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RESEARCH ARTICLE

METHODOLOGY AND SOFTWARE FOR SEARCHING FOR ANOMALIES IN TELEMETRY DATA OF A SOLAR POWER PLANT BASED ON AN ARTIFICIAL NEURAL NETWORK - AUTOENCODER

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Abstract

Objectives: Development of a new methodology and software for detecting anomalies in the operation of PV-modules based on an artificial neural network type autoencoder trained on telemetry data from a solar power plant.

Methods: The methodology is based on statistical studies of deviations of measured from recovered neural network values of current and voltage of all PV-modules of the power plant. Additionally, a criterion for evaluating the presence of faults in the operation of the PV-module based on statistical studies is introduced.

Results: Using the developed methodology and software for anomaly detection in telemetry data over six months of observations with different evaluation criteria, from 14 to 45 anomalies were detected in 33 PV-modules. All cases were analyzed for the causes of the anomalies in the operation of the PV-modules.

Conclusion: It was established that using four standard deviations for the daily average measured values of current ΔI and voltage ΔU as a criterion for detecting anomalies allows identifying faulty PV-modules. Using three and two standard deviations as a criterion for detecting anomalies helps identify reduced efficiency in PV-module operation due to degradation, excessive shading, and other factors.

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Introduction:-

The increasing production of electricity using solar power plants promotes the improvement of systems for monitoring their technical condition and the development of methods for automatically detecting defective PV-modules and anomalies in their operation. Currently, cloud resources (URL:<https://www.solarfeeds.com/mag/solar-monitoring-systems-in-the-world/>,<http://www.sunsniffer.de/solution/what-is-sunsniffer.html>,<https://www.solareye.eu/platform/?r=site/page&view=features>,<http://www.pvsyst.com/en/>) are used to monitor the technical condition of PV-modules operating as part of power plants, which ensure the collection, storage, and visualization of telemetry when equipping solar power plants with appropriate equipment. The telemetry data in cloud services generally includes voltage, temperature, current of each PV-module, and illumination level for all panels of the power plant. The detection of faults in the operation of PV-modules and the classification of these faults depend on the attention and qualification of the specialist using the cloud resource. In

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the context of anomaly detection in the functioning of PV-modules, some researchers suggest using their modeling [1-3], comparing the modeling result with telemetry. While other specialists [4-10] consider the possibilities of using algorithms to calculate the maximum power point (MPP) and compare it with the actual obtained values. There are works that develop and complement both considered methods [11-14], creating a digital twin for each PV-module based on telemetry results. Active research is being conducted on the use of neural networks for detecting anomalies in the operation of PV-modules. The authors [15] provide a review of neural network applications for detecting anomalies in PV-modules. However, the applications considered by the authors are aimed at detecting surface defects of PV-modules based on photographs and focus on image analysis. Study [16] describes the use of generalized regression neural networks (GRNNs) to build volt-ampere characteristics for six different PV-modules (differing in materials). Training of the neural network was carried out on data measured in the laboratory under normal conditions: STC. The use for detecting anomalies in operation was not considered. The authors [17] compare different types of neural networks for predicting solar power plant production depending on weather conditions. Study [18] used an autoencoder to detect anomalies in the signal at the inverter output based on the irradiance measurement signal. All the considered studies do not use telemetry results and have difficulties in applying them to detect anomalies in the operation of individual PV-modules at the power plant. The goal of this study is to develop a methodology and software for detecting anomalies in the operation of PV-modules based on telemetry results presented by a cloud resource (URL:<http://www.sunsniffer.de/solution/what-is-sunsniffer.html>) using an artificial neural network type autoencoder.

Experimental Methodology:

The study used telemetry results from the Südstadt-Forum power plant located in Nuremberg, Germany. The installation includes three inverters (models SUN2000-20KTL, Sinvert PVM17, and Sinvert PVM20) with 16 strings (chains of PV-modules) and 287 PV-modules. All strings consist of 18 photovoltaic monocrystalline modules M190 (STORM Energy GmbH, Germany).

Telemetry data is stored in a cloud storage with an API including the following parameters: voltage, current, temperature in the PV-module housing, illumination level, and timestamp. The interval for recording these parameters is 2 minutes. The dataset was collected from June 2019 to November 2019 inclusive, and the same period in 2018.

To implement and verify the proposed methodology and algorithm, the following development tools were used: Python, Tensorflow.

The study was conducted according to the following algorithm:

1. Preparation of telemetry data (initial datasets for training and testing the autoencoder).
2. Training the autoencoder.
3. Searching for anomalies in the operation of PV-modules using the trained autoencoder.

The prepared dataset for training the autoencoder and analyzing the operability of PV-modules was filtered to use only data collected on sunny days. Filter parameters: current – 0–15 A, illumination – 360–1500 W/m², current derivative – -0.2–0.2, illumination derivative – -3.8–3.8. The filtered results were used to prepare input data vectors for training the autoencoder and data vectors for testing it. The input data vector had a dimension of 200 x 3 and included telemetry results from 10:00 to 17:00 hours with the following parameters: timestamp, temperature in the PV-module housing T, illumination level G. The test data vector had a dimension of 200 x 3 and included the following parameters: timestamp, temperature in the PV-module housing T, illumination level G. The output of the autoencoder in both cases was a vector of 200 x 3, that is, when test data was input, the neural network should reconstruct voltage and current values based on temperature in the PV-module housing and illumination level.

The developed artificial neural network is an autoencoder consisting of seven layers of neurons. Its more detailed structural diagram with activation functions of layers is shown in Figure 1.

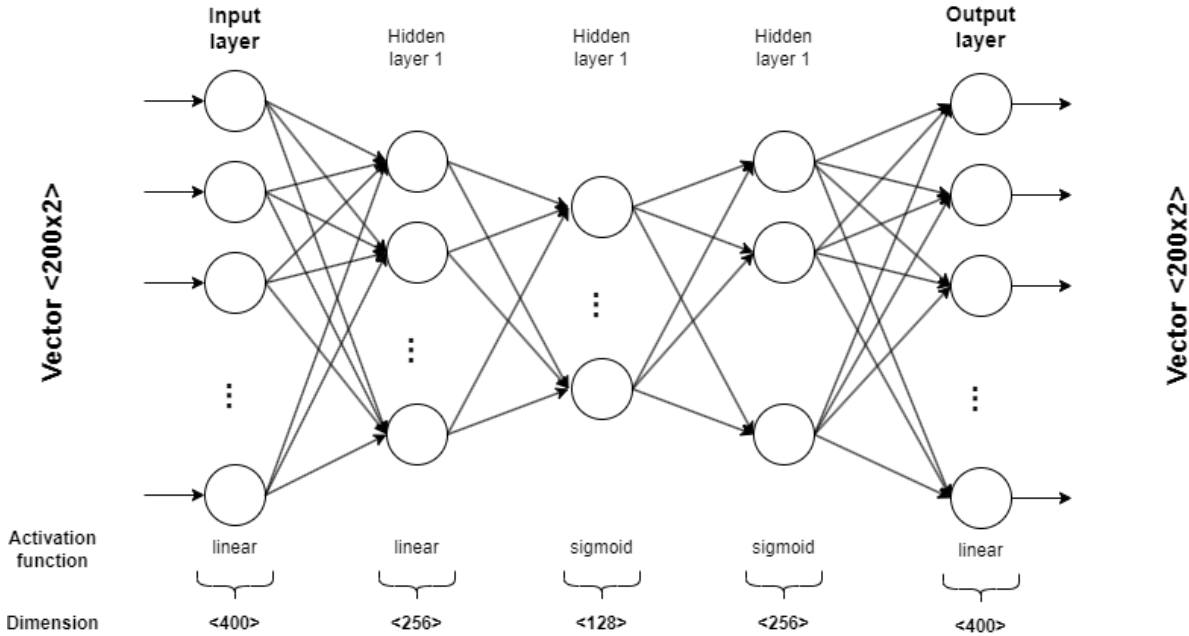


Fig. 1:- The architecture of the developed and used autoencoder.

