



Journal Homepage: -[www.journalijar.com](http://www.journalijar.com)

## INTERNATIONAL JOURNAL OF ADVANCED RESEARCH (IJAR)

Article DOI:10.21474/IJAR01/17372  
DOI URL: <http://dx.doi.org/10.21474/IJAR01/17372>



### RESEARCH ARTICLE

#### METHODS AND SOFTWARE TOOL FOR AUTOMATING STATIC AND DYNAMIC SEARCH FOR ANOMALIES IN TELEMETRY DATA OF A SOLAR POWER PLANT

Valevich S.V.<sup>1</sup>, Dzik K.S.<sup>2</sup>, Pilecki I.I.<sup>3</sup>, Kruse I.<sup>4</sup>, Asimov R.M.<sup>2</sup> and Asipovich T.A.<sup>3</sup>

1. Belarusian State University of Informatics and Radioelectronics.
2. Sensotronika LLC.
3. Sunsniffer, LTD.
4. Belarusian State Economic University.

#### Manuscript Info

##### Manuscript History

Received: 05 June 2023  
Final Accepted: 09 July 2023  
Published: August 2023

##### Key words:-

Solar Panel, Normalized Power Value,  
Anomaly Search

#### Abstract

**Annotation:** The search for faulty, and therefore operating in an abnormal mode, solar panels at a power plant is an urgent task in the context of the development and growth of the share of solar energy in electricity generation. The purpose of the study is to develop new methods and software algorithms for finding anomalies in the operation of solar panels based on the results of a digital twin created and trained according to the telemetry data of a solar power plant.

**Methods:** The developed methods are based on studies of deviations of power values at the point of maximum efficient operation of the solar panel calculated by a digital twin from the average statistical values for the power plant. In addition, the normalized power value at the point of maximum efficient operation of the solar panel is introduced. Results. Using the developed methods of static search for half a year of observations, 18 anomalies in the operation of the solar panels of the power plant were detected and confirmed using direct

**Observation:** 16 using the static analysis method and 2 using the dynamic analysis method.

**Conclusions:** It has been established that when using normalized power values in MPP PN in the analysis of deviations, it is possible to detect anomalies in the operation of solar panels.

Copy Right, IJAR, 2023.. All rights reserved.

#### Introduction:-

The growth in electricity generation through solar power plants stimulates the development of systems for monitoring the technical condition of power plants, as well as ways to automate the search for faulty solar panels and the facts of their abnormal functioning.

To monitor the technical condition, cloud resources are used [1 - 4], which allow collecting telemetry data when equipping solar power plants with appropriate equipment. Cloud resources allow through a web interface to analyze the main parameters of the power plant in general and specific panels in particular. As a rule, the values of voltage, temperature, current strength of each panel and illumination for all panels of the power plant are stored in cloud services. Detection of anomalies in the operation of specific solar panels and their classification depends on the

**Corresponding Author:- Dzik K.S.**

Address:- Belarusian State University of Informatics and Radioelectronics.

attention of the qualifications of the user of the cloud resource, as well as on the availability of functions for the resource to detect anomalies in operation and faulty solar panels.

To solve the problem of finding anomalies in the operation of solar panels using telemetry data, a number of studies suggest modeling solar panels [5–7]. Other authors [8 - 14] use methods and algorithms for estimating the so-called maximum power point (MPP - combinations of current and panel voltage at which energy removal is optimal) for solar panels of a power plant under certain conditions. However, these methods either require the installation of additional equipment with the extraction of additional data for the application of methods and algorithms, or do not take into account the fact that solar panels are connected in series in chains and may not work in their optimal mode.

The above disadvantages of methods for modeling the performance of solar panels are eliminated by the authors [15 - 18]. The results of the digital twin operation make it possible to use the calculated MPP power and volt-ampere characteristics for each panel to find anomalies in the operation of solar panels.

The purpose of this work is to develop a methodology and software for detecting anomalies in the operation of solar panels based on the results of telemetry based on the MPP power obtained using a digital twin of a solar power plant.

### Experimental method

Power plant information: located in Nuremberg, Germany, named Südstadt-Forum, used for data aggregation and calculations in this article. The installation consists of three inverters (models SUN2000-20KTL, Sinvert PVM17 and Sinvert PVM20) with 16 strings (strings of solar panels) and 287 solar panels. All chains consist of 18 photovoltaic monocrystalline modules - M190 (STORM Energy GmbH, Germany).

Digital Twin: The Digital Twin platform provides an API [18, 19] that accepts monitoring data for a certain period and returns the physical-mathematical model parameters for all solar panels.

The input data for the API includes the following parameters: voltage  $U$ , current  $I$ , temperature in the solar panel case  $T$ , light level  $G$ , timestamp  $t$ . The interval for fixing the listed parameters is 2 minutes. The dataset was collected using telemetry from June 2019 to November 2019 inclusive. In these calculations, only those data points were used that satisfy the following conditions: solar radiation  $G > 300 \text{ W h / m}^2$ , current in the circuit  $I > 2 \text{ A}$ , module voltage  $U > 10 \text{ V}$ .

The result of the digital twin (API) operation includes the following parameters, determined in simulated standard test conditions (STC) for each solar panel of the power plant: output power at the maximum power point (MPP)  $P_{\text{mpp}}$ ; voltage  $U_{\text{mpp}}$  and current  $I_{\text{mpp}}$  at MPP; series and parallel electrical resistance; short circuit current and open circuit voltage.

Node.JS was used to implement and test the proposed methods, along with async / await parallelization to speed up calculations with a large number of solar panels.

