UDC 621.314 https://doi.org/10.20998/2074-272X.2024.4.06

A. Lanani, D. Djamai, A. Beddiaf, A. Saidi, A. Abboudi

Photovoltaic system faults detection using fractional multiresolution signal decomposition

Introduction. *In this paper, we present an innovative methodology based on fractional wavelets for detecting defects in photovoltaic systems. Photovoltaic solar systems play a key role in the transition to a low-carbon economy, but they are susceptible to various defects such as microcracks, wiring faults, and hotspots. Early detection of these anomalies is crucial to prevent energy losses and extend the lifespan of installations.* ***Novelty*** *of the proposed work resides in its pioneering nature, leveraging a family of fractional wavelets, with a specific emphasis on fractional Haar wavelets. This approach enhances sensitivity in anomaly detection, introducing a fresh and promising perspective to enhance the reliability of photovoltaic installations.* ***Purpose*** *of this study is to develop a defect detection methodology in photovoltaic systems using fractional wavelets. We aim to improve detection sensitivity with a specific focus on low-amplitude defects such as microcracks.* ***Method****. Our innovative methodology is structured around two phases. Firstly, we undertake a crucial step of filtering photovoltaic signals using fractional Haar wavelets. This preliminary phase is of paramount importance, aiming to rid signals of unwanted noise and prepare the ground for more precise defect detection. The second phase of our approach focuses on the effective detection of anomalies. We leverage the multiresolution properties of fractional wavelets, particularly emphasizing fractional Haar wavelets. This step achieves increased sensitivity, especially in the detection of low-amplitude defects.* ***Results.*** *By evaluating the performance of our method and comparing it with techniques based on classical wavelets, our results highlight significant superiority in the accurate detection of microcracks, wiring faults, and hotspots. These substantial advances position our approach as a promising solution to enhance the reliability and efficiency of photovoltaic installations.* ***Practical value****. These advancements open new perspectives for preventive maintenance of photovoltaic installations, contributing to strengthening the sustainability and energy efficiency of solar systems. This methodology offers a promising solution to optimize the performance of photovoltaic installations and ensure their long-term reliability.* References 21, tables 3, figures 10.

Keywords: **fault detection, photovoltaic systems, microcracks, wiring defects, hot spots, preventive maintenance, multiresolution analysis, fractional wavelets.**

Вступ*. У статті ми представляємо інноваційну методологію, засновану на дробових вейвлетах для виявлення дефектів у фотоелектричних системах. Фотоелектричні сонячні системи відіграють ключову роль у переході до низьковуглецевої економіки, але вони схильні до різних дефектів, таких як мікротріщини, несправності проводки та гарячі точки. Раннє виявлення цих аномалій має вирішальне значення для запобігання втратам енергії та продовження терміну служби установок.* ***Новизна*** *запропонованої роботи полягає у її новаторському характері, в якій використовується сімейство дробових вейвлетів з особливим упором на дробові вейвлети Хаара. Цей підхід підвищує чутливість виявлення аномалій, відкриваючи нову суттєву перспективу для підвищення надійності фотоелектричних установок.* ***Метою*** *дослідження є розробка методології виявлення дефектів у фотоелектричних системах з використанням дробових вейвлетів. Ми прагнемо покращити чутливість виявлення, приділяючи особливу увагу дефектам малої амплітуди, таким як мікротріщини.* ***Метод****. Наша інноваційна методологія складається із двох етапів. По-перше, ми робимо вирішальний крок щодо фільтрації фотоелектричних сигналів з використанням дробових вейвлетів Хаара. Цей попередній етап має першорядне значення, оскільки його мета - позбавити сигнали від небажаного шуму та підготувати ґрунт для більш точного виявлення дефектів. Другий етап нашого підходу спрямовано на ефективне виявлення аномалій. Ми використовуємо властивості множини роздільної здатності дробових вейвлетів, приділяючи особливу увагу дробовим вейвлетам Хаара. На цьому етапі досягається підвищена чутливість, особливо у разі виявлення дефектів малої амплітуди.* ***Результати****. Оцінюючи ефективність нашого методу та порівнюючи його з методами, заснованими на класичних вейвлетах, наші результати підкреслюють значну перевагу у точному виявленні мікротріщин, несправностей проводки та гарячих точок. Ці суттєві досягнення роблять наш підхід багатообіцяючим рішенням для підвищення надійності та ефективності фотоелектричних установок.* ***Практична цінність****. Ці досягнення відкривають нові перспективи для профілактичного обслуговування фотоелектричних установок, сприяючи підвищенню стійкості та енергоефективності сонячних систем. Ця методологія пропонує багатообіцяюче рішення для оптимізації продуктивності фотоелектричних установок та забезпечення їхньої довгострокової надійності.* Бібл. 21, табл. 3, рис. 10.

Ключові слова: **виявлення несправностей, фотоелектричні системи, мікротріщини, дефекти проводки, гарячі точки, профілактика, множинний аналіз, дробові вейвлети.**

Introduction. Photovoltaic (PV) solar energy plays a crucial role in the transition to a low-carbon economy. However, the efficiency and reliability of PV systems are susceptible to various defects, such as microcracks, hot spots, and wiring faults. Early detection of these anomalies is essential to prevent energy losses and extend the useful life of PV installations.