To determine the criteria for detecting PV-modules in an abnormal operating mode, we used the average daily deviations of the measured values of current ΔI and voltage ΔU from those restored by the autoencoder, as well as the number of lines l in the vector, the average deviations in which in voltage or current exceeded the established value meaning.

$$\Delta I = \frac{\sum_{i=1}^N I'_i - I_i}{N} \tag{1}$$

where I' – is the current restored by the autoencoder, I – current strength measured during telemetry collection, N – number of points during the day used for calculations.

$$\Delta U = \frac{\sum_{i=1}^N U'_i - U_i}{N} \tag{2}$$

where U' – is the voltage recovered by the autoencoder, U – voltage measured during telemetry collection, N – number of points during the day used for calculations.

Next, the standard deviation for ΔI and ΔU of each of the PV-modules for a set of sunny days was calculated using the formulas.

$$\sigma_I = \sqrt{\frac{\sum_{i=1}^M |\Delta I_i - \Delta I_{av}|^2}{M}} \tag{3}$$

$$\sigma_U = \sqrt{\frac{\sum_{i=1}^M |\Delta U_i - \Delta U_{av}|^2}{M}} \tag{4}$$

where ΔI_{av} и ΔU_{av} – are the arithmetic mean for ΔI and ΔU , respectively ΔI_i and ΔU_i – values of ΔI and ΔU , for one panel, respectively; M – number of values of the analyzed sample.

PV-modules satisfying the following conditions were considered as anomalies:

$$\Delta I > K\sigma_I \text{ or } \Delta U > K\sigma_U \tag{5}$$

where K is a coefficient that is a criterion for detecting an anomaly in PV-modules. The K coefficient values of 2, 3 and 4 were used in the experiment.

Thus, lists of PV-modules and anomalies in them were generated.

Research Results:-

The table contains the result of applying condition (5) when searching for anomalies in the operation of PV-modules of a power plant for six months (June - November) 2019. At the same time, only sunny days of the considered period participated in the search for anomalies: June 28 and 30, July 26, August 18-20, September 4 and 18, October 14 and 26, November 13, 14 and 26. Thus, the sample for analysis included the results of calculating the average daily deviations of current ΔI and voltage ΔU for 287 PV-modules for thirteen days.

The minus sign of the average deviation of the measured values of current ΔI and voltage ΔU from those reconstructed by the autoencoder indicates that for given input curves of illumination and temperature, the PV-modules under study produced measured current and voltage higher than those calculated by the artificial neural network for such input data. This situation is typical for the average deviation of the measured current values ΔI and indicates that the PV-module operated in a more efficient mode than expected from the results of the neural network calculation. Positive values of ΔI and ΔU indicate a decrease in the measured characteristics relative to those expected by the neural network. The table records both types of abnormal operation of PV-modules.

Anomaly results for six months (June – November) 2019

Criterion and Number of PV-modules/anomalies	PV-modulenumber	Month	Average daily deviations of measured current ΔI , A	Average daily deviations of measured voltage ΔU , V
For $\Delta I > 4\sigma_I$ or $\Delta U > 4\sigma_U$; 5 PV-modules; 14 anomalies	Module 2,2_2	August	- 3,65	2,62
		November	-0,26	5,54
	Module 2,3_10	June	-0,76	10,84
		July	0,25	10,57
		August	-1,61	13,01
		September	0,54	5,48
		October	0,18	6,77
		November	0,48	9,67
	Module 2,4_14	August	-1,58	7,26
		September	-0,99	3,7
	Module 1,4_3	July	2,59	6,96
		August	2,44	6,52
		November	0,07	4,44
	Module 1,1_15	August	-1,14	6,04
For $\Delta I > 3\sigma_I$ or $\Delta U > 3\sigma_U$; 18 PV-modules;	Module 1,1_2	June	-1,98	2,52
	Module 1,1_11	November	-0,13	5,52
	Module 1,11_14	August	-0,77	6,31
	Module 1,11_15	November	-0,63	4,22

29 anomalies	Module 1,12_11	June	-1,95	2,31
	Module 2,2_15	August	-1,48	5,51
	Module 1,9_2	August	-2,28	4,34
	Module 1,9_3	August	-1,93	1,9
	Module 1,9_10	August	-2,14	3,3
	Module 1,9_16	August	-1,41	6,34
	Module 1,9_18	August	-2,31	3,43
	Module 1,5_7	November	0,88	6,25
	Module 1,5_8	June	-1,65	3,76
		August	-2,47	2,02
November		0,68	6,15	
For $\Delta I > 2\sigma_I$ or $\Delta U > 2\sigma_U$; 33 PV-modules; 45 anomalies	Module 1,2_8	June	0,17	3,87
	Module 1,2_11	June	0,14	3,65
	Module 1,2_12	June	0,20	3,77
	Module 1,2_14	June	0,17	3,66
	Module 1,3_12	June	0,15	4,56
	Module 1,3_15	June	-0,41	3,83
	Module 1,3_16	June	-0,52	4,29
	Module 1,11_5	June	-1,95	2,68
	Module 1,11_11	August	- 0,99	4,95
	Module 1,11_18	August	-1,23	4,49
	Module 1,12_1	August	-1,45	3,76
	Module 2,3_12	June	0,91	-3,81
	Module 1,4_1	July	0,87	-4,52
	Module 1,5_14	November	1,23	5,54
	Module 1,6_18	November	0,16	4,48
	Module 1,8_4	August	-1,36	4,32

Application of different values of the anomaly detection criterion K results in detection of different numbers of anomalies in PV-modules: from 14 anomalies in 5 PV-modules with $K = 4$ to 45 anomalies in 33 panels with $K = 2$. When using the anomaly detection criterion $K = 4$, the developed software says about the presence of 14 anomalies in five PV-modules with numbers: Module 2,2_2, Module 2,3_10, Module 2,4_14, Module 2,4_3 and Module 1,1_15. The average daily deviations of the current ΔI of the measured values from those restored by the autoencoder vary from -3.65 to 2.59 A (average value -0.25 A), and the average daily deviations of voltage ΔU - from 2.62 to 13.01 V (average value 7.1 V).

If $K = 3$ is used as a criterion, the number of anomalies increases to 29 in 18 PV-modules. The range of changes in the average daily deviations of current ΔI and voltage ΔU remains the same, and the average values are -0.79 A and 5.63 V. That is, the average value of ΔI shifts to the negative side, which indicates anomalies associated with PV-modules operating more efficiently than the artificial neural network expected under given conditions, the average ΔU value decreases.

An anomaly detection criterion of $K = 3$ increases the number of anomalies to 45 in 33 PV-modules with average ΔI and ΔU values of -0.6 A and 4.73 V, respectively.