### Data preparation:

The original data points resulting from the DT calculation have the following features: MPP power in STC, module ID, calendar month.

For data analysis, normalized power values in MPP  $P_N$  for data analysis, normalized power values in MPP

$$P_N = \frac{P_{\text{mpp}} - P_m}{P_m} \cdot 100, \% \quad (1)$$

where  $P_m$  – is the global median power value. Calculated as the average of all row medians:

$$P_m = \frac{\sum_i^n P_s}{n}, B_T \quad (2)$$

where  $P_S$  – is the median power  $P_{mpp}$  for a single string of series-connected solar panels,  $n$  is the number of strings in the power plant.

Data variance is calculated both for the chain level and for the panel level using the formula:

$$S^2 = \frac{\sum(X - M)^2}{N - 1} \quad (3)$$

where  $S^2$  – is the sample variance,  $X$  – is the value in points,  $M$  – is the mean value of the sample,  $N$  – is the number of points.

To search for anomalies in the operation of solar panels, two methods were tested: search for static anomalies (Criteria static analysis), search for dynamic anomalies (Criteria dynamic analysis). Both proposed methodologies were applied at two levels of analysis: at the level of single solar panels and at the level of arrays of panels.

When searching for static anomalies, the normalized power values in MPP  $P_N$  for solar panels (panel chains) were compared with a given threshold value. When the  $P_N$  threshold was exceeded for one month, the chain/panel was marked as operating abnormally. The threshold values were 5 and 10%.

The technique for searching for dynamic anomalies includes the same two levels: chains of panels and single solar panels. If the deviation of the normalized value at the point of maximum power  $P_N$  of the chain (single panel) in the previous month from the current month is greater than the threshold value, then an anomaly in their work was noted. The threshold values were 5 and 10%.

This technique for assessing the presence of anomalies in the operation of a solar power plant helps to identify additional dynamic changes that may be missed when using a static analysis technique. For example, some problems may be found when cleaning the module regularly.

The results of the proposed methods are compared with the results of the verification process on the Sunsniffer web portal [2], the average module analysis [20], fault detection and methods for observing and evaluating voltage and current [21], and the static anomaly search technique in solar power plant telemetry data [22].

The methodology for the analysis of observation and estimation of voltage and current is described in [21]. This technique allows you to recognize the type of defect by special design parameters:  $R_V$  and  $R_I$  - indicators of voltage and current of the solar panel;  $I_M$  and  $V_M$  - output voltage and current at the point of maximum power of the solar panel in fail-safe operation;  $R_{VM}$  and  $R_{IM}$  - indicators of voltage and current of the solar panel in fail-safe mode;  $R_{VS}$  - voltage indicator in the presence of a short-circuited solar panel in one of the chains;  $R_{IO}$  - indicator of the presence of solar panels in the chain; open circuit failure;  $T_{IO}$  – open circuit fault detection threshold is given by;  $T_{VS}$  - short circuit threshold, indicates the presence of one or more short-circuited solar panels in the chain;  $T_{IP}$  – partial shading error threshold;  $R_{VP}$  and  $R_{IP}$  - indicators of voltage and current of partial circuits;  $\epsilon$  is the allowable bias factor when a fault is detected, it affects the sensitivity of the calculation algorithm. These parameters are necessary for the classification of defects. The result of using the technique makes it possible to group solar panels by types of defects: open circuit, short circuit, partial shading, degradation failure, etc. The values of  $P_{MPP}$ ,  $V_{MPP}$ ,  $V_{OC}$ ,  $I_{SC}$ ,  $K_i$  of solar panels obtained from the DT API digital twin [154] and telemetry data of specific points (G and T) were used as initial data for calculating the listed parameters.

The parameters calculated in this way are necessary for the implementation of the defect classification algorithm. It groups defects into several types: open circuit, short circuit, partial shadowing, etc. A description of the algorithm and the application of parameters can be found in [21]. The technique uses a special coefficient:  $\epsilon$  is the allowable bias coefficient when a fault is detected.

In addition, all modules with detected anomalies were visually inspected and their total power output was evaluated.

## Results and Discussion:-

### The results of the method of searching for static anomalies

The application of the technique for searching for static anomalies at the level of solar panel chains at a threshold value of 10% does not allow detecting anomalies.

When using a threshold value of 5%, the technique shows the presence of an abnormal operation mode for a chain of panels with the number String 1.1. This panel chain shows a deviation of minus 7.5% in August.

At the level of analysis of a particular solar panel, a threshold value of 10% was used, since the threshold value of 5% gives a large number of many abnormal solar panels that are healthy. The results of the 10% module threshold are shown in Table 1.

