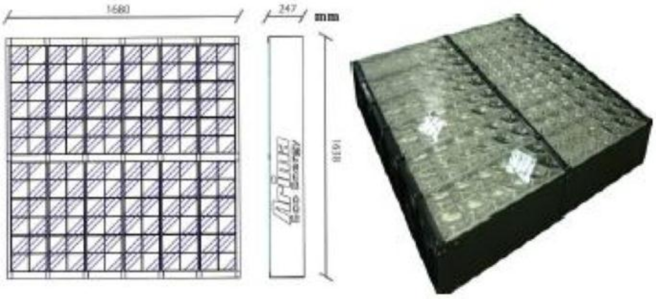

Figure 3: The modules used in the HCPV installed in Fleri.

Table II: Module Parameters.

Cells	Multijunction III-V
Number	144
Dimensions	5.5x5.5 mm
Weight	60 kg
Certification	IEC- 62108
Cooling system	Natural Conention
Module Power	440 W
V_{OC}	440 V
I_{SC}	1.29 A
V_{MPP}	400 V
I_{MPP}	1.1 A

THE CONCENTRATING PHOTOVOLTAIC SYSTEMS (CPV)

The high cost of modules technology, made up of Si, GaAs or other semiconductors, is leading cell photovoltaic manufacturers to find new solutions with higher efficiency values. CPV systems are a concrete answer to this new demand, by concentrating the sunlight by optical devices like lenses or mirrors reduces the area of expensive solar cells or modules, and increases their efficiency. These systems present the advantage to reduce the active photovoltaic surface used for the photoelectric conversion exploiting an optical system that concentrates on it the direct solar radiation. This leads these systems to reach efficiency values up to almost 50% . Despite of this main advantage they still present some disadvantages. The use of only direct solar radiation component is achieved by a complex system constitute of a fragile set of components that may incur in frequent faults [m]. Moreover it has been demonstrated that with particular meteorological conditions, even if they reach higher efficiency values, the overall yearly energy production may be less than fixed angle PV systems one. The main components of CPV systems are usually the following: optical concentrator, heat sink, sun-tracker, inverter. The concentrator is usually an optical system constituted by lenses or mirrors with the aim at concentrating the sun light on the photovoltaic cell. Fresnel lens is the most used lens in CPV systems. This optical system could be of three types: point focus when there is one focus for each cell, linear focus when radiation is focused in one line and dense-array when there is a focus for groups of closed cells.

Figure 4: Tracker Control Unit (left) and Solarimeter (right).

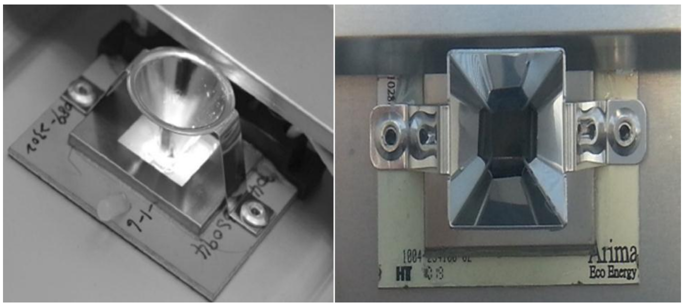

Figure 5: Aluminum reflective concentrators.

The receiver is constituted of photovoltaic cells, they are usually multi-junction GE III-V. The IIIV multi- junction solar cell offers extremely high efficiencies and best response to high temperatures compared with traditional solar cell made up of a single layer of semiconductor material.

Multi-junction solar cells can make better use of the solar spectrum by having multiple semiconductor layers with different bandgap energy. Each layer, usually an III-V semiconductor, is designed to absorb a different portion of the spectrum. By increasing the number of the spectral regions and thus reducing the energy intervals of each region, the energy losses through thermalization may be reduced. The heat sink is necessary for the systems to keep the temperature relative low and minimize the losses of energy production due to the typical thermal drift that usually occurs in CPV systems. The tracking system is necessary to follow the direct component of the sunlight, typically it is an electromechanical system at one or two axes with the aim at keeping the modules always in an horthogonal position with solar radiation, it has to be accurate especially with high concentration degrees.

These systems may differ one to each other in function of the concentration degree of solar radiation. The low concentrating photovoltaic systems (LCPV) with a concentration degree up to 40 times uses generally silicon cells with high efficiency. The high concentrating photovoltaic systems (HCPV) are able to reach concentration degree up to 500 times with multi-junction cells.