In response to this complex challenge, the scientific community has developed a range of sophisticated methodologies. Among these highly relevant and frequently utilized approaches in this field, the method based on Independent Component Analysis stands out [1, 2]. The latter distinguishes itself by its ability to provide remarkable spatial resolution in detecting microcracks. Significantly, defect detection based on Support Vector Machines offers another valuable perspective for identifying various anomalies in PV installations [3, 4]. In parallel, artificial intelligence plays a crucial role in the field of defect diagnosis, where the utilization of Convolutional Neural Networks has yielded promising results for defect detection in PV systems [5, 6]. The approach based on Deep Neural Networks has also garnered increasing interest for its potential in defect detection in PV modules [7]. Furthermore, methods based on wavelet transforms have proven effective in detecting defects by analyzing the frequency variations of PV signals, offering a robust and sensitive approach to anomaly detection [8, 9]. Finally, recent studies [10-13] have successfully combined neural networks with Discrete Wavelet Transform (DWT) for defect diagnosis in PV systems. This innovative approach has demonstrated great effectiveness in defect detection and precise localization.

However, despite the undeniable advantages of these methods, limitations persist, especially in terms of sensitivity to the subtlest signal variations. It is precisely at this stage that fractional wavelets come into play, offering an alternative approach capable of overcoming these challenges.

The purpose of the paper is to present an innovative approach based on fractional wavelets aimed at enhancing fault detection in PV systems. Fractional wavelets provide a multiresolution representation and can be adapted to capture features at different scales in signals with remarkable precision. This capability stems from the flexibility, selectivity, and high accuracy of the filters comprising fractional wavelets. En incorporating these properties into fault diagnosis, our aim is to enhance the level of sensitivity and precision in detecting anomalies, be they microcracks in solar cells, wiring defects, or hot spots. Moreover, this approach allows for a more accurate localization of faults, thereby facilitating their intervention and repair. This promising methodology paves the way for a new generation of diagnostic techniques for PV installations, offering significant advantages in terms of reliability and operational efficiency.

Fractional wavelets. Fractional wavelets represent a powerful extension of the well-established tool of wavelets, providing increased flexibility in the multiresolution decomposition of signals. Unlike classical wavelets, fractional wavelets enable the capture of features at different scales with unparalleled precision. This capability stems from the fractional nature of the wavelet filters, which can be tailored to extract crucial information from PV signals, be it microcracks in solar cells, wiring defects, or hot spots.

Over the past few decades, the emergence of fractional wavelets in both continuous and discrete forms has marked a significant conceptual advance. This development has merged the power of classical wavelet transform with the properties of fractional Fourier transform [14]. This synergy has led to a new formulation, simplifying the construction significantly while ensuring increased accuracy. Particularly in the continuous domain, the integration of fractional derivative concepts within mathematical functions has greatly facilitated operations. Examples include generating wavelets from the Gaussian function and its fractional derivatives, as well as using the spline function with fractional degrees [15]. Quincunx wavelets have also been generalized to non-integer orders with a construction based on fractional Quincunx filters, which are generated through the diamond McClellan transform [16].

However, the definition of the discrete fractional wavelet transform has been a gap in scientific literature. To address this deficiency, a robust definition has been developed by discretizing the continuous version. Furthermore, the creation of discrete fractional wavelet bases has materialized through the generalization of the composing filters, leveraging fractional delay [17]. Indeed, from an architectural standpoint, the DWT manifests as a set of iterative filters, conferring upon it a multiresolution characteristic. This paves the way for the utilization of fractional-order filters in the realization of fractional wavelets, thus providing an innovative and accurate approach [18, 19].

The construction typically begins with the selection of a low-pass digital filter, enjoying the property of orthogonality; it is then generalized using fractional operators, ensuring the preservation of required orthogonality, compactness, and regularity properties. The high-pass filter can be derived from the low-pass filter through a simple modulation, thereby allowing, through the cascade algorithm [20], the deduction of the associated scaling function and wavelet function.

Our study focuses on the application of fractional Haar wavelets [18]. These types of wavelets stand out for their intriguing characteristics and properties. Thanks to the flexibility of the associated filters and their exceptional selectivity, they demonstrate an extraordinary ability to optimize a multitude of data processing tasks.

Fractional Haar wavelet. Its principle is based on the generalization of the low-pass filter associated with the ordinary Haar basis through fractional delay [17], where the integer delay Z^{-n}, $n \in Z$, is replaced by a fractional delay Z^{-D}, $D \in \Re$:

$$\widetilde{H}_f(Z) = A + B \cdot Z^{-D}, \qquad (1)$$

where D is the filter order, A and B are its coefficients.

The orthogonality and regularity of the scaling and wavelet functions are ensured by the proper choice of coefficients A and B [18].

To ensure the feasibility of implementing fractional delays, an approximation method based on Lagrange interpolation has been chosen [17]. This approach was favored due to its simplicity in calculating filter coefficients and its ability to generate frequency responses with a flat magnitude at low frequencies.

The fractional high-pass filter will be constructed through a simple modulation of the fractional low-pass filter and deducing, through the cascade algorithm, the associated scaling and wavelet functions [18].