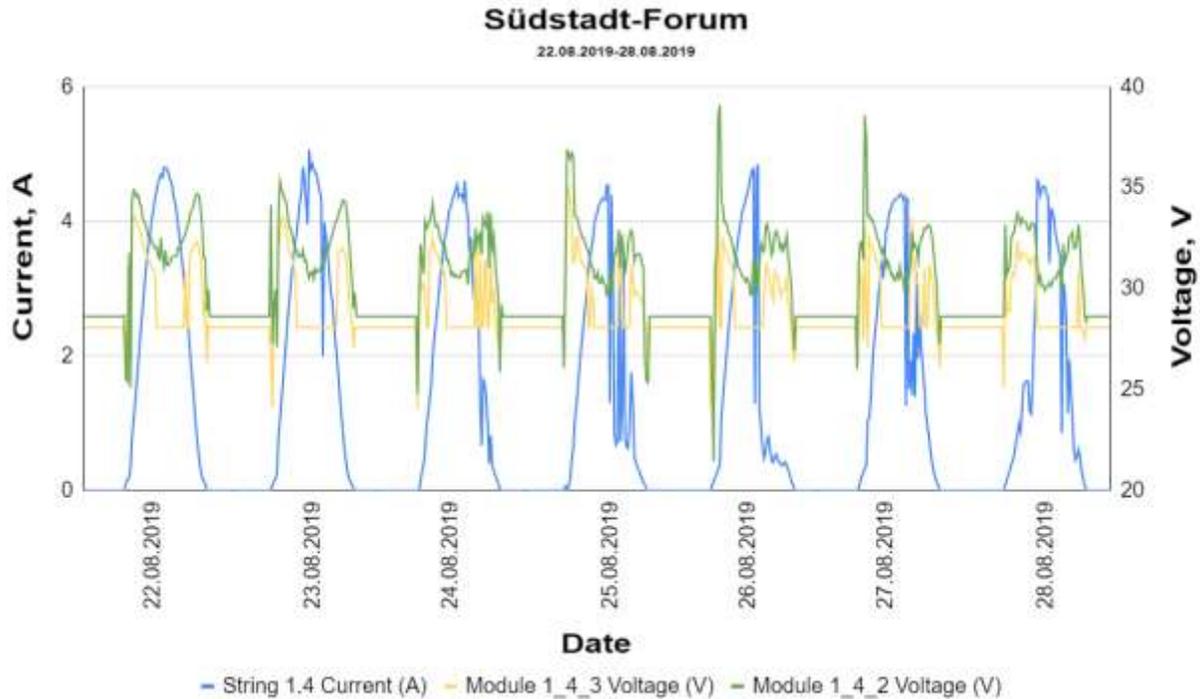
**Table 1:-** Results of using the method of searching for static anomalies at the level of a specific solar panel using a threshold value of 10%.

Anomaliescount	Module	Month	Deviationvalue
7 modules / 16 anomalies	Module 1,1_2	August_2019	-10.8%
	Module 1_4_1	June_2019	17.8%
		July_2019	17.1%
		August_2019	19.8%
		September_2019	19.5%
		November_2019	18.4%
	Module 1_4_3	November_2019	-10.1%
	Module 1,5_6	November_2019	-11.1%
	Module 1,11_1	November_2019	-10.4%
	Module 1,11_15	November_2019	-51.6%
	Module 2,3_10	June_2019	-28.2%
		July_2019	-25.5%
		August_2019	-28.5%
		September_2019	-28.1%
		October_2019	-26.9%
		November_2019	-21.0%

As a result of the analysis, seven solar panels and 16 cases of their abnormal operation were identified. In this case, the following should be noted: eleven cases of anomalous operation occur in two solar panels with numbers Module 2,3\_10 and Module 1\_4\_1; four cases of anomalous operation were recorded additionally in November for four different modules (Table 1); one case was recorded in August at the solar panel with the number Module 1,1\_2.

All detected anomalies were studied from telemetry information collected using the Sunsniffer web portal [2] by comparing the voltage curves during the day on the solar panels under study.

Figure 1 shows the voltage and current curves of Module 1.4\_3 panel versus a healthy Module 1.4\_2 panel between August 22 and August 28, 2019.



**Figure 1:-** Curves of voltage and current of solar panels with numbers Module 1.4\_2 and Module 1.4\_3.

Module voltage curve 1.4\_3 shows the typical behavior of a failed or shaded solar panel. The voltage on the panel drops below the minimum supply voltage of the sensor, the panel and the sensor are disconnected from the circuit (due to the operation of the protective diode). As a consequence, a straight line with zero voltage values is observed on the dependence of voltage on time during the disconnection of the sensor from the circuit. After the voltage is restored, the sensor turns on and continues to send measurements. A similar situation occurs for other solar panels, in which the method of searching for static anomalies with a threshold value of more than 10% indicated the presence of an anomalous mode of their operation. In addition, a visual inspection of the solar panel with the Module number 2,3\_10 shows that the protective glass has mechanical damage: it is broken.

Another method to check the results is to compare the energy actually produced by the solar panels. Figures 2 and 3 show such data for panel chains with numbers String 1\_4 and String 2\_3, respectively, for August 2019 according to the SunSniffer portal.

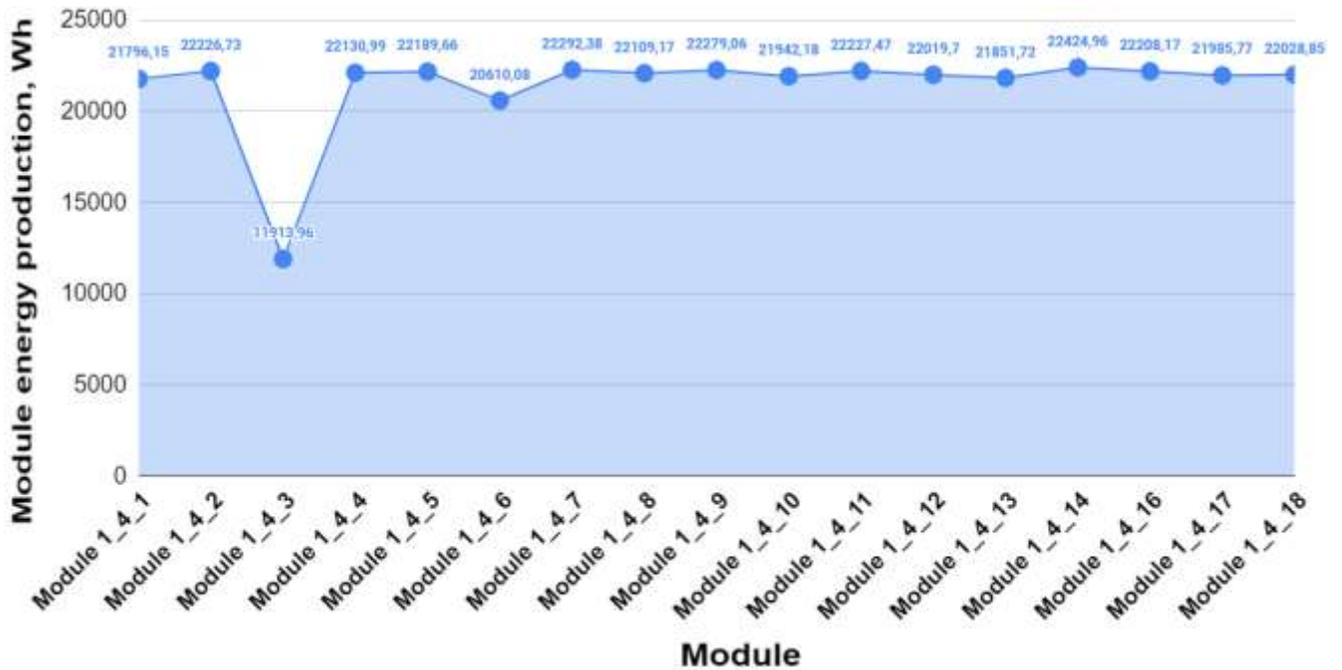


Figure 2:- Energy generated by the solar panels of the chain with the number String 1.4.

It can be seen that the solar panel with the Module number 1.4\_3 generated noticeably less energy (11913 Wh) compared to the other panels of the same chain. The average performance value for this chain in August 2019 is 21425 Wh. Thus, it is shown that the solar panel with the number Module 1.4\_3 has a deviation from normal operation, that is, an anomaly was detected in its operation.

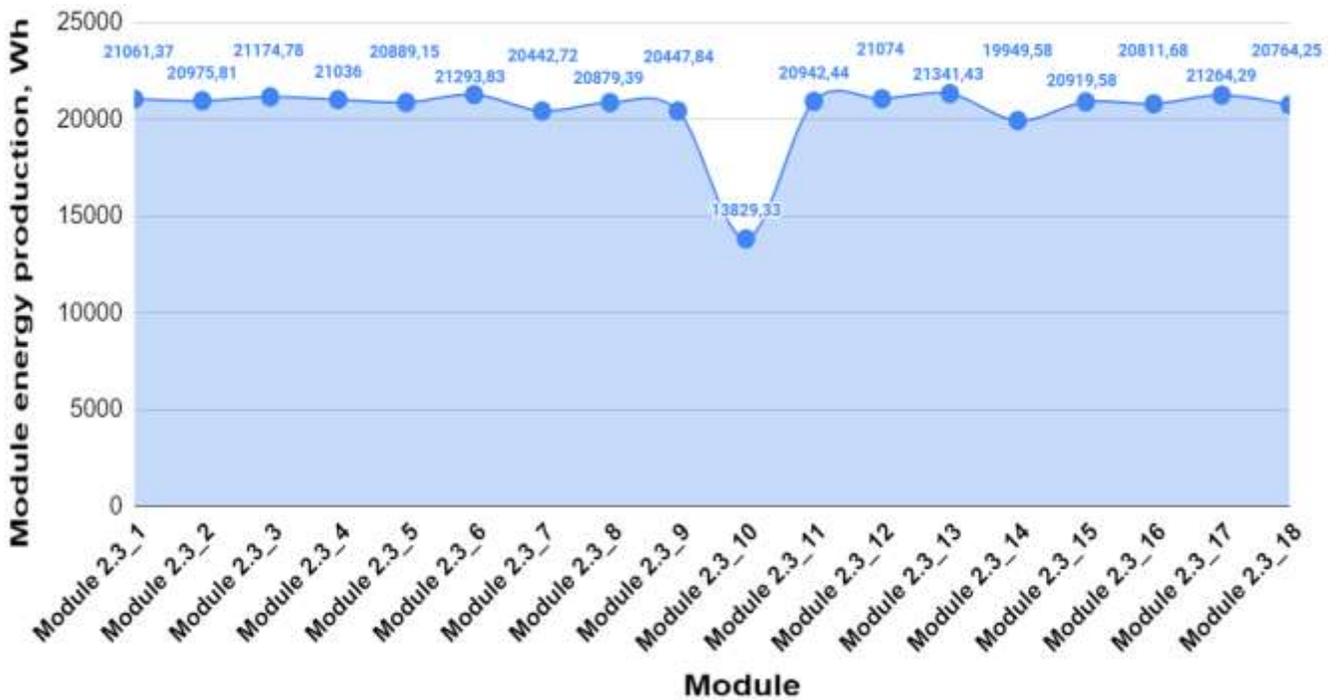


Figure 3:- Energy generated by the solar panels of the chain with the number String 2.3.

A similar analysis for string String 2.3 (see Figure 3) shows that the Module 2.3\_10 solar panel has an actual output of 13829 Wh. The average performance value for this chain in August 2019 is 20505 Wh.