Table III: Traker Specifications

Azimuth tracking range	0° - 270°
Elevation angle tracking range	0° - 80°
Type	Dual axis
Acceptace half angle (AHA)	0,3°
Working maximum wind speed	90 km/h
Weight	450 kg

Table IV: Optical characteristics of Fresnel lens

Primary optics	Fresnel lens
Dimensions lens	240x240 mm
Concentration	476x
Focal distance	200 mm
Secondary optics	Reflective homogenizer

THE CASE STUDY

The HCPV system considered in this paper is installed in Fleri (Sicily-Italy) (Figure 1), has a nominal peak power of 3,5 kW_p and consists of a mechanical bi-axial tracking system conteining a matrix of 8 modules, consisting of multi- junction solar cell on the receiver plate with the Fresnel lens on the top lens plate, surrounded by a metal frame. The main characteristics of this system are reported in Table I.

Each module (Figure 2) is constituted of two parts: the optical group and the tripe-junction cell with its heat sinker. This latter is located on the back of the module. It is essential to the problem of thermal lift. Usually, in traditional systems such as fixed angle PV systems with silicon cells, the thermal power loss coefficient (percentage variation of power for *°C*) at standard test conditions is about 0,40%/*°C* . The considered HCPV suffers less and its coefficient is -0,25%/*°C*. The module's parameters are displayed in Table II.

The concentration of irradiation (476 suns) is achieved by the optical design, using Fresnel lens which has circular symmetry about its axis and concentrates sunlight onto the GaAs solar cell. This optical system is point focus, each cell is provide of its own main and secondary optical lens.

HCPV modules, in contrast to PV, need to be constantly aligned with respect to the direct light sun beam. This is why HCPV are mounted on sophisticated trackers which follow the sun in order to guarantee normal incidence of the direct light beam. If a concentrator is not perfectly aligned with the sun beam, it will lose part of the available energy.

Dual axis sun tracking systems are required for HCPV applications while the tracking system improves the efficiency of PV system. In this system there is a dual axis tracker that can follow the sun both vertically and horizontally and thus it can track the sun's apparent motion virtually anywhere. The solar tracking strategy uses optical tracking technique.

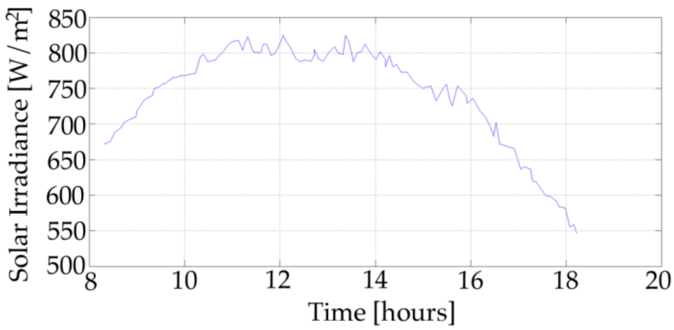

Figure 6: Solar irradiance in the module plane for a typical sunny day (14/05/2012) in Fleri (Sicily-Italy).

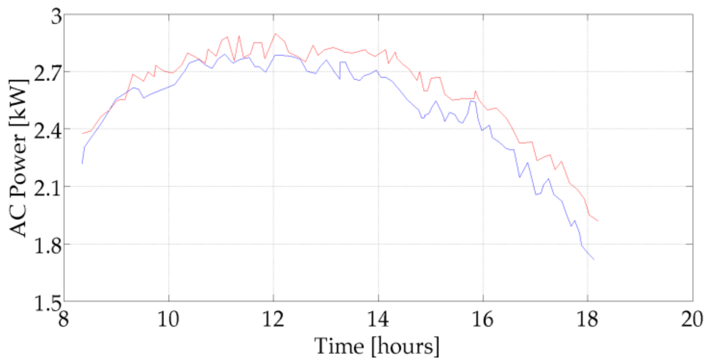

Figure 7: AC Power generation of the HCPV for a typical sunny day (14/05/2012) in Fleri (Sicily-Italy).

These dual axis dries combine the azimuth and elevation movement.

The drive mechanisms include linear actuators, linear drives, swivel drives, worm gears, planetary gears, and threaded spindles. The drive type is a rotary gear drive with a driven motor power of 2500 rpm/48W/24V DC, mechanism used as azimuth and linear drive provides the necessary mechanical movement and torque to enable solar tracking used in elevation angle (3000 rpm/72W/24V CC).