The frequency responses of the designed fractional filters are adjusted by varying the parameter D, as shown in Fig. 1. It appears that the generalization of ordinary filters via the fractional delay Z^{-D} leads to more flexible filters with better accuracy, where key filter parameters are continuously adjusted.

Methodology for fault detection in PV systems via fractional wavelets. In our study, we explored the practical application of the fractional wavelets that we specifically developed. To do so, we selected a widely adopted PV system, comprising solar panels, a DC-DC converter, and a battery for storage (Fig. 2), where we utilized measurements from a system described in [21]. Fault detection was carried out twice, at two different levels of the system, under various meteorological conditions.

Initially, we focused on faults that may occur at the level of the solar panels, such as microcracks and hot spots. We analyzed a signal captured at the output of the solar panel (V_{pv}), presented in Fig. 3. This initial phase was conducted under stable meteorological conditions, characterized by constant solar irradiance. Subsequently, we performed detection after the chopper, aiming to identify connection or wiring faults, using a signal captured after the chopper (V_0), as illustrated in Fig. 3.

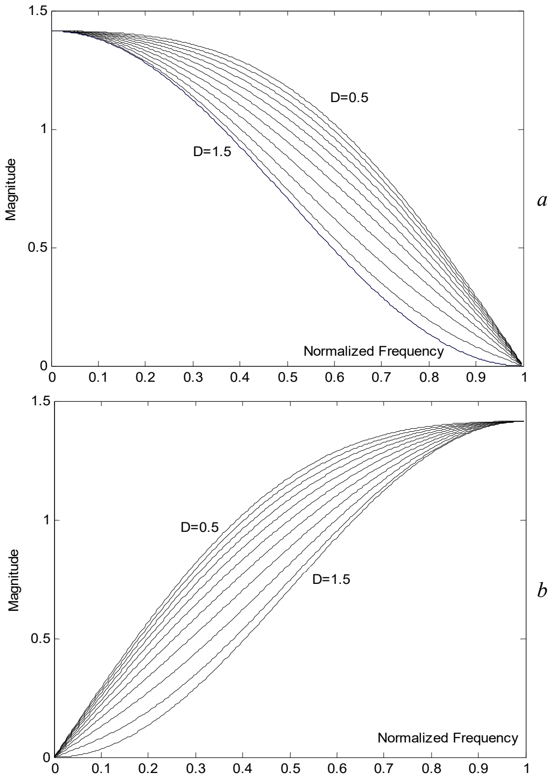


Fig. 1. Frequency responses of the fractional filters: *a* – low-pass filter; *b* – high-pass filter

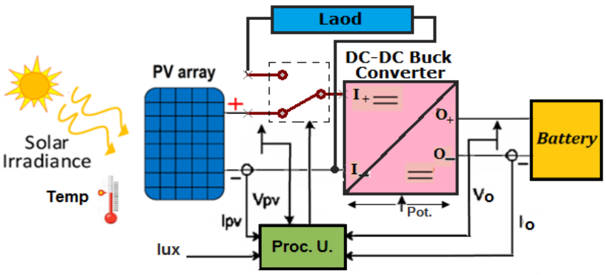


Fig. 2. PV system with a DC-DC buck converter, battery load and processing unit [21]

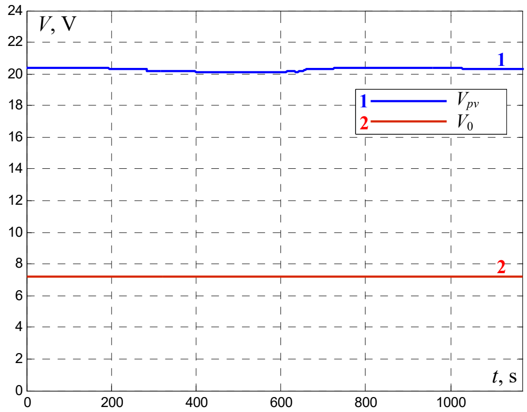


Fig. 3. Signals captured at the output of the solar panel (V_{pv}) and after the chopper (V_0) under stable meteorological conditions [21]

In a second phase, we proceeded with the detection of faults in the same previous system but under unstable meteorological conditions, characterized by the presence of clouds affecting solar radiation. The signals of the system under these conditions are presented in Fig. 4.

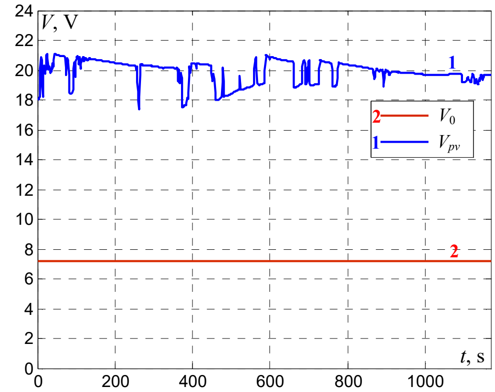


Fig. 4. Signals captured at the output of the solar panel (V_{pv}) and after the chopper (V_0) under unstable meteorological conditions [21]

Defects and noise were added to the signals to reflect various fault scenarios encountered in PV systems (Fig. 5). These anomalies were incorporated precisely and controlled to replicate realistic conditions. Simulated faults included microcracks modeled by pulses, wiring faults represented by voltage drops, and simulated hot spots represented by voltage spikes.