Similarly, all solar panels with anomalies noted in Table 1 were tested. All anomalies detected using the technique were thus confirmed.

It is shown that the method of searching for static anomalies provides anomaly detection in the operation of a solar power plant (16 anomalous conditions were found for seven modules). The observed dispersion of data at the panel chain level is 1.43%; dispersion at the panel level is 2.08%. The sensitivity of the method can be adjusted by adjusting the threshold level in accordance with the specifics of the enterprise.

#### Results of the method of searching for dynamic anomalies

The technique is aimed at finding anomalies in the operation of the solar panel, which depend on time. This helps to identify and investigate some processes that are not permanent in nature, and, in particular, allows you to evaluate the quality of solar panel cleaning.

The chain-level analysis used two thresholds: 10% and 5%. A threshold of 10% does not give a detection result (chains with anomalies were not detected). The threshold of 5% allowed us to detect two anomalies in the same panel chain: July - August, the String 1.1 chain shows a performance drop of 8.4%; August - September, the String 1.1 chain shows a performance gain of 7.9%.

In the analysis at the solar panel level, thresholds of 5% and 10% were used. The results of applying the methodology with a threshold value of 10% are presented in Table 2.

**Table 2:-** Results of applying the dynamic search for anomalies using a threshold value of 10% at the level of solar panels.

Anomaliescount	Module	MonthFrom	MonthTo	Deviation
15 modules / 16 anomalies	Module 1,1_2	July_2019	August_2019	-10,60%
	Module 1,1_3	July_2019	August_2019	-10,40%
	Module 1,1_4	July_2019	August_2019	-12,20%
		August_2019	September_2019	10,80%
	Module 1,1_13	July_2019	August_2019	-10,10%
	Module 1,1_14	July_2019	August_2019	-10,10%
	Module 1_4_9	October_2019	November_2019	-12,50%
	Module 1_4_13	October_2019	November_2019	-12,60%
	Module 1_4_17	October_2019	November_2019	-13,60%
	Module 1,5_6	October_2019	November_2019	-11,40%
	Module 1,5_14	September_2019	October_2019	-10,10%
	Module 1,6_9	September_2019	October_2019	-10,90%
	Module 1,7_8	September_2019	October_2019	-10,30%
	Module 1,8_15	July_2019	August_2019	-10,40%
	Module 1,10_7	July_2019	August_2019	-11,00%
	Module 1,11_15	October_2019	November_2019	-47,70%

The use of the technique made it possible to identify sixteen anomalies in the operation of fifteen solar panels. The solar panel with the Module number 2,3\_10, detected using the static anomaly search technique, shows stable behavior: it has insignificant changes in PN from month to month. It has been established that most of the registered anomalies take place in the periods of July-August, September-October and October-November. This may indicate partial shading of the solar panels.

Using a threshold of 5%, 125 anomalies were found, which is too many for direct analysis.

However, plotting the number of detected anomalies per solar panel (Fig. 4) revealed three solar panels (Module 1.6\_10, Module 1.7\_7 and Module 1.9\_1), whose performance changed three or more times from month to month.

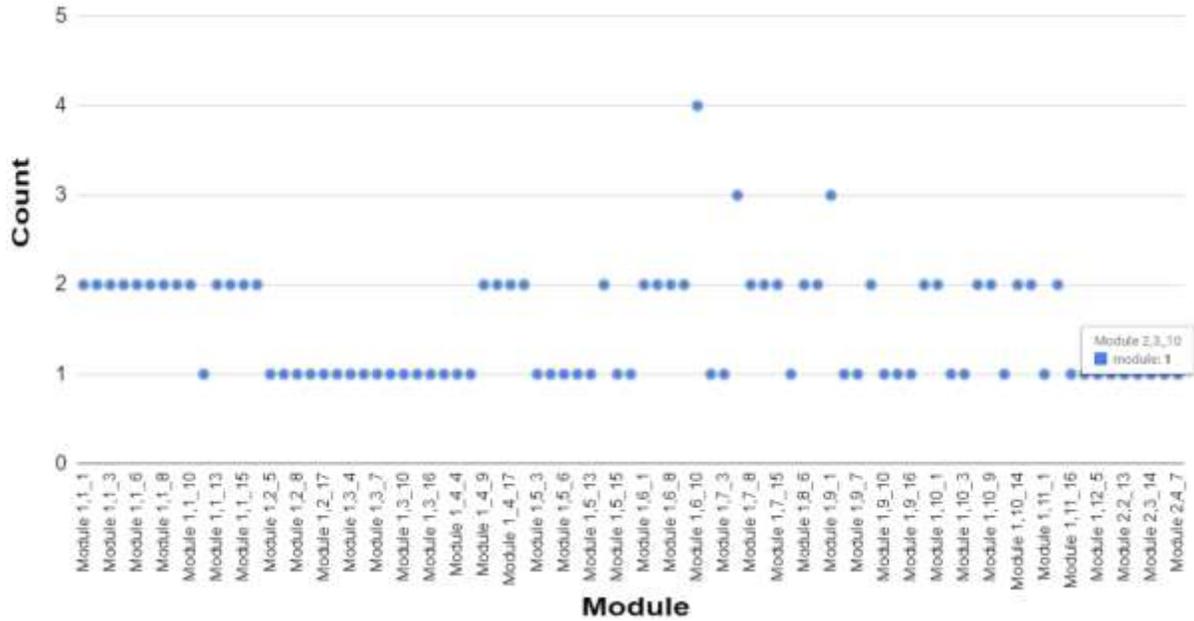


Figure 4:- Distribution of dynamic anomalies of modules (5% threshold).

