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Progress in Smart Industrial Control based on Deep SCADA

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Abstract

The SCADA system, acronym of ''Supervising Control and Data Acquisition'' tends to improve its accuracy in detecting faults. In that, it uses fault diagnosis models based mostly on probabilistic methods with close uncertainties. These models are based on a subjective evaluation by comparing the obtained signal to its reference. Therefore, SCADA precision fault detection varies depending on the operation environment, system design and analysis approach among other factors. The contribution of this research work is to propose a smart strategy that will enrich and enhance failure recognition in SCADA systems by integrating two additional models into the classic technique. The first model is a SOM map- reduce simple classifier and the second model is an evolutionary recurrent self-organizing neural filter for final decision-making. This integrated paradigm improves results accuracy and robustness against signal interference. The proposed idea involves best details around any remotely listed defect. This study has been conducted on Simulink-Matlab, through the analysis of multi signals emitted by sensors and received by corresponding antennas.

Keywords: Smart control, Deep SCADA, neural evolutionary algorithm, failure diagnosis.

1. Introduction

Today, the SCADA supervising system is a main tool for performance at the highest levels technologically and economically. It represents the critical eye overseeing many aspects of the industrial production process. Thus, it makes possible to improve the production efficiency through its accurate data analysis.

On other hand, the use of micro electrical networks has begun to multiply around the world. They are handled by combined systems to offer electricity into faraway locations. In this frame, this research article aims to create a novel SCADA approach applied to the same target, powered on by a renewable energy system. It consists of developing a smart supervision structure that has several technical benefits and is economically better. The proposed solution is important since it addresses and resolves powering isolated sites and allows for remotely controlling and monitoring the sites with greater accuracy.

Indeed, currently SCADA meets multiple threats and attacks, resulting from technological progress and environmental and material conditions. These threats contribute to the degradation of information correctness received from sites under control, through communication networks. In order to effectively overcome this problem touching SCADA information security, this paper presents a new solution. It suggests an integration of two models. The first one stands as a primary filter layer and simple classifier. The other model represents a second rank selective filter. It is based on Smart evolutionary recurrent self-organizing neural map, qualified by a high robustness for decision-making. Likewise, this paper proposes a sensor peer mechanism in site to close hardware disturbances.

The experimentation of adopted strategy, shows that it gives a certain robustness to the system against parasites and different scroungers, and allows an objective evaluation based on decision scores.

After introduction, the second section of this paper is devoted to related works. It highlights SCADA history, Architecture, and challenges.

The third section, details adopted strategy and how to overcome SCADA problematic. The fourth section is dedicated to experimental results and their interpretations.

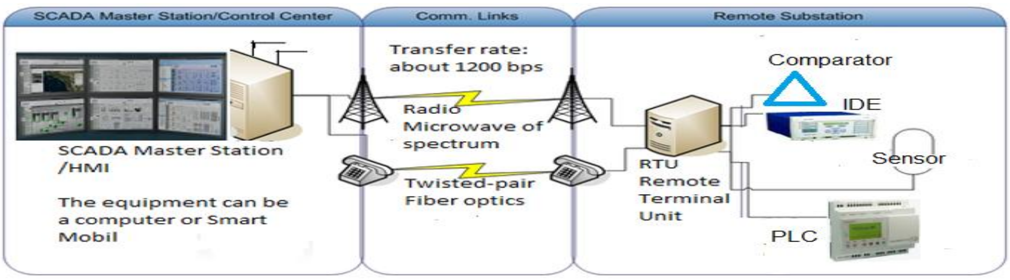
2.Related Works

2.1.SCADA History

In the past factories were operated manually by the human hand. Measurements and controls were done by the human senses and relied heavily on the operator know-how and experience.
The advent of the technology and information age brought with it a revolution of ease and precision in many fields. The Production line automation started with centralized management and devices connected through simple technology.
From there it transformed into smart systems connected over the internet through the TCP/IP protocol [1], [2], [3].
Industrial chains are automated as devices and sensors connect remotely to the network.
Blickey (1985) first described the architectural vision for a remote electromechanical equipment supervision system, highlighting the development of monolithic direct digital control systems in distributed components [4].
Gaushell and Darlington (1987) outlined the SCADA functions and fundamentals of its operations including a brief description of the user interface.
Boyer (1993) defined all components building the recent SCADA system technology. He highlighted the technology of master units remotely receiver and transmitter [5], [6].
Sobota (1998) determined a complex system of data acquisition including a graphical interface for visualization, and real-time storage of monitoring, control history, as well as components for decision support [7].
Zolotova and Stofko (1999) focused their work on the signals processing visualization, taken from the site under control. They performed a combination of hardware, software and artificial intelligence on remote communication in order to ensure real and visible abstract reactions. Treatments are performed on ARMs and well-developed processors to support real-time decision-making [8], [9].
Nowadays, the SCADA system can monitor in parallel many industrial, or other processes, over very long distances regarding satellite frequency scales. It performs, respectively, the following functions: data acquisition in an Internet network or in space by radio frequency, analyzing and processing these data, then making control and correction in a failure case.
These functions are performed through four principal SCADA components: Digital or Analog Sensors with direct interface control Relays to command the production process. Then, Remote Telemetry Units (RTUs) with Programmable Logic Controller PLC deployed on the field in isolated sites. The RTUs are small computerizing units serving as information receiver from different sensors and transmitting instructions to relays. Generally, RTUs are built around a PLC that controls all the necessary actions. All sensors and relays are connected to the PLC input / output modules via fast optical fibers, or through a wireless network protocol [10].