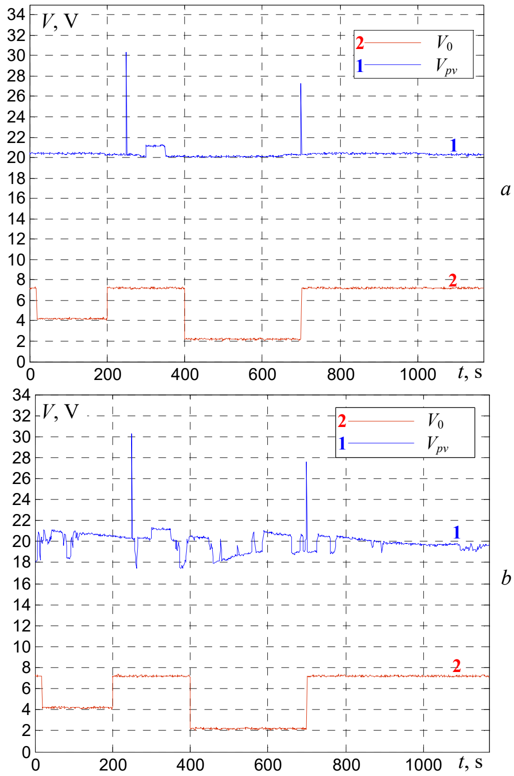


Fig. 5. Solar panel and chopper signals (V_{pv}, V_0) with simulated faults: *a* – stable meteorological conditions; *b* – unstable meteorological conditions

Our approach comprises several steps, as shown in Fig. 6.

Signal denoising using the designed fractional wavelets (pre-processing signal phase). Before proceeding with the fault detection, we denoised the signals using fractional wavelets. This phase is crucial as it aims to accurately detect and isolate various components of noise, thereby preparing the ground for subsequent anomaly detection. These filtered and isolated data were then utilized in our detection approach, contributing to a more precise identification and a better understanding of faults in the studied systems.

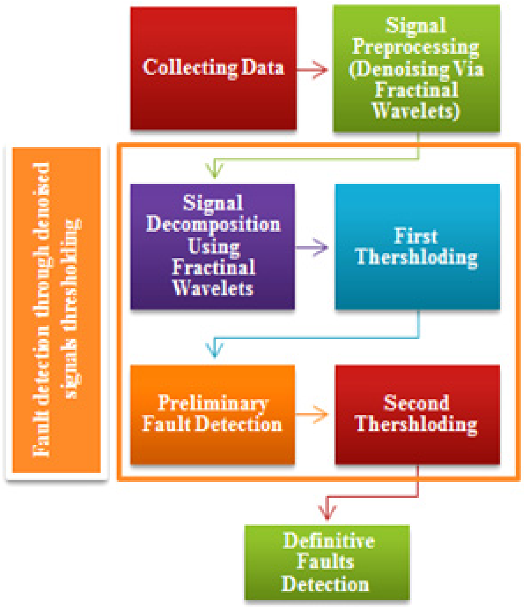


Fig. 6. Proposed method steps

Fault detection through denoised signals thresholding. After an appropriate decomposition of the denoised signals using the fractional wavelets we developed, thresholding was employed as a crucial step in our methodology. The choice of threshold is a delicate process, as it must be precisely calibrated to ensure reliable fault detection. This step is essential for isolating relevant signal details and thereby highlighting anomalies.

The thresholded signal details are carefully examined. Components with amplitudes exceeding the threshold are identified as potential fault points. These points are then located in the original signal, enabling us to accurately determine their temporal location.

In order to enhance detection precision and eliminate any points identified as faults erroneously, a second thresholding process was conducted on all initially identified suspect points.

Once the second thresholding is completed and the suspect fault points are detected, we compare their locations with the actual locations of anomalies previously introduced into the signals. This allowed us to quantify the performance of our method. We defined the following terms to evaluate these performances:

- True Positive (TP): The number of actual faults correctly detected.
- True Negative (TN): The number of points correctly identified as non-faulty.
- False Positive (FP): The number of points identified as faulty when they are not.
- False Negative (FN): The number of actual faults not detected.

$$Sensitivity = \frac{TP}{TP + FN}; \quad (2)$$

$$Specificity = \frac{TN}{TN + FP}; \quad (3)$$

$$Precision = \frac{TP}{TP + FP}. \quad (4)$$

This quantitative evaluation of performance has allowed us to validate the effectiveness of our fractional wavelet-based approach in the accurate and reliable detection of faults in PV systems.

Results and discussion. After applying our fractional wavelet-based methodology to simulated signals from various levels of the PV system and under different meteorological conditions, we conducted a detailed analysis to assess the effectiveness of our approach.

Firstly, concerning the detection of faults at the solar panel level, we analyzed the signals under different meteorological conditions. The use of fractional wavelets allowed for a precise decomposition of the signals, providing a fine separation between their various components, which was crucial for improved fault detection, notably for microcracks and hot spots as illustrated in Fig. 7. The detailed thresholded components revealed salient points corresponding to abnormal voltage variations. These points serve as potential indicators of faults in the PV system.