The movement is controlled both with astronomical equipment and optical system. The astronomical equipment uses astronomical equations of the movement of earth around the sun and is not affected by the presence of clouds. The optical system takes advantage of sensors present in the system to follow the apparent movement of sun but suffers of the presence of clouds (Figure 3).

The dual axis sun tracking systems is used to optimize and reduce the tilt angle. This misalignment angle at which the performance of concentrator is reduced by more than 10% is

called acceptance angle. The maximum acceptance angle for the HCPV under consideration is 0, 3°. The specifications of the tracking system are shown in Table III.

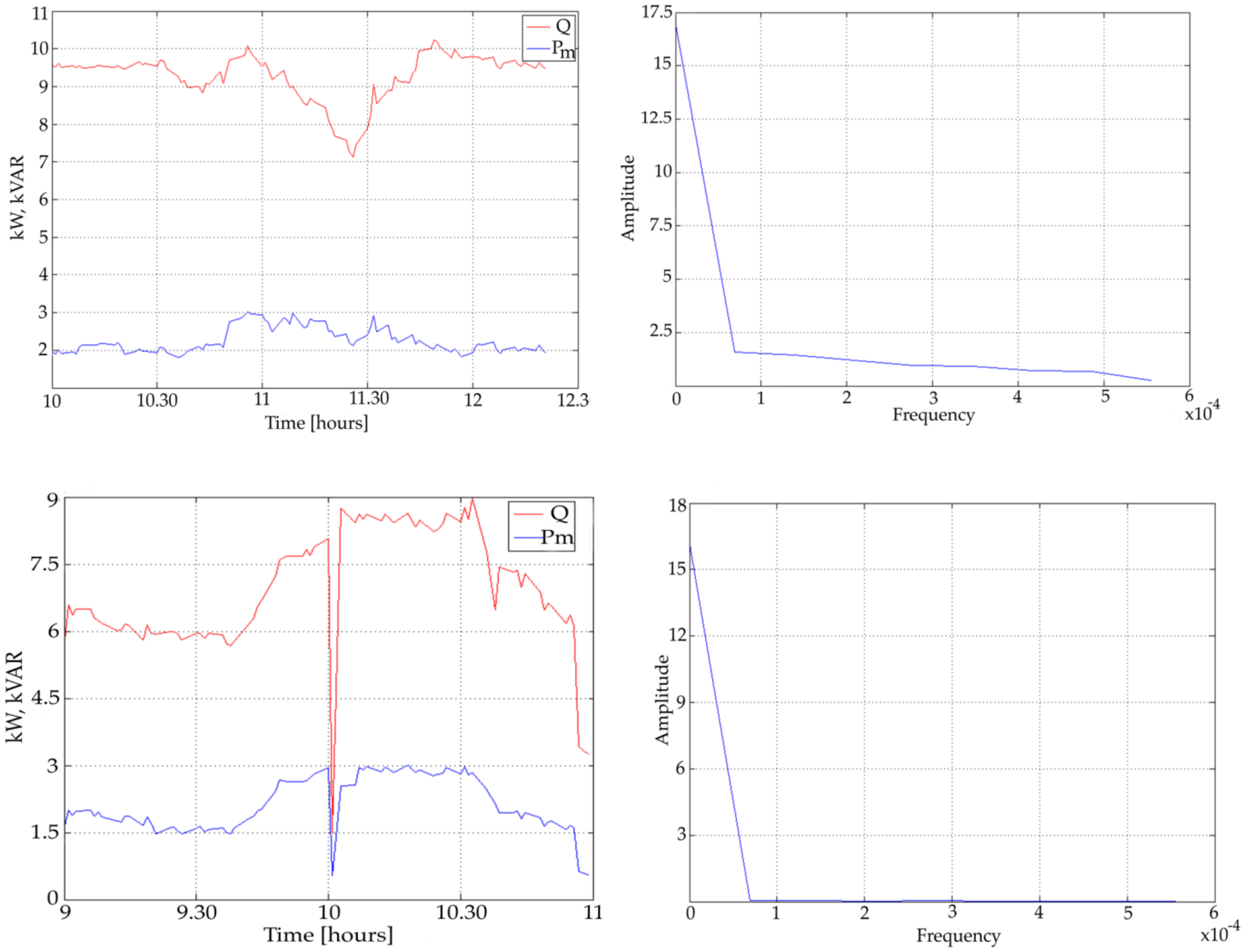

Figure 6: Top diagrams display the mean and reactive power during a windowed interval of time in normal operating conditions and its windowed Fourier transform while bottom diagrams display the mean and reactive power during a windowed interval of time in a faulty condition and its windowed Fourier transform.