The remote SCADA main unit is a central processor that handles all information received from RTUs, through internet communication networks or antennas. It is often called a master unit. It provides an operating SCADA interface to regulate the supervised process in response to appropriate sensor input/output signals. Eventually, the determination of the communication network between SCADA master terminal unit MTU and the RTUs, must be done according to a judicious choice [11],[12].

Figure. 1. Synoptic diagram of traditional SCADA system



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2.2. SCADA System Architecture

The Master Unit, as a SCADA system head, allows the PLC or RTU parameter Adjustments according an appropriate database [13].

The SCADA system includes as main components:

a. An operator Interface called HMI which stands for a software and hardware part used in an emergency case.

b. A computer monitoring system collects process data, and sends orders (control). It acts as Master Terminal Units MTU.

c. An RTU constituted around a computing electronic device, converting received information to digital data signals to be sent and treated by MTU. It acts as a slave regarding MTU [14].

d. A PLC built around a microprocessor with memory and input/output blocs. It featured by its configuration flexibility and its robustness against the RTU [15].

e. Communication Infrastructure is the link between MTU monitoring system and Remote Terminal Units (RTU).

f. Data History, such as a centralized archive for the purposes of analysis, statistical control and process planning.

2.3. SCADA Security Challenges

Ethernet technology is widely used in industrial automation. They offer connectivity between devices on the infrastructure as well as allow for remote access and control over the Internet Protocol. The Smart Grid is based on these capacities [16].

This System standardization and new features have brought vulnerabilities over the management computing world to industrial systems. So-called proprietary systems, often poor in security mechanisms, are not immune to vulnerabilities that can be exploited by motivated and organized attackers [17].

As the IT world manages to regularly address vulnerabilities, included through patch applications released by software manufacturers and vendors, the industrial world, due to its availability and safety constraints, cannot adopt the same protections. This difference in responsiveness to public vulnerabilities is principal risk that can affect industrial information.

3.SCADA Proposed Strategy

SCADA system equipment must be protected from environmental threats; such as dust effects, dirt, water, corrosives, other fluids and contamination by careful selection of a suitable location or provision of enclosure for adequate protection.

Multiple electromagnetic SCADA threats can be avoided by adequate system design, and coverage with Faraday cages, to neutralize the effects of radiation from outside. Regarding SCADA hardware security, it should be placed within secure areas.

The majority of serious threats, for SCADA system signals, arise from communication networks sharing, which is inevitable. This situation introduces attack threats, which can be under several types:

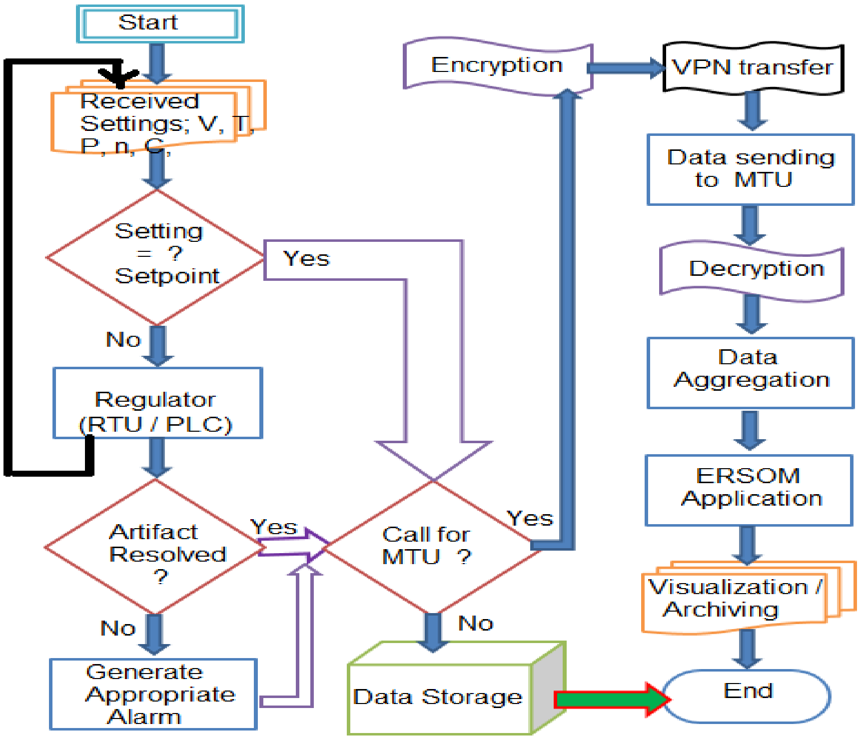
- Unauthorized access by a user (hacking).
- Listening; recording of transmitted data.
- Data interception, modification, retransmission, loss of relevant information.