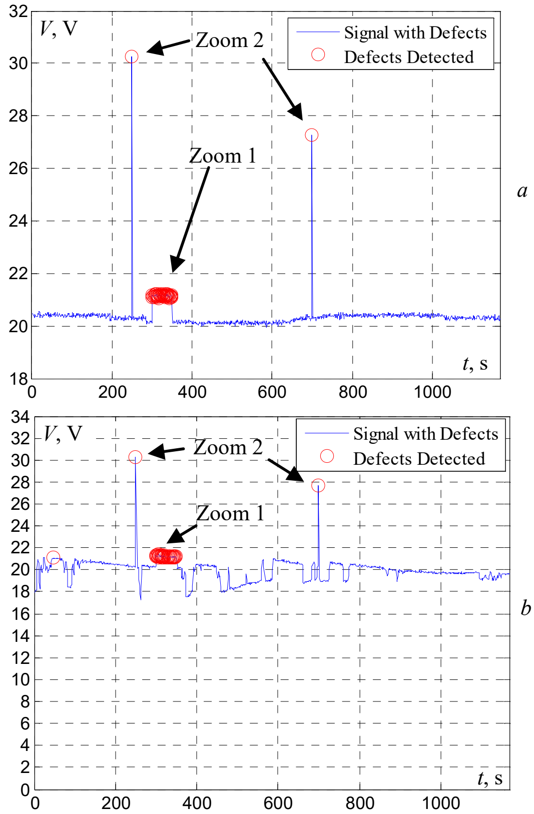


Fig. 7. Fault detection using the proposed method at the solar panels level: *a* – stable meteorological conditions; *b* – unstable meteorological conditions

Microcracks are subtle yet critical anomalies in solar cells. Through our methodology, we were able to accurately detect these micro-cracks, even when they were of low amplitude and under unstable meteorological conditions (Fig. 8). This demonstrates the heightened sensitivity of our approach.

Hot spots. Our methodology proved particularly effective in detecting hot spots, which can cause serious damage if not detected in time. By analyzing the signals using our fractional wavelets, we accurately and reliably identified the voltage peaks caused by hot spots (Fig. 9). This ability to spot these critical anomalies demonstrates the effectiveness of our approach in detecting the most serious defects in all meteorological conditions.

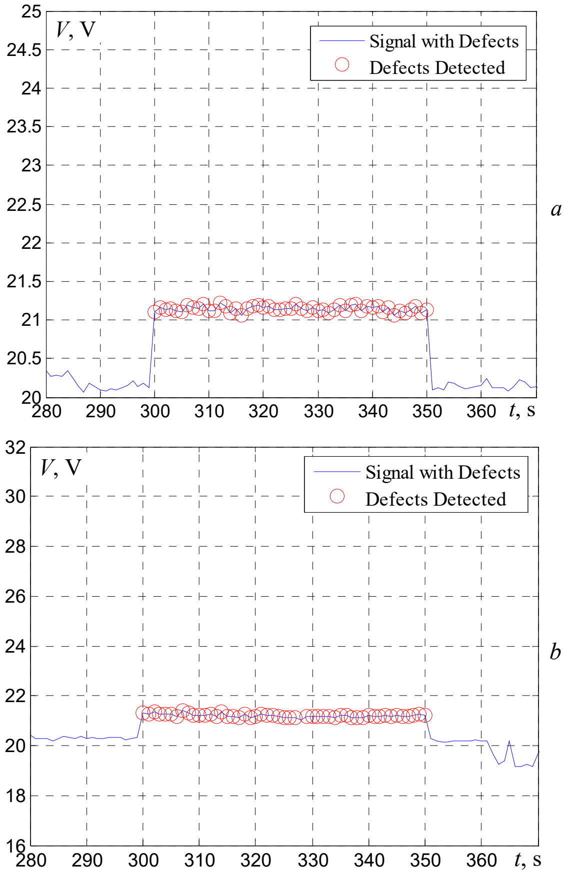
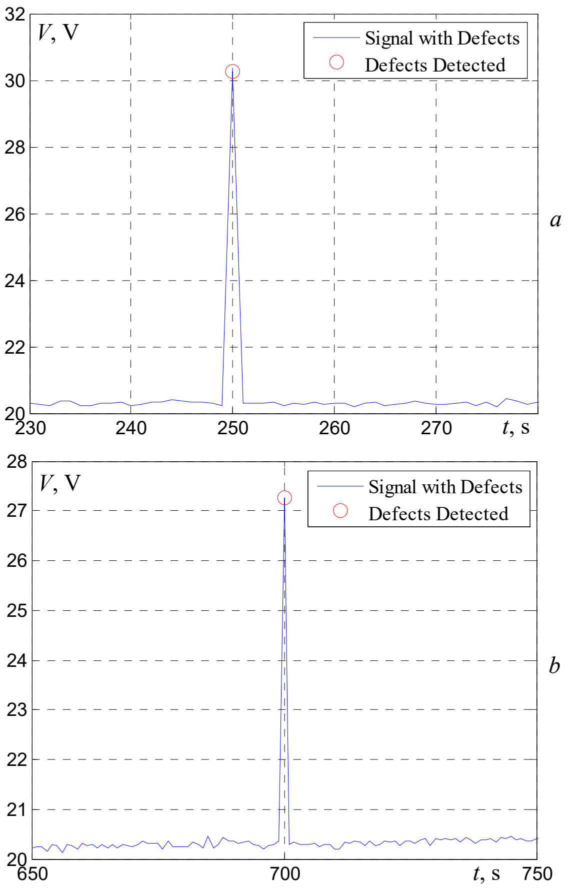