It should be noted that these particular modules were not identified during dynamic or static analysis at the 10% threshold. In general, for the analysis at the level of panel chains, the variance of the data obtained, calculated by formula (3), is 1.43%, at the panel level - 2.08%.

The dynamic anomaly detection technique is suitable for detecting time-related issues (for example, some modules have slower performance during or after a certain month). Its detection ability is highly dependent on the selected threshold value. In addition, it was found that the methods of static and dynamic searches for anomalies complement each other and should be used together.

**Comparison of methods**

**Comparison:**

Average module analysis [20], General analysis with criteria [22], and methods for searching for static anomalies

Table 11 reflects the results of calculations at the level of chains of panels of methods "Average module analysis" [20], "Criteria static analysis" [22] and methods for searching for static anomalies.

**Table 11:-** Comparison of the results of using panels of methods "Average module analysis" [20], "Criteria static analysis" [22] and methods for searching for static anomalies at the chain level.

StringNo.	Method	June	July	August	September	October	November
String 1.1	[20]	---	---	10,09%	---	---	---
	[22]	---	---	10,8%	---	---	---
	MICT	---	---	---	---	---	---
String 1.2	[20]	---	---	---	---	10,67%	---
	[22]	---	---	---	---	---	---
	MICT	---	---	---	---	---	---
String 1.3	[20]	---	---	---	---	---	13,44%
	[22]	---	---	---	---	---	---
	MICT	---	---	---	---	---	---
String 1.4	[20]	18,87%	16,51%	18,80%	20,11%	12,79%	24,06%
	[22]	17,8%	17,1%	19,8%	19,5%	---	18,4%
	MICT	---	---	---	---	---	---
String 1.5	[20]	---	---	---	---	11,54%	---
	[22]	---	---	---	---	---	11,1%

	МПІСТ	---	---	---	---	---	---
<b>String 1.6</b>	[20]	---	---	11,15%	---	11,97%	---
	[22]	---	---	---	---	---	---
	МПІСТ	---	---	---	---	---	---
<b>String 1.7</b>	[20]	---	---	10,05%	---	10,25%	---
	[22]	---	---	---	---	---	---
	МПІСТ	---	---	---	---	---	---
<b>String 1.8</b>	[20]	---	---	11,42%	---	---	---
	[22]	---	---	---	---	---	---
	МПІСТ	---	---	---	---	---	---
<b>String 1.11</b>	[20]	---	---	---	---	---	51,47%
	[22]	---	---	---	---	---	51,6%
	МПІСТ	---	---	---	---	---	---
<b>String 2.2</b>	[20]	---	15,18%	---	---	---	12,33%
	[22]	---	---	---	---	---	---
	МПІСТ	---	---	---	---	---	---
<b>String 2.3</b>	[20]	31,84%	27,15%	29,28%	27,90%	27,50%	20,83%
	[22]	28,2%	25,5%	28,5%	28,1%	26,9%	21,0%
	МПІСТ	---	---	---	---	---	---

In all cases, the reason for the abnormal behavior of the panel chain is a specific solar panel, the weak performance of which leads to a decrease in the overall performance of the entire chain.

Table 12 shows solar panels with reduced power generation efficiency and their design power (according to API DT) during the period of application of solar panel anomaly detection techniques.

**Table 12:-** List of solar panels with low Pmpp calculated using digital twin.

Causeoftheanomaly	Month	DT calculated P <sub>mpp</sub> for the module, W	Deviationfrommedian, %
Module 1,2_17	October	167,32 W	5%
Module 1,3_13	November	167,7 W	5%
Module 1,4_15	October	167,67 W	5%
Module 1,5_14	October	159,43 W	10%
Module 1,6_9	October	161,19 W	9%
Module 1,6_10	August	163,04 W	8%
Module 1,7_8	October	162,06 W	8%
Module 1,7_10	August	164,7 W	7%
Module 1,8_15	August	162,19 W	8%
Module 2,2_11	July	158,97 W	10%
Module 2,2_12	November	165,36 W	6%

Table 12 also displays the percentage deviation for the median of all solar panels, 176.26 W, from June 2019 to November 2019.

Interestingly, all of these solar panels are within 5–10% of the global median, indicating that the mean modulus analysis is more sensitive than the static analysis and static anomaly search technique.

**Comparison: Static module analysis n Voltage and Current Observation and Evaluation technique**

The use of the "Voltage and Current Observation and Evaluation" technique with a standard value of  $\epsilon = 2\%$  does not allow detecting any anomalies. The technique shows that there are no defects or anomalies in the solar panels of the power plant. Setting the coefficient  $\epsilon$  to a larger value increases the sensitivity of the algorithm. These results of applying the technique with different values of  $\epsilon$  are presented in Table 13.

**Table 13:-** Results of the method "Voltage and Current Observation and Evaluation" by the number of anomalies found with different values of the coefficient  $\epsilon$

$\epsilon$	Faults
2 %	0

5,5 %	0
5,8 %	44
6 %	312
6,5 %	1147
7 %	1387
10 %	1714

Further, the results were analyzed in more detail with a value of  $\varepsilon = 5.8\%$  (the minimum value at which the technique gives the presence of abnormally operating solar panels). At the same time, the technique makes it possible to detect 44 combinations with defects (36 solar panels with 44 anomalies).

All detected defects, according to [21], belong to the "Degradation fault" type (degradation of some electrical parameter, the method offers a general classification of degradation). They are presented in table 14 grouped by months.