One of the simple adopted solution is to use private network, inside or outside the establishment. When connectivity, to other networks, is required, data encryption techniques must be executed. Additionally, serious consideration must be given to strengthen the following additional security:

- Physical disconnection while no need service.
- Use of optical fiber, which is characterized by its robustness in adverse environment, and its best transfer rate celerity.
- Unidirectional circulation of information flow.

In order to overcome the problems experienced by the available SCADA model, this paper proposes to enrich it by integration of a security module for transmitted information, via a VPN Virtual Private Network application, and an encryption algorithm. The VPN allows users to create a direct link between remote computers, which isolates their exchanges from the rest of the traffic. This method is being followed by an aggregation module, in order to resolve the Big Data slowness. Eventually, the outputs will be introduced to an Intelligent Self-organizing Neuronal Evolutionary Recurrent module, characterized by its robustness in adverse conditions, with a very high anomaly recognition rate, of up to 99%, for dynamic signals such as provided by machinery. The following algorithm summarizes the principle of the adopted strategy.

Figure .2 : Algorithm of Adopted Strategy



Upon reception of signals at MTU supervision center, a decryption operation is carried out followed by a first filtering layer and data aggregation. It consists of applying simple fast classifiers for Big Data, such as SVM Support Vector Machine, or K-Means Algorithms.

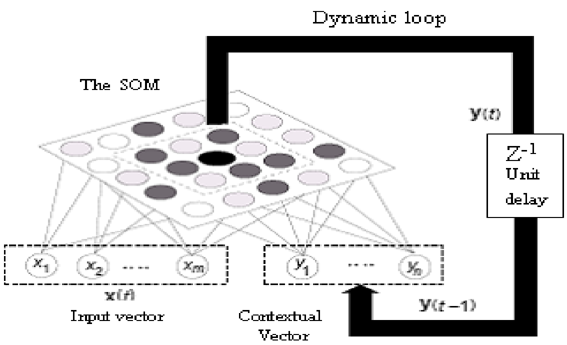
As example, we take a signal (1) that represents the variable T(temperature), and the signal (2) which represents the variable L(light). Both are measured and transmitted from appropriate sensors via RTU to MTU. After their decryption, they undergo a decomposition into a Mel-frequency cepstral coefficients matrix (MFCCs).

We consider only the first 12 decomposition windows to avoid signal redundancy. Every signal will be characterized so by a 12-columns matrix of MFCC. The Mappers receive these matrices and order them into clusters having the same features, according to the defined function. Some coefficients can be slightly distant indicating the presence of an anomaly. Thereafter, a grouping of clusters with the same class K will be carried out. Eventually, each reducer will translate one set of clusters into its corresponding signal with appearance, if is there, of the anomaly type.

After this phase, the signals must go through a Smart ERSOM Evolutionary Recurrent Self Organizing Map system, which represents a second-order filter, more selective, and precise in decision-making.

The SOM is a powerful neural model with unsupervised learning. It is well adapted to Signals recognition of different natures. The unsupervised character allows it to be applicable in Big Data classification. The recurrent loop offers it the temporal aspect, as shown below.

Figure .3. Representation of RSOM Recurrent SOM



Every Signal represented by its MFCC matrix should be concatenated horizontally, using the command 'Hconcat' in Matlab, to form a vector. This later, will be introduced to the RSOM model. For each iteration, the resulting vector should be reintroduced in the map and it is called contextual vector. It participates in the novel iteration (competition between neurons), till a predefined iteration number will accomplish, to converge towards a precise solution. After a certain iteration number, the map SOM starts to treat sequentially another vector, and so on. The provided results will be shown under the simulation form (figure 11), with different recognition scores.