Fig. 8. Zoom 1: detection of micro-cracks: *a* – stable meteorological conditions; *b* – unstable meteorological conditions



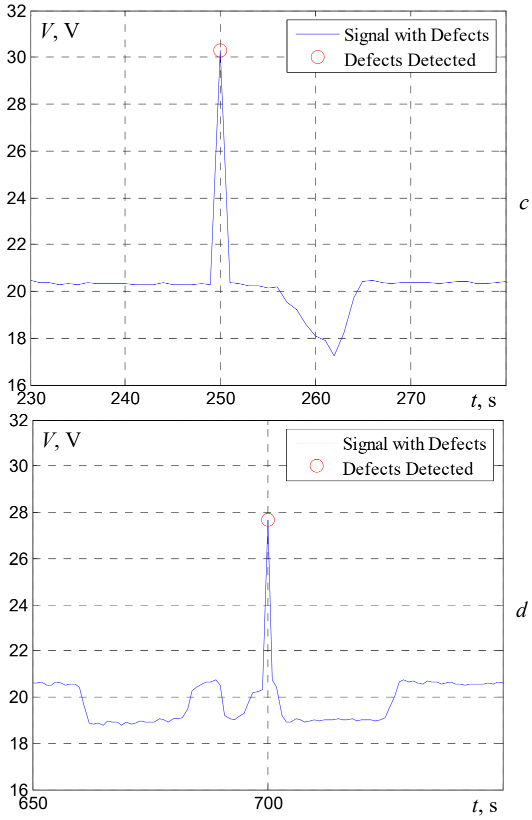


Fig. 9. Zoom 2: detection of hot spots: *a*, *b* – stable meteorological conditions; *c*, *d* – unstable meteorological conditions

Wiring defects. During the detection of wiring faults after the chopper, our method demonstrated remarkable effectiveness. By decomposing the captured signals using our fractional wavelets, we were able to precisely isolate abnormal voltage variations associated with wiring faults. This ability to detect wiring faults, even in scenarios where voltage fluctuations are subtle, underscores the robustness and accuracy of our approach in identifying critical system anomalies, as clearly illustrated in Fig. 10.

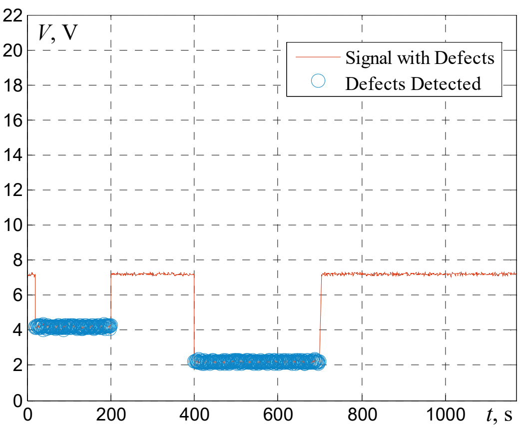


Fig. 10. Fault detection using the proposed method at the chopper level (detection of wiring faults)

In order to quantify the performance of our methodology, we calculated various metrics, including True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), as well as sensitivity, precision, and specificity. These calculations were conducted for each signal and under different meteorological conditions to capture the variability of our approach's performance in realistic scenarios.

Subsequently we compared the results obtained with those of classical wavelets commonly used in fault detection in PV systems. Specifically, we examined Haar, Daubechies, Coiflets, Symlets, Meyer wavelets, and bi-orthogonal wavelets. The performance evaluation results are presented in Tables 1 – 3.

Table 1

Results of fault detection at the chopper level using different wavelet families

Wavelet type	Number of detected faults	TP	TN	FP	FN	Sensitivity, %	Specificity, %	Precision, %
Fractional wavelet (developed model)	**482**	**482**	**687**	**0**	**0**	**100**	**100**	**100**
Haar	424	410	673	14	72	85.06	97.96	96.7
db6	444	438	681	6	44	90.87	99.13	98.65
coif5	440	431	678	9	51	89.42	89.69	97.95
sym5	429	417	675	12	65	86.51	98.25	97.20
dmey	446	444	685	2	38	92.11	99.71	99.55
bior3.3	439	429	677	10	53	89.00	98.54	97.72
rbio4.4	430	407	664	23	75	84.44	96.65	94.65

Table 2

Results of fault detection at the solar panel level using different wavelet families (stable meteorological condition)

Wavelet type	Number of detected faults	TP	TN	FP	FN	Sensitivity, %	Specificity, %	Precision, %
Fractional wavelet (developed model)	**53**	**53**	**1116**	**0**	**0**	**100**	**100**	**100**
Haar	48	27	1095	21	26	50.94	98.12	56.25
db6	51	34	1099	17	19	64.15	98.48	66.67
coif5	50	37	1103	13	16	69.81	98.83	74.00
sym5	52	35	1099	17	18	66.04	98.48	67.31
dmey	51	48	1113	3	5	90.57	99.73	94.12
bior3.3	52	40	1104	12	13	75.47	98.93	76.92
rbio4.4	51	36	1101	15	17	67.93	98.66	70.59

Table 3

Results of fault detection at the solar panel level using different wavelet families (unstable meteorological condition)

Wavelet type	Number of detected faults	TP	TN	FP	FN	Sensitivity, %	Specificity, %	Precision, %
Fractional wavelet (developed model)	**53**	**52**	**1115**	**1**	**1**	**98.11**	**99.91**	**98.11**
Haar	29	0	1087	29	53	00	97.40	00
Db6	49	37	1104	12	16	69.81	98.92	75.51
coif5	45	32	1103	13	21	60.38	98.84	71.11
sym5	48	29	1097	19	24	54.71	98.30	60.42
dmey	49	45	1112	4	8	84.91	99.64	91.84
bior3.3	42	18	1092	24	35	33.96	97.85	42.86
rbio4.4	47	35	1104	12	18	66.04	98.93	74.47

The results revealed an exceptional sensitivity of our approach, reaching 100 % for both the chopper signal (Table 1) and the solar panel signal under stable meteorological conditions (Table 2), demonstrating a robust capability to accurately detect real faults. Furthermore, the high specificity and precision indicate correct identification of non-faulty points. In contrast, under unstable meteorological conditions, our method's performance remained satisfactory, as evidenced by a low number of false positives (Table 3), highlighting its capability to mitigate false detections.

These results demonstrate the power and precision of our methodology based on fractional wavelets for fault detection in PV systems. The advantages of this approach are particularly evident in detecting low-amplitude faults and subtle anomalies, reinforcing its relevance in the context of solar installation inspection.

In comparison with classical wavelets, our methodology has demonstrated a superior ability to isolate relevant signal details. This is attributed to the significant flexibility and selectivity of the filters comprising the fractional wavelet, leading to a more precise detection of anomalies. This quantitative evaluation confirms the effectiveness of our fractional wavelet-based approach in accurately and reliably detecting faults in PV systems. These promising results pave the way for practical applications in the field of solar installation maintenance and optimization.

Conclusions. Our study has highlighted the remarkable effectiveness of fractional wavelets in the accurate detection of faults in photovoltaic systems. Through this innovative approach, we achieved significant selectivity and precision, enabling reliable detection of anomalies such as microcracks, wiring faults, and hot spots.

The implementation of our methodology yielded extremely promising results. We also conducted a comprehensive comparison with other commonly used wavelet types. This comparative study demonstrated that our fractional wavelet-based approach significantly outperforms methods based on classical wavelets.

These advancements open new perspectives for preventive maintenance of eco-friendly energy installations, contributing significantly to the sustainability and overall efficiency of solar energy. A major innovation lies in the ability of our approach to synergistically combine with other cutting-edge methods, notably convolutional neural networks. This synergy expands possibilities for even more precise fault detection, solidifying our fractional model as a benchmark in the analysis of photovoltaic systems.

Conflict of interest. The authors declare that they have no conflicts of interest.

REFERENCES

1. Tsai D.-M., Wu S.-C., Chiu W.-Y. Defect Detection in Solar Modules Using ICA Basis Images. *IEEE Transactions on Industrial Informatics*, 2013, vol. 9, no. 1, pp. 122-131. doi: https://doi.org/10.1109/TII.2012.2209663.

2. Qureshi F.A., Uddin Z., Satti M.B., Ali, M. ICA-based solar photovoltaic fault diagnosis. *International Transactions on Electrical Energy Systems*, 2020, vol. 30, no. 8, art. no. e12456. doi: https://doi.org/10.1002/2050-7038.12456.

3. Badr M.M., Hamad M.S., Abdel-Khalik A.S., Hamdy R.A. Fault Detection and Diagnosis for Photovoltaic Array Under Grid Connected Using Support Vector Machine. *2019 IEEE Conference on Power Electronics and Renewable Energy (CPERE)*, 2019, pp. 546-553. doi: https://doi.org/10.1109/CPERE45374.2019.8980103.

4. Wang J., Gao D., Zhu S., Wang S., Liu H. Fault diagnosis method of photovoltaic array based on support vector machine. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 2023, vol. 45, no. 2, pp. 5380-5395. doi: https://doi.org/10.1080/15567036.2019.1671557.

5. Saraswathi Devi K.V.B., Srivenkatesh M. Convolutional Neural Networks for Fault Detection in Grid-Connected Photovoltaic Panels. *Ingenierie des Systemes d'Information*, 2023, vol. 28, no. 6, pp. 1619-1625. doi: https://doi.org/10.18280/isi.280619.

6. Lu S.-D., Wang M.-H., Wei S.-E., Liu H.-D., Wu C.-C. Photovoltaic Module Fault Detection Based on a Convolutional Neural Network. *Processes*, 2021, vol. 9, no. 9, art. no. 1635. doi: https://doi.org/10.3390/pr9091635.

7. Kellil N., Aissat A., Mellit A. Fault diagnosis of photovoltaic modules using deep neural networks and infrared images under Algerian climatic conditions. *Energy*, 2023, vol. 263, part C, art. no. 125902. doi: https://doi.org/10.1016/j.energy.2022.125902.

8. Haque A., Bharath K.V.S., Khan M.A., Khan I., Jaffery Z.A. Fault diagnosis of Photovoltaic Modules. *Energy Science & Engineering*, 2019, vol. 7, no. 3, pp. 622-644. doi: https://doi.org/10.1002/ese3.255.