**Table 13:-** Results of the "Voltage and Current Observation and Evaluation" method with  $\varepsilon = 5.8\%$ .

ModuleName	August_2019	July_2019	October_2019	September_2019
Module 1,4_13	23	–	–	–
Module 1,4_17	–	–	–	10
Module 1,4_3	–	–	2	–
Module 1,10_1	–	5	–	–
Module 1,10_15	–	16	–	–
Module 1,10_18	–	–	–	6
Module 1,10_6	–	–	2	1
Module 1,10_8	–	–	2	10
Module 1,11_12	22	16	–	–
Module 1,11_15	22	–	–	–
Module 1,12_2	20	–	–	–
Module 1,2_14	2	–	–	–
Module 1,3_14	–	–	–	10
Module 1,3_15	–	–	–	10
Module 1,3_7	21	–	–	10
Module 1,5_10	–	–	1	–
Module 1,5_12	–	–	1	–
Module 1,5_13	21	–	–	–
Module 1,5_14	21	–	–	–
Module 1,5_15	–	–	1	–
Module 1,5_2	21	–	–	–
Module 1,5_3	21	–	–	–
Module 1,5_7	–	–	–	12
Module 1,6_1	16	–	–	–
Module 1,6_18	15	–	–	–
Module 1,6_2	17	–	–	–
Module 1,6_3	4	–	–	–
Module 1,7_7	–	1	–	–
Module 1,9_12	24	–	1	–
Module 1,9_13	6	–	2	–
Module 2,1_1	21	–	–	10
Module 2,1_5	–	–	–	7
Module 2,2_13	–	–	2	10
Module 2,2_2	–	–	3	–
Module 2,4_14	35	–	–	–
Module 2,4_9	–	–	1	–

36 defective solar panels were found (of which eight have anomalies for more than one month). The following should be noted:

- the technique does not have a stable result: in one month the panel shows the presence of a degradation fault, and in the other it does not. This circumstance complicates the interpretation of the results of the application of the technique.
- solar panels, the anomalies in the operation of which were detected and confirmed by other methods (Table 1, Figures 2 and 3), basically, were not included in the analysis results as defective. Only the solar panel with the Module number 1.11\_15, according to the results of the analysis in August, had anomalous work.

Table 14 provides a summary of the methods used in the study to search for anomalies in the operation of solar panels based on telemetry data.

**Table 14:-** The result of a quantitative comparison of the detected anomalies using the considered methods.

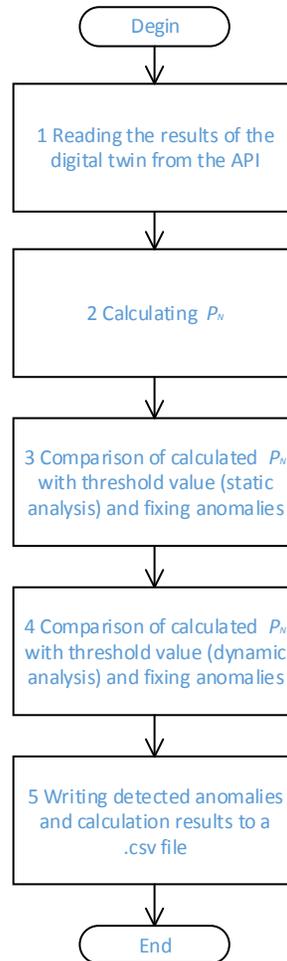
Method	Modules	Anomalies
Criteria static analysis (10 %)	7	16
Criteria dynamic analysis (10 %)	15	16
General analysis with criteria (point data) [22]	5	19
General analysis with criteria (line data) [22]	8	18
Average module analysis [20]	11	24
Voltage and Current Observation and Evaluation technique (2 %) [21]	0	0
Voltage and Current Observation and Evaluation technique (5,8 %) [21]	36	44

The following criteria were chosen for comparison: the optimal ratio of solar panels to anomalies. It can vary from 1 to 6 (1 module and 6 months). 1 and 5-6 are extreme cases, 2-4 are considered optimal values. Borderline cases are less accurate (for 1 - the technique detects mostly single anomalies, for 5-6 - the technique detects only stable anomalies that are easy to find).

According to the data obtained for general cases, the best results are shown by the General analysis with criteria (panel chain analysis level) and Criteria static analysis (10%) methods. Both of these methods demonstrate the optimal ratio of solar panels to anomalies, ensuring the detection of the most important anomalies (on average, each panel has a little more than 2 points, that is, anomalies that repeat in different months are detected).

For comparison, in the “General analysis with criteria (level of analysis of specific panels)” method, this ratio tends to 5 points, for Criteria dynamic analysis (10%) it is close to 1 point per solar panel. In the first method, the average value of criticality anomalies can be missed, and in the second one, there are too many false positives, which complicates the analysis and detection of real anomalies. Both techniques can be used in extreme cases (when you need to find only the most critical or episodic anomalies that do not regularly affect performance, but appear in individual months).

Based on the research carried out, a software tool was developed. The algorithm of the software tool is shown in Figure 5. The input data for the software tool are json objects from the digital twin API, and the output data is the result of calculating the normalized power values in MPP for each solar panel, the deviation level of the solar panel  $P_N$  from the threshold value in percent, and list of numbers of solar panels in which anomalies were found and criteria for found anomalies.



**Figure 5:-** Block diagram of the software algorithm for finding anomalies in the operation of solar panels, developed on the basis of the proposed methodology.