The weight vector Vpi that represents a neuron i, while receiving j input data, is expressed as follows:

$$V_{pij} = \{w_{i1}; w_{i2}; w_{i3};...; w_{ij}\} \tag{1}$$

Each neuron will receive elements characterizing the input vector. The Best Matching Unit, is calculated by the Euclidean distance between the input and the neuron weight:

$$E_i = \|x(t) - w_i\| \tag{2}$$

The winner neuron "v" is the one that minimizes the quantization error

$$E_v = \min E_i \quad ; i \in N \tag{3}$$

In each iteration, one neuron unit called BMU will be activated.

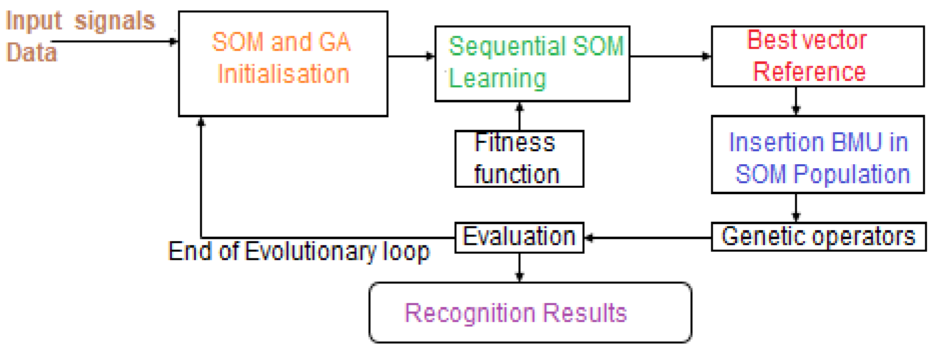
Using recurrence loops is the best way to consider the time factor. It is similar to the sequential logic case in the design of dynamic memories.

By introducing the leakage integrators (filters), from the SOM outputs to its inputs, provides a time vector of leakage difference expressed as follow:

$$y_i(t) = (1-\alpha).y_i(t-1) + \alpha.(x(t) - w_i(t)) \tag{4}$$

Where α is between (0 and 1), designating a leakage coefficient.
NB. A high value of α means a short memorization, however a low value of α involves a long memorization, with a slow activation weakening. In the case where (α = 1), RSOM transforms into normal SOM.
During different iterations, SOM converges towards a local optimum. To extend the search space, we adopted a model hybridizing the SOM with a GA genetic algorithm, as shown below.

Figure .4. Representation of ERSOM algorithm



The optimization of obtained solutions is guided by an associated cost function to GA named fitness:

F= 1 / (sqrt (sum ((Ref-Po). ^2))) (5)

F is a cost function. *Ref* represents the reference vecteur that should be directly recorded on machinery site under normal operating conditions. *Po* represents the weight vector corresponding to each individual in the actual population. In fact, this function is nothing other than an Euclidean distance calculated between the reference vector and each individual. The one with the highest score is considered as elite. A decreasing scores order will be assigned to individuals in accordance with the Matlab command (sort).
The algorithm works as follows:
Take a SOM map made up of 100 x100 neurons. Each neuron represents an individual in the GA population. A neuron is made up of a processor center called Soma, an axon, and (m) dendrites (m = dimension of the input vector). In our case, the input vectors are of dimension 12 (12 MFCC).

Step 1: Initialization of GA population

At the start of vectors analysis relating to received signals, the weights (Wmn) of SOM were initialized linearly to give them the same chance.

Step 2: Evaluation

After analyzing, only one neuron will win; the one that best represents the input signal vector, in one iteration.
Certainly, there are also neighboring neurons which are close to the reference vector.
The application of the fitness function F on population gives a score to each individual, according to their adaptation degree to receive and present the real input signal.

Step 3: Selection

The selection of individuals for the next generation will be made using the following relationship, accompanied by an integration of the first 10 individuals.
The chosen selection is geometric normative with (p = 0.08) as selection ratio:

$$p_i = \frac{q}{1-(1-q)^p}(1-q)^{r-1} \tag{6}$$

With q is the probability of selecting the best individual, r is the individual rank, and p represents the population size.

Step 4: Reproduction

The reproduction is based on heuristic recombination and an experimentally choosing mutation rate around 0.006.
The stop criterion is to reach 200 Generations.

In addition, a hardware solution is suggested. Knowing that the majority of scientific research, in remote processes supervision field, focus on various techniques of protection and information security, coming from various sensors implanted on equipment to be controlled.
They are rushing into proposal solutions relating to sampled signals security, traveling along the communication parts. Everything happens, as if these signals emitting by different sensors are correct and precise. They forget that the signals to be protected, at the communication network level, can be incorrect in the event of a fault or a fatigue condition resulting in one of the sensors.
To remedy this last situation, our strategy proposes the implantation of two sensors for each process to be controlled. The analysis process should be conducted by comparison, using comparator loop, and a developed PLC program, taking into consideration if there is an important value difference measured between the two sensors, it means that one of them is defective. In this case, the RTU should signal an alarm towards the MTU, which reflects it on the HMI.

Noting that the accuracy of the sensors is one of the most important factors in the production accuracy, it appeals to the notion of loyalty and fairness.
The fidelity of a sensor corresponds to the standard deviation (sigma σ) of a measurement set, made for a given measure. More the Sigma standard deviation is higher, less the sensor is faithful. It therefore, characterizes the measurement uncertainties of a sensor depending on random errors that may occur under the effect of electromagnetic noise.
The standard deviation is a dispersion indicator; it is equal to the square root of the variance.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}.\left(x_i - \underline{x}\right)^2} \tag{7}$$

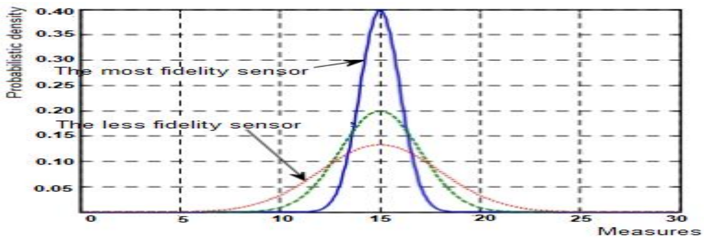
With, x_i represents n measures. $\underline{x}$ is the average value.
More, the standard deviation is smaller, more the sensor is faithful. If the standard deviation is small this means that the values are not very dispersed around the central average, we will therefore have a homogeneous series of measured values, otherwise we will have a heterogeneous series indicating the presence of faults in the

machines functioning. We can consider, in output signals analysis, the variance which is the square of the standard deviation.

$$V = \frac{1}{n}\sum_{i=1}^{n}.\left(x_i - \underline{x}\right)^2 \quad (8)$$

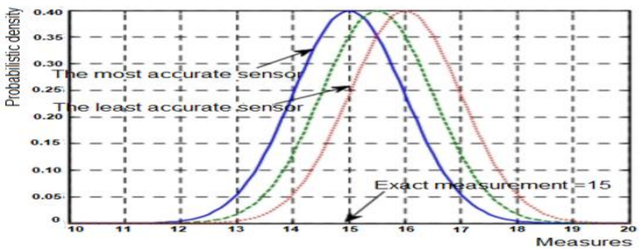
The variance, therefore, represents a precision factor of signals supplied by the sensors, while, the standard deviation represents a fidelity factor.

Figure. 5. Sensor fidelity



The accuracy of a sensor corresponds to the difference between the average value of measurements set made for a measured and the real value for the latter. It corresponds to the systematic errors of the measurement systems. This can be reduced by calibrating and taring the considered sensors:

Figure .6 Sensor accuracy



Precision error can be defined by three variables:
- By the absolute value Ea which delimits an interval around the true value of the measured.
- By the relative error Er which expresses the precision error in percentage in application of the following relation:

$$Er = \frac{Ea}{m}\ x\ 100\% \quad (9)$$

Knowing that m is the measured value.
- By its precision class Cp which expresses the percentage of the precision error in relation to the measurement extent, following the below relationship:

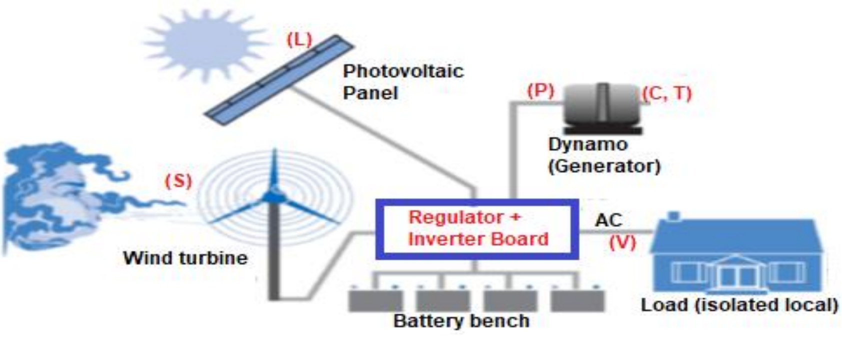
$$Cp = \frac{Ea}{Em}\ x\ 100\% \quad (10)$$

With, Em is the measurement extent.

4.Experimental Results

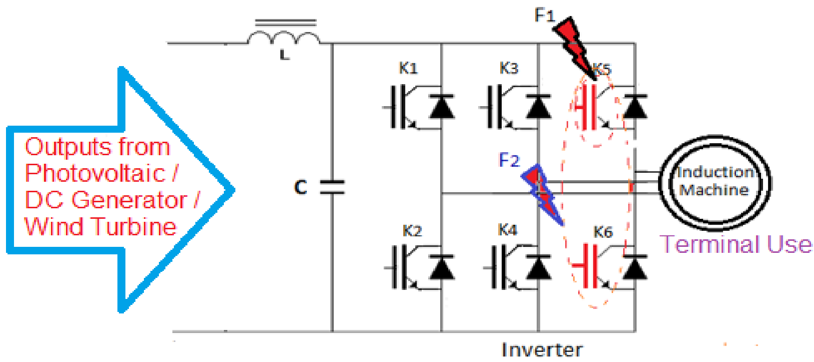
The problem dealt with, in this paper concerns the technical data management emitted from a supplying system for isolated premises, basing on renewable energy production. This management is completed through communication between a PLC, accompanied by RTU elements, and SCADA system. The process to be controlled is a system equipped with photovoltaic panels connected by means of a regulator to a wind turbine, an electric generator and a batch of accumulator batteries as shown in the following figure. The PLC is a high-end S7-400 programmable controller, and the software platform used as a SCADA system is MOVICON software. The technical information to be managed is a series of parameters: P (electrical power), V (electrical voltage), C (mechanical torque of the generator), S (the wind turbine rotation speed), T (the generator operating temperature), L (the light amount received by the photovoltaic panel in order to be transformed into an electric voltage). The process takes place in the following manner: the renewable energy equipment produces a DC voltage which will be stored in accumulator batteries to power on a combined system DC motor-dynamo. The voltage generated by it will be checked by SCADA. It allows to supply an isolated local, under normal conditions, through an inverter. The use of batteries ensures continuity of production service.

Figure .7. Hybrid renewable energy system



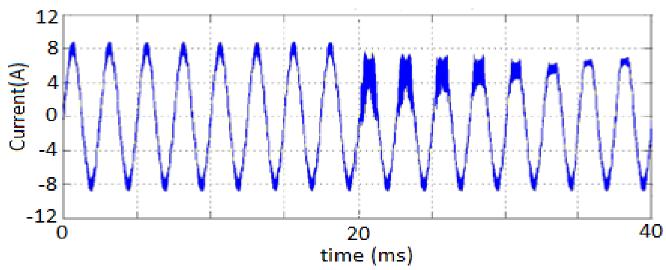
Considering as example, two failures F_1, and F_2, occurred respectively on half-cell or on inverter entire cell as shown in figure below.

Figure .8: Schematic of a fault (F1) in a transistor open circuit and a fault (F2) of a switching cell



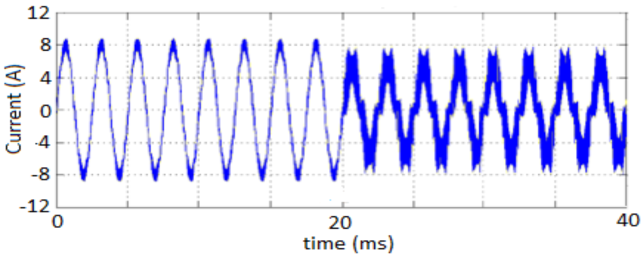
The simulation result of signal waveform representing the supplied current to the motor in charge, subsequent to failure $F_{1,}$ is presented in figure below

Figure .9: Simulation of inverter output current with half-cell malfunction, 20ms



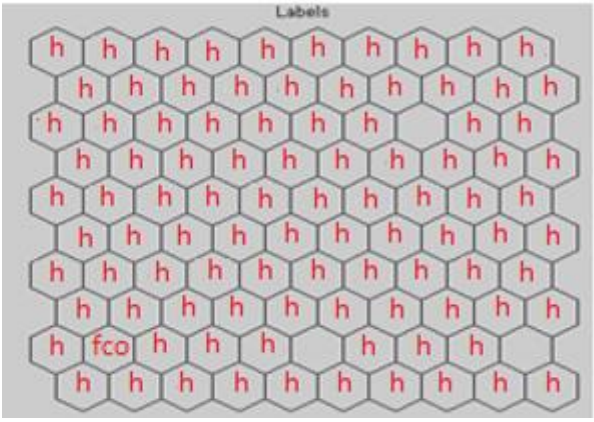
The failure F_2, was experimented on two transistor arms kept in opening mode. The simulation of sent stator current information is given in figure 10.

