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DIGITAL TWIN FOR PV PARAMETER SIMULATION ANALYSIS

R.M. Asimov
PhD, CEO of Sensotronica Ltd

S.V. Valevich
graduate student BSUIR

I. Kruse
CEO of SunSniffer

V.S. Asipovich
PhD, associate professor BSUIR

Sensotronica Ltd, Kulman, 9, 373, Minsk, 220010, Republic of Belarus. E-mail: roustam.asimov@sensotronica.com.
SunSniffer GmbH & Co. KG, Ludwig-Feuerbach-Str. 69, Nuremberg 90489, Germany. E-mail: ingmar.kruse@sunsniffer.de.
Belarussian State University of Informatics and Radioelectronics, P. Brovki, 6, Minsk, 220013, Republic of Belarus. E-mail: v.osipovich@bsuir.by.

R.M. Asimov,

В 1990 г. Окончил Таджицкий Государственный Университет, факультет физики. Занимался исследовательской работой в институте Физики НАН Беларуси и университете Paris-Nord, Франция. В 2012 г. Защитил диссертацию по теме «лазерно-индуцированной фотодиссоциации комплексов гемоглобина". Является автором 134 научных работ, 14 патентов, 7 учебно-методических пособий. В настоящее время возглавляет компанию, резидент Белорусского Парка Высоких Технологий ООО «Сенсотроника». Направления научной деятельности: разработка алгоритмов и технологий обработки больших данных, математическое моделирование фотофизических процессов.

S.V. Valevich,

In 2017 graduated from the Belarusian State University of Informatics and Radioelectronics with a degree in Engineering. In 2018 got a Master's degree in Engineering.

I. Kruse,

Since the early 80s, he develops innovative technology. In 1983, a year before his graduation, he founded his first company. He studied Business Administration in Nuremberg and Computer Science in Atlanta, USA. In 1996 he received a rare license from Apple for the production of Apple computers. Since 2002 he is in the photovoltaic industry. He holds several patents in different fields, including photovoltaics.

V.S. Asipovich

In 2004, he graduated from the Belarusian State University of Informatics and Radioelectronics with a degree in Microelectronics, and in 2005, he got a master's degree in the same specialty. In 2010, he defended the thesis for the degree of a candidate of technical sciences in Devices, systems, and medical items. He is the author of 115 publications, 2 patents, 12 teaching aids. Annually he orally reports at international scientific forums. Main areas of research activity: development of algorithms and technologies for big data processing, research, and development in the software processing of medical images.

Abstract. A method of PV parameters simulations using Digital Twin (DT) has been proposed, implemented, and tested. Simulated prediction results were collected, processed and the accuracy was estimated based on the comparison between the real data and the simulation output values. The results provided the following: predictions based on DT simulation results could be used for short-term predictions (6 month period, 14144674 data points, about 300 PV modules) with 1,75 % deviation accuracy across the PV installation (0,14 – 3,97 % accuracy range for separately analyzed months).

Keywords: Digital twin, Photovoltaic, Simulations, Modeling accuracy.

Introduction

In renewable power generation, photovoltaic as clean and green energy technology plays a vital role to fulfill the power shortage of many countries. Simulation and analysis of PV generator is a vital phase before mount PV system at any location, which helps to understand the behavior and characteristics in real climatic conditions of that location [1].

There are several types of solar PV generating systems, where the differences between each technology reside in the yield, the price as well as the material used. The performance of a PV system depends strongly on meteorological conditions, such as solar radiation and temperature [2].

The effect of irradiance and temperature on the PV module is very crucial when computing the model PV parameters. Simulation of these parameters helps to predict possible faults or choose a better location for PV plant installation. Additionally, current, voltage, and power are valuable indicators for the performance estimation.

Many existing papers and researches suggest PV analytical methods that are suitable for a single parameter or effect, so each plant needs to search and combine suitable devices, sensors and implement particular methods, while it would be great to have some platform that aggregates all params and effects together and provides extensive monitoring data. Digital Twin (DT) concept was proposed to fill this gap [3-5]. It is a laboratory that accumulates data from sensors and allows us to monitor, predict, and fix various issues as soon as possible. DT consists of multiple modules which analyze all existing effects and factors around the PV module’s actual state. For instance, publication [3] demonstrates the ability to diagnose module states using DT.

DT has simulations API which can provide predictions for specific modules based on its pre-calculated module parameters and some environmental data values like temperature and solar irradiation level.

This paper is aimed at the DT system’s ability to produce accurate predictions for individual modules based on input telemetric data. The accuracy level is estimated using the collected data from the 5-month period and existing module parameters gathered from the 6th month.

Simulation parameters calculation.

PV plant in Nürnberg, Germany, named Südstadt-Forum is used for data aggregation and simulations in this paper. The plant includes three inverters (SUN2000-20KTL, