Fault Detection in Primary Distribution Systems using Wavelets

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Abstract—This paper presents a new methodology for phase-to-ground fault detection in primary distribution systems. The wavelet transform is the tool used, through the multiresolution analysis of the current signals measured at the relay point. Traditional tools such as the Fourier Transform and the Short-Time Fourier Transform have a frequency resolution inversely dependent of time resolution, providing a lower level of robustness to the fault detection procedure. In this paper, the proposed technique is designed and validated through several computational simulations in the IEEE 37 bus test feeder. The proposed technique is also compared to a Neural Network approach, using the same simulations and protection philosophy. Test results show that the proposed scheme is an efficient methodology for single phase fault detection in unbalanced distribution systems, including faults with high impedance.

Keywords: Power distribution systems, Power system protection, Fault detection, Wavelet transform.

I. Introduction

DISTRIBUTION protection systems should attend specific technical requisites in order to maintain system's reliability, such as [1]: selectivity, sensibility, security and rapidity. All these aspects are directly related to the fault detection process, as it defines how fast, when and for which parts of the system the protection system will or won't operate.

Thus, the protection system's overall performance is also determined by the fault detection process. To perform the fault detection and the system's protection, several different techniques are used.

The most used technique in distribution systems is the coordination and selectivity of electromechanical protection equipments, such as overcurrent relays, circuit breakers, fuses and secctionalizers [1]. However, it is not always possible to coordinate these equipments, leaving unprotected parts in the system. Also, the detection is usually based in overcurrent schemes, which are not robust to faults with high resistance [1].

Currently, microprocessor-based relays can perform all these detection procedures and also several others [2]. Therefore, higher levels of reliability and security can be easily achieved. However, several fault detection techniques used are DFT-based (Discrete Fourier Transform based), in which the time resolution is lost because of the high frequency resolution. Due to the increasing necessity of precision in the protection system devices, the DFT-based schemes are becoming nowadays even more limited.

On the other hand, several digital signal processing (DSP) techniques have been studied and developed in the recent years, such as neural networks and wavelet transforms. The usage of those techniques in fault diagnosis schemes has been proposed in several works [3]—[5].

The wavelet transform is a robust tool for the fault detection, as it evaluates a wide range of frequencies and not only one, as in the DFT. Moreover, since it performs a multiresolution analysis based in a logarithmic approach, the time resolution is suitable for the fault detection procedure, enhancing high precision in the process.

By the use of Wavelet Transforms, this work presents a novel fault detection scheme for unbalanced distribution systems. The methodology is validated using simulations and also a comparison with an existent neural network approach for the fault detection process.

In the second and third sections, the wavelet transform and the electromagnetic transients caused by faults are respectively introduced. The fourth section presents the proposed fault detection methodology. The fifth and sixth sections present respectively the case study and the results obtained. The conclusions are presented in the seventh section.

II. Discrete Wavelet Transform

The frequency analysis of discrete signals is traditionally performed using Fourier analysis based transformations, such as the Discrete Fourier Transform (DFT) and the Windowed Discrete Fourier Transform (WDFT).

The DFT is known for its high frequency resolution and low time resolution, fact that can be partially solved using the WDFT. The difference between the DFT and the WDFT is that the ladder uses a window to perform the time-frequency transformation [6]. The window used is pre-defined and provides certain compromise between time and frequency resolution. However, the time and frequency resolutions have limited precision, controlled by the pre-defined size of the window [6].

The Discrete Wavelet Transform (DWT) is a frequency analysis tool for digital signals that works as the WDFT, using a window to perform the transformation. However, the window used by the DWT is not static: it suffers dilation and

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translation during the transformation algorithm.

The DWT is given by (1) [6]—[7]:

$$\left(DWT\right)\left(m,k\right)=\frac{1}{\sqrt{a}}\sum_{n}x[n]\cdot g\left(\frac{k-nb_0a_0^m}{a_0^m}\right) \qquad (1)$$

where *x[n]* is a discrete signal with *n* coefficients, *g(.)* is the window function, called the mother wavelet, *a* and *b* are respectively the scaling and translation parameters, function of an integer parameter *m* ($a=a_0^m$ and $b=nb_0a_0^m$, with a_0 and b_0 as constant parameters). Also, *k* is an integer variable that refers to a specific sample of the discrete signal.

The used window is called the mother wavelet and there are several known mother wavelets. In this paper it is necessary to detect singularities (abnormal frequency changes) in the current signals with the highest possible precision. In order to achieve this characteristic, the mother wavelet choice should consider the number of its vanishing moments [8]. With more vanishing moments, higher precision can be achieved in the singularities detection [8]. However, with more vanishing moments, the mother wavelet has also more samples, limiting the number of details in which a specific signal could be analyzed, since the mother wavelet suffers dilation as the details increase. Thus, the mother wavelet used in this paper is the *Daubechies8* [6]—[10], since it has the better relation between number of coefficients and vanishing moments.

The scale parameter originates a logarithmic frequency scale, as shown in Fig. 1 [10]. The DWT output is a set of details, each of one corresponding to a frequency bandwidth, as in Fig. 1. The higher is the detail number, lower is the frequency. The first detail has *n/2* samples and the d^{th} detail has $n/2^d$ samples, since for each frequency scale that the DWT is computed, the original signal is decimated, leaving a total of *n* points for the signal in the wavelet domain also.

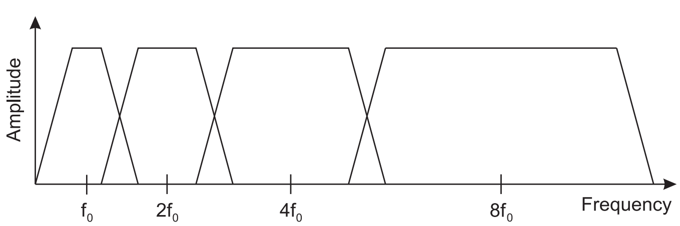

Fig. 1. Frequency spectrum using the Discrete Wavelet Transform.

When an interpolation is performed after the decimation of the signals in the wavelet domain, the transformation has the advantage of being time invariant and is called the Stationary Wavelet Transform (SWT) [11]–[12]. The disadvantage is that the SWT is a redundant transformation, leaving *n* points for each scale in the wavelet domain, therefore using more digital memory than the DWT. However, this is the transformation used in this paper, as the time invariant characteristic provides higher time precision to the analysis.

III. Electromagnetic Transients in Power Systems due to Faults

A qualitative understanding of the analyzed signals during fault occurrence becomes necessary before presenting the developed detection methodology.

Faults are common disturbances in power systems and this phenomenon is associated to different natures, such as: insulators breakdown, lightning, trees and animals in contact with electrical equipments. Due to its stochastic nature, faults are also hardly avoidable and its frequency characteristics seen from the relay point becomes also different in each fault case and distribution system.

Several aspects, such as the fault location and its resistance, the total line length, its impedance and geometry and also the mutual coupling between phases can interfere in the spectra of fault induced transients [13]—[14], causing its frequency characteristic to be also stochastic, by nature. Thus, fault induced transients can vary inside a limited frequency bandwidth. However, they are unknown before the fault occurrence. This is the main reason for using a wavelet domain analysis instead of a DFT-based one. The wavelet domain analysis is more adequate to the fault detection based in the frequency analysis, as it covers a wide frequency bandwidth and not only one frequency value, as the DFT.

Typically, the fault induced transients are inside a limited frequency bandwidth, which corresponds to frequencies from 0.1 Hz up to 1 kHz, as shown in Fig. 2 [14], where the frequency spectrum of common electromagnetic transients in power systems are defined.

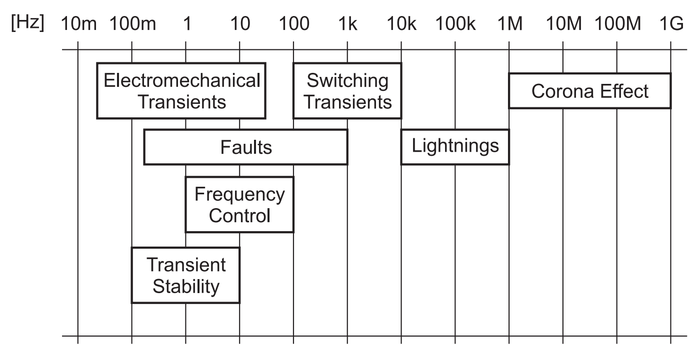

Fig. 2. Frequency spectrum of power system transients.