Figure.10: Simulation of inverter output current with entire cell malfunction, 20ms



The experimentation of the Evolutionary Recurrent Self Organization Module ERSOM, in presence of commutation frequency fault operated on the inverter such as indicated above, gives the following simulation result

Figure .11. Inverter anomaly identification using ERSOM model



The ERSOM learning type is sequential. The displayed variables through the Evolutionary RSOM topology are anomaly symbols. These data are indicated by their appropriate frequency, mentioned as follows:

- h indicates healthy state frequency.
- fco indicates commutation frequency fault.

A comparative study was conducted over various measurements of six variables, from controlled stand figure10.This study was supported, rather than traditional subjective evaluation using only visualization mode, with a scored objective assessment presented by applying a precise Matlab or Python program. Table 1 highlights the improvements provided by our proposed strategy compared to the basic SCADA solution.

Table .1. Comparative results between models in Failure Detection Rates FDR

Data Settings	Failure Detection Rate FDR In Basic SCADA	Failure Detection Rate FDR In Smart adopted SCADA
P (power energy)	90,2 %	98 %
V (voltage)	91,9 %	98,7 %
C (couple)	84,5 %	90,1 %
S (speed)	86 %	95 %
T (temperature)	92 %	99,2 %
L (light)	94,7 %	99,5 %

The following curves and histogram demonstrate the importance of the novel applied paradigm.