The optical system is composed of two parts: a primary optic and a secondary one. The main optic is constitute of Fresnel lenses made in PMMA. The efficiency of these lenses is about 90%. It suffers usually of a deflection of the light beam caused by the not uniform polymers. The secondary optics is a reflective homogenizer that distributes homogenously the radiation concentrated by the lens on the whole active surface (in Figure 4 are shown the reflectors cones). In Table 4 are reported the main characteristics of the optical system.

The photovoltaic cells, used in the HCPV, are triple-junction III-V Ge with an efficiency of 39%. The combination of these cells with a point focus Fresnel lens (IEC 62108) with a concentration of 476 x allows to reach an overall efficiency of about 25%. The triple-junction allows to convert the photoelectric radiation to electrical energy with a more extended range of wave lengths (300-1700 nm) in comparison with the typical cell of silicon (300-1140 nm).

EXPERIMENTAL DATA

The data have been collected at 15-minute intervals, in particular, the irradiation (kW/m^2), the modules temperature (°C), the inverter's current (A), the produced energy (kWh) and the active power (kW). The data is recorded during the period starting from January 2014 to December 2014.

In Figure 6 and 7 there are reported the direct radiation in the modules and the power calculated during a sunny day.

In order to analyze the system performances it was used the Performance ratio (PR). The performance ratio is calculated by:

$$PR = \frac{YF}{YR}$$

Where:

– The Array Yield (YF) is the ratio between the energy production E [kWh] and the peak power of the system P_0 [kWp]. It normalizes the energy produced with respect to the system size, being a convenient way to compare the energy produced by systems of differing size;

- The Reference Yield (YR) is the ratio between the solar radiation directed perpendicularly to the active surface (EDNI) [kWh/m^2] and the Direct Normal Irradiance (DNI) (i.e. 850 [W/m^2] for concentrated PV systems). It represents the number of working hours at the DNI considered.

PR compares the real production of the system with the attended one. Moreover, it is a good performances index because it shows the proportion of the energy loss (e.g. due to thermal losses and conduction losses, inverter inefficiency, wiring, mismatch and other losses when converting from D.C. to A.C power) and of energy consumption for operation. The theoretical power in a HCPV system is calculated as:

$$P_{HCPV} = P_{HCPV} \cdot \sigma \cdot C \cdot \eta_S \cdot A_{HCPV} \cdot \eta_S \tag{1}$$

Where

- I_{HCPV} is the direct component of solar radiation;
- $\sigma * C$ is concentration coefficient net of optical losses;
- A_{HCPV} is the photovoltaic surface;
- η_S and η_i are the efficiency of the module and the inverter.

In this paper we have considered four different categories of system's functioning. More specifically :

1. Sun tracking system malfunction ;
2. Cloudy conditions and temperature sensor malfunction;
3. Darkness and night time;
4. Normal functioning.

METHODOLOGY

The conventional way of modeling of the algorithms for the failures detection and classification needs to be augmented or replaced with intelligent techniques that are robust and fault-tolerant. The Neural Networks (NN) provides a promising alternative in the situations outlined above [24, 25].

One of the primary objectives of the renewable sources is to operate economically and reliably. This depends greatly on accurate demand forecasting and renewable generation forecasting. The purpose of demand forecasts is to predict the power that will be consumed by the load. In conventional power systems, demand depends on the weather, type of day and random activities or incidents.

There are various techniques based on statistic and on artificial intelligence which can forecast the load for the next 24 hours with a good degree of accuracy. Due to high variations in the load profile, it is difficult to accurately forecast demand. Hence, the models developed should try to predict the load with reasonable accuracy. Some of the factors to be considered while developing the NN model are:

– Increased responsiveness of demand to predicted real-time electricity prices as compared to conventional grids.
– Classification of load profiles of different customer classes based on the consumption of electricity.
– Need to input past demand as different components (like base load, peak load, valley load, average load and random load), instead of combining them into a single input.
– Type of day (weekday/weekend) input may not have much effect on forecasting for a Hospital Smart Grid, whereas it is a major factor impacting the load profile of a Residential Smart Grid.