9. Suman T., Mahela O.P., Ola S.R. Detection of transmission line faults in the presence of solar PV generation using discrete wavelet. *2016 IEEE 7th Power India International Conference (PIICON)*, 2016, pp. 1-6. doi: https://doi.org/10.1109/POWERI.2016.8077203.

10. Jayamaha D.K.J.S., Lidula N.W.A., Rajapakse A.D. Wavelet-Multi Resolution Analysis Based ANN Architecture for Fault Detection and Localization in DC Microgrids. *IEEE Access*, 2019, vol. 7, pp. 145371-145384. doi: https://doi.org/10.1109/ACCESS.2019.2945397.

11. Jayamaha D.K.J.S., Lidula N.W.A., Rajapakse A.D. Wavelet Based Artificial Neural Networks for Detection and Classification of DC Microgrid Faults. *2019 IEEE Power & Energy Society General Meeting (PESGM)*, 2019, pp. 1-5. doi: https://doi.org/10.1109/PESGM40551.2019.8974108.

12. Bengharbi A.A., Laribi S., Allaoui T., Mimouni A. Photovoltaic system faults diagnosis using discrete wavelet transform based artificial neural networks. *Electrical Engineering & Electromechanics*, 2022, no. 6, pp. 42-47. doi: https://doi.org/10.20998/2074-272X.2022.6.07.

13. Sakhara S., Brahimi M., Nacib L., Layadi T.M. Application of a wavelet neural network approach to detect stator winding short circuits in asynchronous machines. *Electrical Engineering & Electromechanics*, 2023, no. 3, pp. 21-27. doi: https://doi.org/10.20998/2074-272X.2023.3.03.

14. Tao R., Deng B., Wang Y. Research progress of the fractional Fourier transform in signal processing. *Science in China Series F*, 2006, vol. 49, no. 1, pp. 1-25. doi: https://doi.org/10.1007/s11432-005-0240-y.

15. Unser M., Blu T. Fractional Splines and Wavelets. *SIAM Review*, 2000, vol. 42, no. 1, pp. 43-67. doi: https://doi.org/10.1137/S0036144598349435.

16. Feilner M., Jacob M., Unser M. Orthogonal quincunx wavelets with fractional orders. Proceedings *2001 International Conference on Image Processing (Cat. No.01CH37205)*, 2001, vol. 1, pp. 606-609. doi: https://doi.org/10.1109/ICIP.2001.959118.

17. Laakso T.I., Valimaki V., Karjalainen M., Laine U.K. Splitting the unit delay [FIR/all pass filters design]. *IEEE Signal Processing Magazine*, 1996, vol. 13, no. 1, pp. 30-60. doi: https://doi.org/10.1109/79.482137.

18. Abderrahim L., Salama M., Abdelbaki D. Novel design of a fractional wavelet and its application to image denoising. *Bulletin of Electrical Engineering and Informatics*, 2020, vol. 9, no. 1, pp. 129-140. doi: https://doi.org/10.11591/eei.v9i1.1548.

19. Lanani A., Abboudi A. New Fractional Wavelet with Compact Support and Its Application to Signal Denoising. *Journal of Nano- and Electronic Physics*, 2023, vol. 15, no. 2, art. no. 02023. doi: https://doi.org/10.21272/jnep.15(2).02023.

20. Daubechies I. Orthonormal bases of compactly supported wavelets. *Communications on Pure and Applied Mathematics*, 1988, vol. 41, no. 7, pp. 909-996. doi: https://doi.org/10.1002/cpa.3160410705.

21. Saidi A., Azoui B., Ghenai C., Lekmine F. Design and Conception of Platform that Allows to Connect Different Solar Panels and Loads through a DC-DC Buck Converter. *Journal of Nano- and Electronic Physics*, 2022, vol. 14, no. 6, art. no. 06004. doi: https://doi.org/10.21272/jnep.14(6).06004.

Received 30.01.2024
Accepted 26.03.2024
Published 20.06.2024

Abderrahim Lanani [1,2]*, Doctor of Technical Science, Associate Professor,*
Djemouai Djamai [1]*, Doctor of Technical Science, Associate Professor,*
Abdelaziz Beddiaf [1,2]*, Doctor of Technical Science, Associate Professor,*
Abdelkader Saidi [1]*, PhD Student,*
Abdelaziz Abboudi [1]*, PhD, Professor,*
[1] Abbes Laghrour University, Khenchela, 40000, Algeria,
[2] SATIT Laboratory,
Abbes Laghrour University, Khenchela, 40000, Algeria,
e-mail: lanani_arahim@univ-khenchela.dz (Corresponding Author);
ddjamai@yahoo.fr; beddiafaziz@yahoo.fr;
saidi.abdelkader@univ-khenchela.dz;
aboudiabdelaziz23@gmail.com

How to cite this article:
Lanani A., Djamai D., Beddiaf A., Saidi A., Abboudi A. Photovoltaic system faults detection using fractional multiresolution signal decomposition. *Electrical Engineering & Electromechanics*, 2024, no. 4, pp. 48-54. doi: https://doi.org/10.20998/2074-272X.2024.4.06