Figure.12. Comparative curves between models in FDR

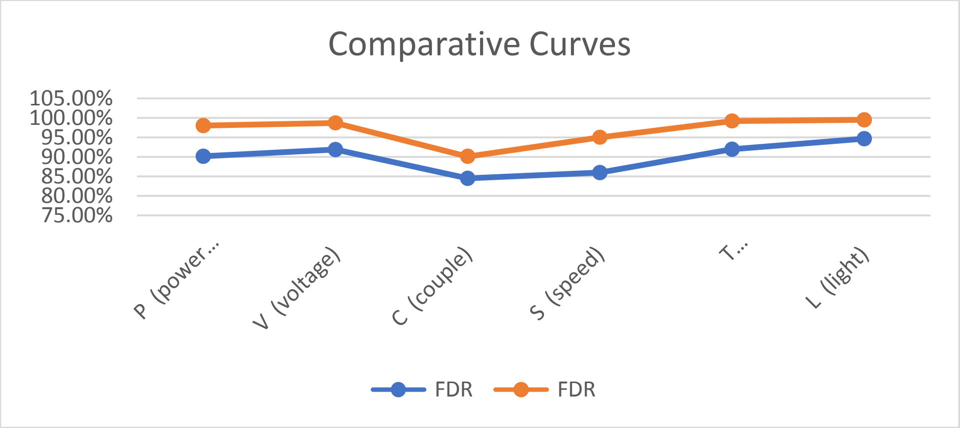


Figure.13. Compared Models in Radar form

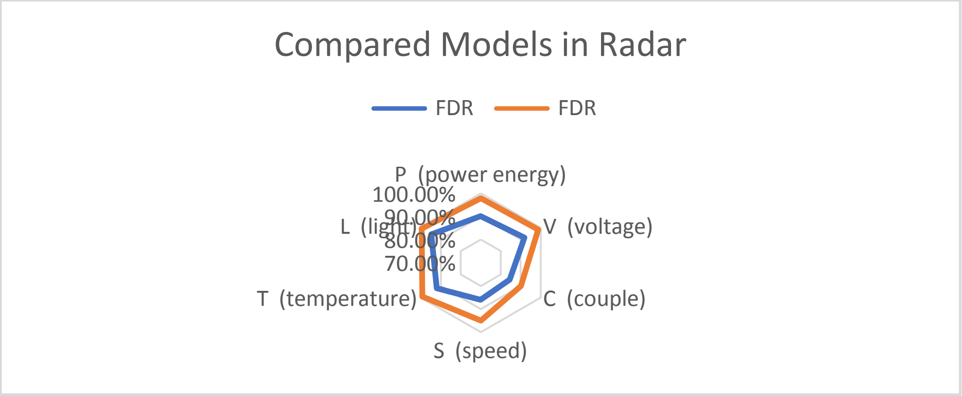
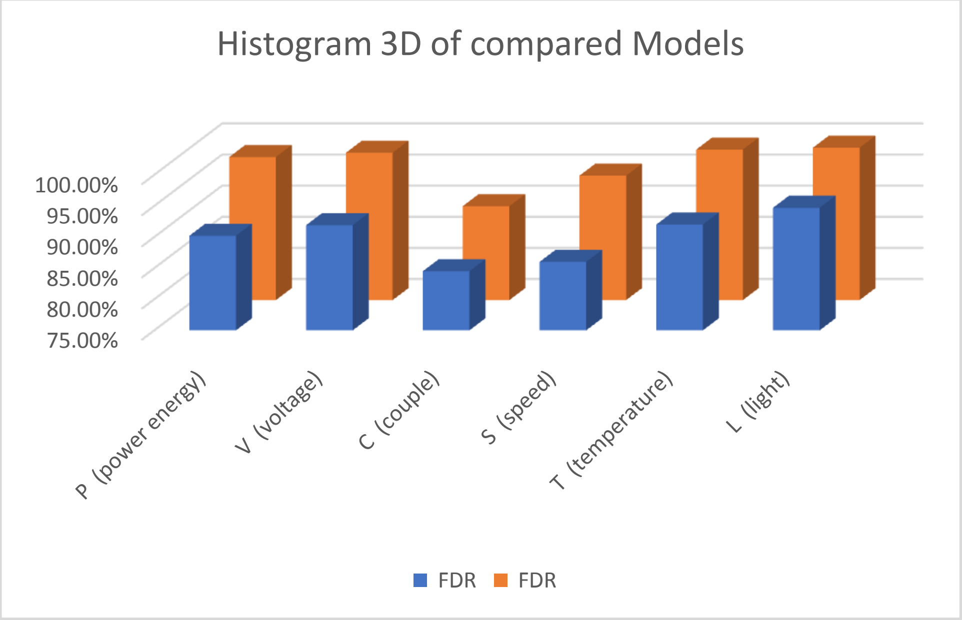


Figure.14. The histogram of Compared Models



5.Results Interpretation

The figure 9 expresses that the distortion in the obtained current signal is due to a high impedance of the opened transistor (F1). Only the free wheel diode remains functional. It manifests itself in inverter mode by the loss of alternating phase current. Thus, in the case where the upper arm transistor is kept off and the current in the corresponding phase is positive, it will stay linked to the negative potential owing to the freewheel diode. The phase current remains zero until the reference current is positive (Figure 8). When the phase current changes the sign, the faulty transistor is no longer involved in the commutation, so the current can be controlled. Significant distortion of current results in a significant fluctuating power and involves an increase in the effective current from the normal regime, since the resulting harmonics generate only losses.
In figure 10, the phase is no longer connected only through the anti parallel diode of the switching cell. Spontaneous conduction of a fault in the diodes arm depends on the currents developed by the filter cell and controls the remaining arm. The garbled deformation related to current waveform is more increased compared to first issue. The current in the phase concerned is rather low or almost zero.

The obtained scores in Table 1, as well as the curves and the corresponding histogram show that the adopted strategy brings an improvement of around 7% compared to the basic SCADA system. This assures that the proposed solution could be promising, since it offers certain defect identification rates which can reach 99%. The small rate remaining to reach 100% can be corrected by a judicious choice and good maintenance of related sensors and communication networks between RTUs and MTUs.

Eventually, from obtained figure 11, we deduce that this adopted ERSOM model has multiple factors which can affect the fault identification rates, such as:
- The dimension of input vector to be recognized.
- The size and the topology of the proposed model RSOM.
- The type of sequential or parallel learning.
- The number of learning cycles. To allow ERSOM model convergences towards an optimal result, we use in our experimentation, 100 iterations to avoid very long learning times. The obtained result on ERSOM map highlights that over 100 presented neurons, we have 97 identifications and 3 non-identifications. This implies that this model is qualified by a high robustness and it can offer 97% of resulting failures. This result is very encouraging.

6.Conclusion

The present work shows that the implementation of a SCADA system in a micro-grid has become a primary necessity. Thanks to multiple advantages offered by the novel strategy, isolated locals benefit from a continuous and qualified electrification. However, the SCADA system is not intended to completely replace the man. The steering and decision-making remain devolved to the operator.
Several attempts have been made to improve the intelligibility, profitability and efficiency of the SCADA system in terms of recognizing faults. These models remain trapped by the security problem of their communication networks. To remedy this situation, this paper details a promising intelligent approach. Its experimentation offers a fault recognition rate improved by an average of 7% compared to the classic system.

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