IV. Proposed Technique

In this section the proposed phase-to-ground fault detection algorithm is presented in four different processes, explained in the following subsections, using the theory summarized in the earlier sections.

A. Base Characteristics Extraction

Every power system, except for some rare cases, differ from all the others by having its own characteristics. Thus, the base characteristic of the system performance is used to determine the system's operating condition in steady-state.

The main information used for fault detection is the digital signal's detail *D* energy. The interest detail is the detail that corresponds to the highest frequency components present in the current signals during a fault occurrence. As seen before, these frequencies can get up to 1 kHz. Thus, the proposed methodology uses the measured energy of the highest frequency components in this bandwidth, which corresponds to frequencies from 750 Hz up to 1 kHz. Since the signals sampling period may vary from application to application, the detail *D* also varies. Moreover, when different mother wavelets are used, the interest detail also changes.

The energy variation is the detection parameter. In this way, a base energy could be used, which is the extracted characteristic in this process.

This process is executed while the distribution system is in steady state operation, before the detection process, without contingencies, in every time the protection engineer thinks it is necessary. The procedure is shown in Fig. 3.

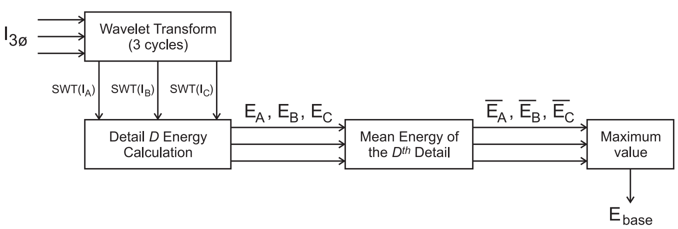

Fig. 3. Base Characteristics Extraction.

First, the SWT is executed in the three-phase current signals measured at the substation, using 3 cycles of each phase, in a 1 cycle window and a quarter cycle of step (a total of 9 windows). The energy of each interest detail of the SWT is calculated using the Parseval's Theorem, given by (2) [15]:

$$E = \sum_{n=-\infty}^{+\infty} X^2[n] \tag{2}$$

where *X[n]* is the n^{th} sample of the transformed signal of the D^{th} detail.

After, the mean energy of the 9 windows is calculated, for each one of the phases. The base energy is the higher value among them. The mean energy is used as a parameter because even minimally in steady state the current's signals frequency characteristics may vary according to system, time and phase. DSP phenomena related to the wavelet filtering in the boundaries of the signal can also occur, leading to high frequency signals appearing in the DSP algorithm execution [16]. The white noise also plays an important role, changing the signal's frequency characteristic.

B. Online Characteristics Extraction

With the base energy of the interest detail determined, the fault detection algorithm has conditions to be executed. In this part of the process, one cycle current signals measured at the substation with one quarter cycle step are used to determine the actual system's operation state. The one quarter cycle step is used in order to improve a fast detection scheme, which could detect a fault in less than one quarter of a cycle.

The procedure inputs are the three phase currents. The interested detail's energy of the three phase current signals are calculated and normalized by the base energy obtained in the first step. The normalized energies for each one of the phases are the outputs of this process, which are the inputs of the next process, as shown in Fig. 4.

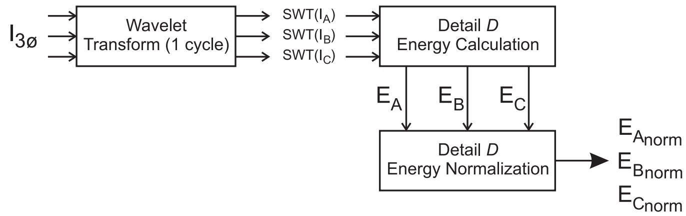

Fig. 4. Online Characteristics Extraction.

C. Fault Detection

The fault detection procedure is executed using the normalized detail *D* signal's energy. Fig. 5 shows the steps executed in this process.

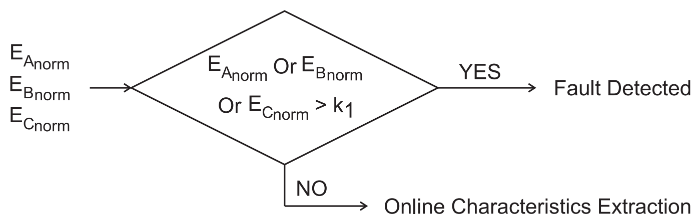

Fig. 5. Fault Detection Process.

The normalized energies are directly compared with a pre-defined threshold. If the normalized energy of any of the three phases reaches the threshold, called *minimum detection index*, k_1, a fault state is confirmed.

The minimum detection index value can be determined by the protection engineer criteria and depends on the system and protection philosophy. High loads entering the system, possibly causing an erroneous operation of the protection system, white noise, which inserts high frequency components in the measured signals, system's fault characteristics and the security margins to be achieved are important parameters to be considered in the determination of k_1.

The use of simulations using electromagnetic transient programs (EMTP) are stimulated, as the topology of electric power systems is complex and the analysis needed also covers a wide range of frequencies. During the simulation procedure, the models used should cover all the analysis frequency range, in order to provide the highest precision between the real and simulated data.

Fig. 6 shows an example of a phase-a fault case simulated in the test system (IEEE 37 Bus Radial Test Feeder) and its wavelet coefficients in each detail, including the interest detail. During fault occurrence, the high frequency components can be easily used to detect the fault. The sampling frequency of the signal is of 11580 Hz and the Daubechies8 mother wavelet was used, yielding detail 3 as the interest detail.

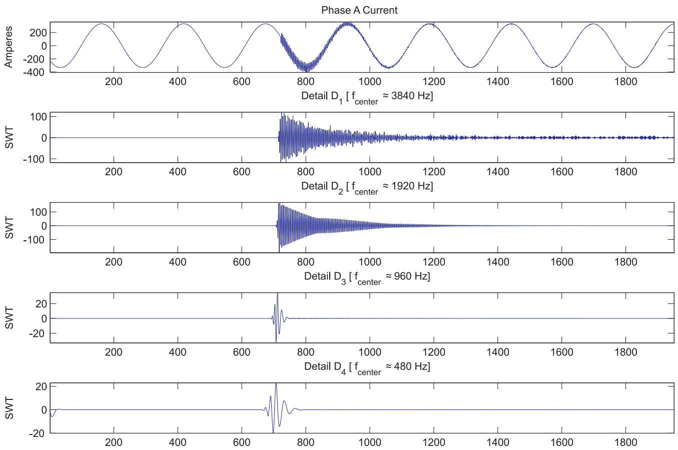

Fig. 6. SWT details during fault occurrence.

D. Post-Fault Procedure

After the fault is detected by the algorithm in the preceding procedure, the algorithm enters in the post-fault state of operation. This procedure is executed in order to avoid successive fault detections for the same fault due to the reflections of the traveling waves in the system. The high frequency waves tend to continue in the system until they are totally suppressed, providing energy to the high frequency components, even after the fault detection, since it is executed in the first cycle after the fault.

The post fault procedure combines a new base characteristics extraction, an online characteristics extraction and the fault detection process itself.

The base energy previously extracted is momentarily substituted by three new base energies, one for each phase of the system. These new base energies are the ones calculated on each phase in the first cycle after the fault detection, as it is the cycle with the highest frequency components due to faults, since the traveling waves are attenuated in the system as the time passes.

With the new base energy for each phase, the online characteristics extraction procedure in this process normalizes the energy values calculated for the interest details, as explained in Section IV-B, however with new base energies.

The fault detection process in the post-fault state is the same as described on Section IV-C, except that the index previously used, k_1, is momentarily substituted by another index, k_2 (*minimum post-detection index*). The design of k_2 is also performed by the protection engineer and must consider the same parameters as considered in the design of k_1.

The algorithm exits the post fault state in two different occasions: after a pre-defined number of cycles or after the three-phase high frequency components energy in the interest detail are below the $k_1 \cdot E_{(A)(B)(C)Norm}$ threshold value, which is the threshold value in the pre-fault state. In this process, it is used the mean energy of 9 different consecutive windows, covering exactly 3 cycles (1 cycle windows, with a step size of a quarter of cycle).

After the algorithm exits the post fault state, it goes back to its initial state, using the minimum detection index, k_1, to the faults detection's procedure and the previously calculated base energy.