### Conclusions:-

It has been established that, based on the normalized power values in MPP  $P_N$  for all panels of a solar power plant, it is possible to detect anomalous operation of individual panels using the Criteria static analysis and Criteria dynamic analysis algorithms.

Among the methods considered in the work for finding anomalies in the operation of solar panels, the best is The Average module analysis; its results are close to those of the Criteria static analysis (10%), except for anomalies that are within less than 10% deviation (Table 11).

### List of sources used:-

1. Top 10 Solar Monitoring Systems in the World in 2022 [Electronic resource] – Mode of access <https://www.solarfeeds.com/mag/solar-monitoring-systems-in-the-world/>
2. SunSniffer [Electronic resource] – Mode of access <http://www.sunsniffer.de/solution/what-is-sunsniffer.html>. – Date of access: 3.12.2019.
3. SolarEye [Electronic resource] – Mode of access <https://www.solareye.eu/platform/?r=site/page&view=features> – Date of access: 5.06.2018.
4. PVsyst [Electronic resource] – Mode of access <http://www.pvsyst.com/en/> – Date of access: 5.06.2018.
5. Dorin P., Farcas C., Ciocan, I. Modelling And Simulation Of Photovoltaic Cells. ACTA Technica Napocensis, 2008, vol. 49, no 1, pp. 42 – 47.

6. Adeniyi O.D., Ali D.A., Olutoye M.A., Adeniyi M.I., Azeez O.S., Otaru A.J. Eniafe B.O. Modeling and Simulation of Energy Recovery from a Photovoltaic Solar cell. Nigerian Journal of Technological Research, 2016, vol. 11, pp. 26 – 31.
7. Salmi T., Bouzguenda M., Gastli A., Masmoudi A. MATLAB/Simulink Based Modelling of Solar Photovoltaic Cell. International Journal of Renewable Energy Research, 2012, vol. 2, no 2, pp. 213 – 218.
8. Tina G., Cosentino F., Ventura C. Monitoring and Diagnostics of Photovoltaic Power Plants. In: Sayigh A. (eds) Renewable Energy in the Service of Mankind, 2016, Vol 2. pp. 505 – 516. Springer, Cham
9. Ibbini, M., Adawi A. Analysis and design of a maximum power point tracker for a stand-alone photo voltaic system using simscape. International Journal of Advanced Trends in Computer Science and Engineering, 2019, vol. 8, no 1, pp. 54-57.
10. Rashid Md. M., Habib A., Mahdi Hasan M. Design And Construction Of The Solar Photovoltaic Simulation System With The Implementation Of MPPT And Boost Converter Using Matlab/Simulink. Asian Journal of Current Research, 2018, vol. 3, no 1, pp. 27-36.
11. Leopoldo G.-A., Belem S., Otniel P.-R., Juan C. Á.-V., Pánfilo R. M.-R., Rigoberto M.-M. Flatness-Based Control for the Maximum Power Point Tracking in a Photovoltaic System. Energies, 2019, vol. 12, pp. 1843 – 1862. doi:10.3390/en12101843
12. Kishor N., Villalva M., Mohanty S.R., Filho E. Modeling of PV module with consideration of environmental factors. In Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES p. 121 – 126.
13. Kishor N., Mohanty S.R., Villalva M., Filho E. Simulation of PV array output power for modified PV cell model. In 2010 IEEE International Conference, Kuala Lumpur, IEEE, p. 321
14. Wang Y., Chun-Sheng W., Hua L., Hong-Hua X. (2008). Steady-state model and power flow analysis of grid-connected photovoltaic power system. In 2008 IEEE International Conference on Industrial Technology, 2008, Chengdu, IEEE, p. 1 - 6.
15. Asimov R.M., Valevich S.V., Kruse I., Asipovich V.S: Virtual laboratory for testing of solar power plants in big data analysis. In Collection of materials of the V International Scientific and Practical Conference «Big Data And Advanced Analytics», March 13–14, Minsk, BSUIR, pp. 61–65 (2019)
16. Asipovich V.S., Asimov R.M., Chernoshey S.V.: Digital twin in the Analysis of a Big Data. In Collection of materials of the IV International Scientific and Practical Conference «Big Data And Advanced Analytics», May 3–4, Minsk, BSUIR, pp. 69–78 (2018)
17. Valevich S., Asimov R., Kruse I., Asipovich V. Digital Twin For PV Module Fault Detection. Journal of Engineering Science, 2020, XXVII (4), 80–87.
18. Asimov R.M., Valevich S.V., Kruse I., Asipovich V.S. Digital Twin for PV plant’s power generation analysis. In Collection of materials of the VI International Scientific and Practical Conference «Big Data And Advanced Analytics», May 20-21, Minsk, BSUIR, pp. 78-88 (2020)
19. С. В. Валеvич, В. С. Осипович, И. Крузе, Р. М. Асимов Информационное обеспечение мониторинга технического состояния солнечных электростанций. Информационныетехнологии, 2020, – №10. Т. 26, – С. 594–601.
20. Asimov R.M., Valevich S.V., Kruse I., Asipovich V.S.: Digital Twin for PV plant’s power generation analysis. Collection of materials of the VI International Scientific and Practical Conference «BIG DATA and ADVANCED ANALYTICS», May 20-21, Minsk, BSUIR, pp. 78-88 (2020)
21. Pei, Tingting; Hao, Xiaohong: A Fault Detection Method for Photovoltaic Systems Based on Voltage and Current Observation and Evaluation, Energies 12, no. 9: 1712. <https://doi.org/10.3390/en12091712> (2019).