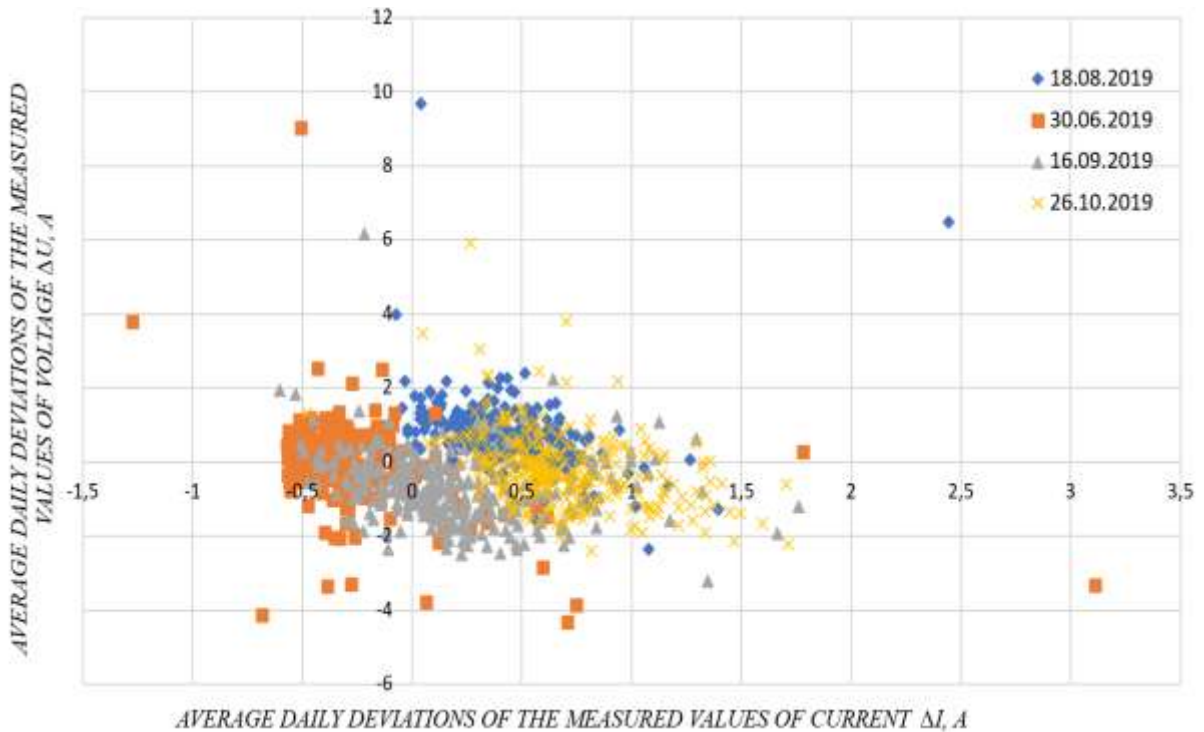


Fig. 4:- The result of constructing the average deviations of the measured values of current ΔI and voltage ΔU from those reconstructed by the autoencoder for all PV-modules of the power plant for the following four sunny days: June 30, August 18, September 16, October 26, 2019.

Let's analyze the voltage, current, illumination and temperature curves measured and reconstructed by the autoencoder for some PV-modules from the table.

The abnormal operation of the Module 2.3_10 PV-module persists for all six months, while the average daily deviations of the measured voltage values ΔU varies from 5.48 V (at $\Delta I = 0.54$ A) to 13.01 V (at $\Delta I = -1.61$ A). The anomalous operation of the PV-module with Module number 2.3_10 is confirmed by other methods of searching and analyzing anomalies [20, 21], including those based on an assessment of electricity generation.

In Fig. Figure 5 shows the curves for the PV-module with Module number 2.3_10. The curves show that the voltage measured for the Module 2.3_10 PV-module is 10 V lower than that calculated by the autoencoder for the illumination curve and temperature measured on August 18, 2019. This may indicate that one of the protective diodes in the PV-module, which are designed to disconnect from PV-module parts circuits. Similar conclusions for this PV-module and a comparison voltage curve with the working panel are given in [20]. In this case, the current curve calculated by the autoencoder practically coincides with the curve constructed from the measurement results. The difference is observed only at the beginning of the day: from zero to the hundredth point, the current strength has values close to zero and then sharply increases to 2.2 - 2.3 A. This behavior of the curve is most likely due to shading of the PV-module in the morning, given that The light sensor does not fall into the shading area, since the curve constructed from its readings has a smooth increase during this period.

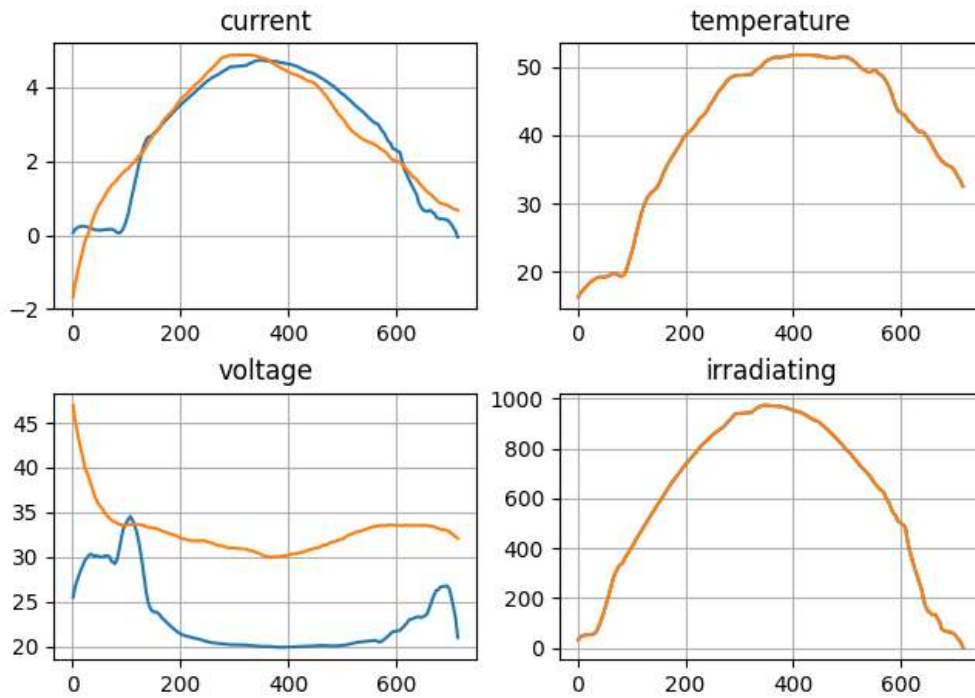


Fig. 5:- Curves of current, voltage (measured values in blue, calculated by the autoencoder in orange), temperature in the panel and irradiation (measured in orange) during the day for a PV-module with Module number 2.3_10

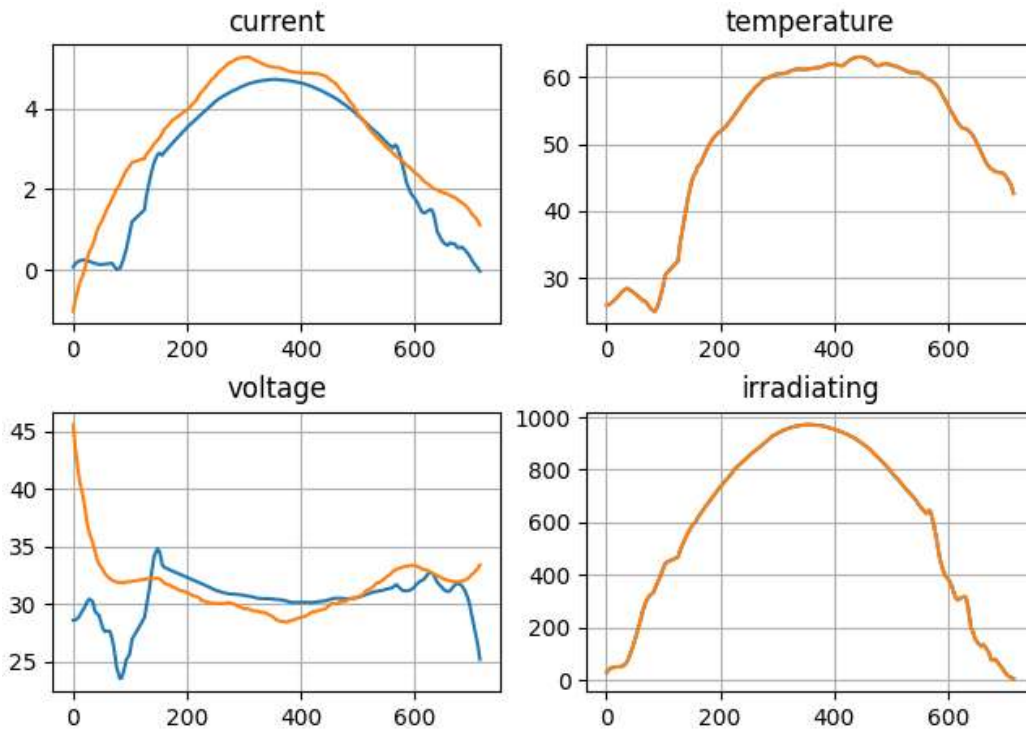


Fig. 6:- Curves of current I , voltage U (measured values in blue, calculated by the autoencoder in orange), temperature in the panel T and irradiation G (measured in orange) during the day for a PV-module with Module number 2.3_11.

Based on the results of the research, a software tool was developed, the operating algorithm of which is presented in Fig. 7. The input data for the software tool is the telemetry results from the database from the API (URL:

<http://www.sunsniffer.de/solution/what-is-sunsniffer.html>), and the output data is a list of PV-modules with those detected in them anomalies in relation to the analyzed date.

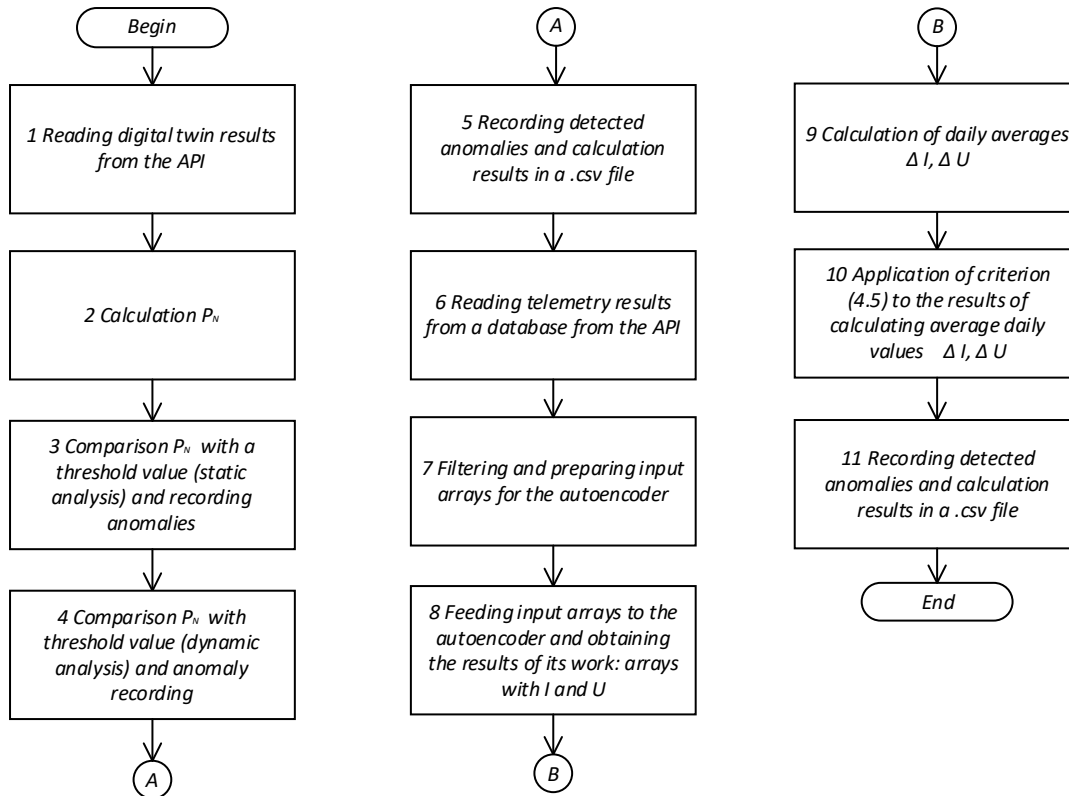


Fig. 7:- Block diagram of the software algorithm for detecting anomalies in the operation of solar panels, developed on the basis of the proposed methodology.

Conclusion:-

The results of the study showed that using an autoencoder to search for anomalies in the operation of solar power plant panels makes it possible to detect anomalies. It has been established that using four standard deviations for the average daily measured values of current ΔI and voltage ΔU as an anomaly detection criterion makes it possible to detect faulty PV-modules. And using three and two standard deviations as an anomaly detection criterion means a decrease in the efficiency of PV-modules associated with degradation, excessive shading and other factors.

To increase the accuracy of searching for anomalies in the operation of PV-modules when using the developed software, a combination of two artificial neural networks (autoencoders) should be used, where the telemetry result immediately after installation of the power plant is used as a training dataset for one neural network, and as a training dataset for another neural network – a separate PV-module, which neutralizes the influence of the effects of such factors as degradation and pollution on the result of autoencoder training.

Authors' Contribution:

Konstantin Sergeevich Dik developed the software, prepared the dataset, trained the artificial neural network, conducted a comparative analysis of voltage, current, and temperature curves of PV-modules with detected anomalies. He worked with graphic material and edited the manuscript text. Ivan Ivanovich Pilecki formulated conclusions based on the study results. Ingmar Kruse interpreted the obtained results and conducted an expert review of the study results. Rustam Mustafyevich Asimov developed the anomaly detection methodology based on the autoencoder results. Vitaly Semyonovich Osipovich developed the anomaly detection methodology based on the autoencoder results and designed the architecture of the artificial neural network.

All authors participated in formulating hypotheses, objectives, and tasks of the study.

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