V. Case Study

To show the effectiveness of the proposed algorithm, faults were simulated using ATP/EMTP Software in the IEEE 37-bus radial test feeder, fully described in [17]—[18]. This feeder is an actual distribution system located in California, USA. It is a three-phase system, with nominal voltage of 4.8 kV, non-transposed asymmetric underground lines, unbalanced loads and delta-connected loads. The usual fault detection scheme for phase-to-ground faults in this system is an overvoltage alarm [19]. The fault detection scheme was first tested as an offline tool, in order to understand its limitations and to verify its precision.

A. Proposed Methodology

For the design of k_1 and k_2 variables, each line section had 3 fault points analyzed, producing a total of 103 fault points. Also, the faults were simulated with 5 different fault resistances: $R_F = 0, 10, 20, 50$ and $100\ \Omega$, producing a total of 515 A-g fault cases. With these test cases statistical analysis, k_1 and k_2 values were designed.

The time-step simulation used was of 192 samples/cycle, or 11,564 kHz. With this time step and with daubechies8 (db8) mother wavelet, the details central frequency of the wavelet transform were approximately of: D_1 = 3840 Hz, D_2 = 1920 Hz, D_3 = 960 Hz and D_4 = 480 Hz. Referring to Section III, our interest detail is, in this case, the third one, since the objective is to analyze the fault induced transients highest frequency components.

All the detection and signal processing routines were implemented in Matlab®. The results of the statistical analysis are shown in Table I, for details 2 and 3 of the wavelet transform. In the 1st window post-fault (one cycle window), the fault occurs in ¾ of the analyzed cycle, and in the 4th window post-fault, the fault occurs exactly in the beginning of the analyzed cycle, covering the fault induced transients highest energy's case (the first cycle after the fault).

TABLE I
ENERGY CALCULATED FOR D_2 AND D_3 OF THE CURRENT SIGNALS MEASURED AT THE SUBSTATION [$A^2 \cdot S^2$]

	Phase A		Phase B		Phase C	
	D_2	D_3	D_2	D_3	D_2	D_3
	Steady State					
Min	0.011	0.04	0	0.001	0.008	0.031
Max	0.011	0.042	0	0.002	0.008	0.033
Mean	0.011	0.04	0	0.001	0.008	0.032
	1st Window Post-Fault					
Min	0.011	0.04	0	0.001	0.008	0.031
Max	616.4	62.1	141.0	15.2	167.8	15.8
Mean	27.9	4.5	6.8	1.1	7.5	1.1
	4th Window Post-Fault					
Min	0.011	111.5	0	40.5	0.009	17.6
Max	64.8k	970.5	15.8k	246.0	16.7k	239.8
Mean	6.2k	502.1	1.5k	130.4	1.6k	120.7

With the usage of the SWT, it is possible to analyze the details differences, since different details have the same number of coefficients.

From Table I, the 3rd detail's choice is numerically justified, as this is the detail in which the minimum energy level suffers its highest elevation during a fault in the faulty phase or in the non faulty phases. The minimum energy levels are associated with faults in the end of the feeder with high resistance.

With the values from Table I, k_1 can be easily determined by the relation between the base energy and the 4th window post fault minimum energy from D_3. The base energy used is the worst case, which is the highest energy value in steady state: $0.042 \approx 0.05$. Approximating the minimum energy from the 4th window post-fault to 100, the relative value becomes 2000, which yields: $k_1 < 2000$. The designed value for k_1 was of 500, for validation purposes.

The minimum post-detection index, k_2, is a non-critical parameter, and must be always greater than 1. The value chosen for the validation tests was 2.

Moreover, the number of post-faults cycles chosen, in which the post-fault procedure is executed, was 6, since by this time, the major part of the high frequency components should have been sufficiently attenuated.

B. Neural Networks Approach

In order to compare the results obtained with the proposed methodology, a Neural Network detection scheme, proposed in [20], was also tested.

Using the same 515 simulations used to design k_1 and k_2 values, the neural network was trained, using Matlab, using the same network topology as [20]. The neural network converged in less than 3000 epochs.

VI. Results

A. Proposed Methodology

To validate the designed parameters of the proposed methodology, phase-to-ground faults in the three phases and in the 103 fault points of the system were simulated. Also, faults with resistance $R_F = 0, 10, 20, 50, 100, 500, 1000, 1500$ and $2000\ \Omega$ were simulated, providing 2781 test cases. All the simulated cases presented only one fault, thus, it shouldn't occur any post fault detection. The fault detection and the post-fault detection results were analyzed.