In this paper we face the problem of faults prediction by using an approach based on neural networks and on a new time-frequency feature extraction technique. An extended statistical study of the historical data series of reactive power and mean power generated by the HCPV shown that when a fault approaches, the reactive power is affected by a series of bad anomalous effects. It is virtually impossible to determine the peculiar modification of each singular side effect as much as their composition, but it is possible to intercept the time window and the spectral signature that these effects generate respect to the normal functioning.

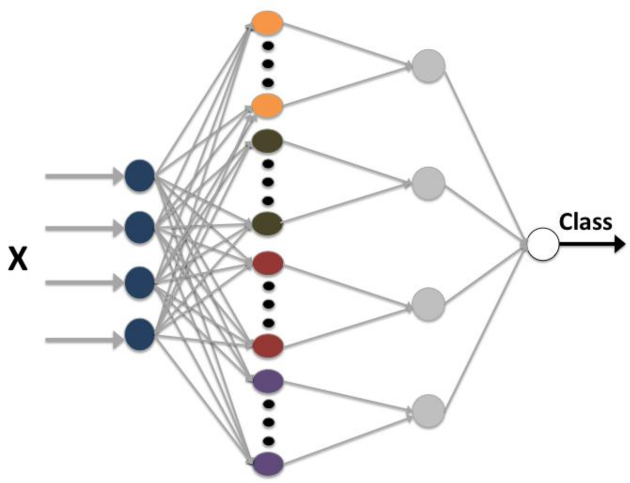

Figure 8: The proposed cascade PNN architecture.

The implementation was done in order to obtain the correct prediction of what should be the time serie progression relative to a windowed interval of time, and, simultaneously, intercept the spectral characteristics of such predicted progression to identify an overcoming fault.

In order to characterizing the spectral signature we have calculated the expected and variance values of the mean and reactive power both in the time domain and in the Fourier domain these calculation are performed by using a sliding window. The time amplitude of the window is 2,5 hours.

In Fig. 5 is shown a sample of the expected and variance values of the mean and reactive power in regular and faulted conditions (Sun tracking system malfunction).

VII. THE PROPOSED NEURAL NETWORK ARCHIECTURE

The PNN implementated in this paper is organized as multilayered feedforward network with four layers:

- Input layer.
- Pattern layer.
- Summation layer.
- Output layer

The PNN is created by a set of multivariate probability densities which are generated from the training vectors presented to the PNN. The input instance with unknown category is propagated to the pattern layer. The outputs are a linear combination of the hidden nodes outputs. More specifically, the k-th network output has the form [26]:

$$y_k(x(t)) = \sum_{j=1}^{M} w_{k,j}\, \phi_j(x(t)) \quad (2)$$

where

$$\phi_j(x(t)) = exp\left\{-\frac{1}{2\sigma_j}\left(x(t)-\mu_j\right)^T \Sigma_j^{-1}(x(t)-\mu_j)\right\} \quad (3)$$

μj and Σj are the function center (mean vector) and covariance matrix of the j-th basis function respectively and σj is a smoothing parameter controlling the spread of the j-th basis function.

RESULTS AND DISCUSSION

To evaluate the pattern recognition algorithm, dataset is randomly split into three parts: a training set consisting of 900 data points (600 data points representative of the various kind of faults and 100 representative of normal operative condition) a validation set consisting of 100 data points and a testing set consisting of 100 data points. The training set is used to find the model parameters in the used PNN network. These parameters are the number of neuron for each class and the the weights value.

The resulting network after the training phase and pruning is shown in Fig. 8. It consists of 120 neurons (40 for each class). Once the optimal parameters are found the trained algorithm is applied to classify the data points in the testing dataset into one of the two classes. A correct classification rate of 90% average has been obtained.

CONCLUSION

In this study, we developed an expert diagnostic system for the interpretation of four different categories of system's functioning by using an innovative feature extraction tequiniques and a probabilistic neural networks (PNN). More specifically :

1. Sun tracking system malfunction.
2. Cloudy conditions and temperature sensor malfunction.
3. Darkness and night time.
4. Normal functioning.

The stated results show that the proposed method can make an efficient interpretation with an accuracy of 90\%.

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