Table II shows the percentage of correct results, considering the different processes: detection (parameter I) and post-detection (parameter II). The values are relative to the number of cases for each fault simulated (103 for each fault resistance in each phase).

TABLE II
Results For the Proposed Fault Detection Scheme

R_F	Phase A		Phase B		Phase C	
	I	II	I	II	I	II
0	100%	100%	100%	100%	100%	100%
10	100%	100%	100%	100%	100%	100%
20	100%	100%	100%	100%	100%	100%
50	100%	100%	100%	100%	100%	100%
100	100%	100%	100%	100%	100%	100%
500	100%	100%	100%	100%	100%	100%
1000	100%	100%	100%	100%	100%	100%
1500	100%	100%	100%	100%	100%	100%
2000	100%	100%	100%	100%	100%	100%

Through these results, it is verified that the proposed algorithm for fault detection is extremely efficient. It can be seen that with the designed values, based on fault simulations, in which the higher fault resistance value was $100\ \Omega$, the algorithm performed correctly the fault detection for faults with at least $2\ k\Omega$, which can be considered a high resistance fault.

The post detection index (II) indicates if an erroneous post detection occurred in the studied cases. In the analyzed cases, there were no successive detections for the same fault, which is the desired result, confirming that the parameters were correctly designed for the situation.

Still, it can be identified a certain generalization tendency in the proposed algorithm, disclosing its robustness in relation to the fault resistance effects. Moreover, the design developed considering phase *a* to ground faults was expanded for the three phases of the system in an efficient way.

The mean time needed by the algorithm to analyze each window with the stationary wavelet transform was of 26.997 ms, considering all fault cases. This is a very large time for a real time application, since the entire algorithm is intended to be performed each quarter of cycle, which has a total of 4.17 ms. However, the algorithm was not implemented in an embedded system, which could offer a higher processing speed and less time consuming. Moreover, the stationary wavelet transform was executed for all the details, replying a lot of useless results. The SWT could also be performed only for the interest detail, providing highest speed for the algorithm.

B. Neural Networks Approach

The same fault cases used to validate the proposed methodology were used to validate the trained neural network. The results are shown in Table III.

It can be verified that the neural network scheme did not succeeded in the fault detection for the non-trained phases, showing its low capacity of generalization in this aspect. However, the neural network scheme could achieve accurate results for faults with high resistance, such as 1500 kΩ. However, these results were not as accurate as the ones achieved with the proposed wavelet scheme, since for faults with no resistance the neural network also had difficulties to detect the simulated fault cases.

TABLE III

RESULTS FOR THE NEURAL NETWORKS APPROACH DETECTION SCHEME

R_F	Phase A	Phase B	Phase C
0	96.1%	97.1%	93.2%
10	100%	100%	37.9%
20	100%	100%	53.4%
50	100%	100%	80.6%
100	100%	100%	74.8%
500	100%	72%	91.3%
1000	100%	91.3%	50.5%
1500	100%	98.6%	0%
2000	66%	96.1%	0%

VII. CONCLUSIONS

A novel methodology for fault detection in distribution systems based in the fault induced transients and the multiresolution analysis was proposed in this paper. The usage of new tools, such as wavelets, made possible the correct fault detection in several studied cases, showing its efficiency and robustness to system's phase and fault resistance designs.

The proposed methodology is based in the steady-state operation of the system, since the configuration adopted in the relay parameters are continuously updated. Through the present paper it is clearly advantageous the usage of simulation tools to design the methodologies parameters.

The wavelet transform demonstrated to be a very robust analysis tool, becoming possible the analysis of the whole system's frequency spectrum during the analyzed disturbances.

On the other hand, a new developed technology to fault detection, the neural network, showed to be limited in some aspects, as shown previously.

The wavelet-based fault detection approach described in this paper was implemented as a software tool for CEEE-D (Companhia Estadual de Distribuição de Energia Elétrica do Rio Grande do Sul) and it is currently under testing, being used as an offline tool with data from real systems. Improvements in the algorithm could be done in order to achieve a higher processing speed, becoming possible its online usage as a part of the protection system.

VIII. ACKNOWLEDGMENT

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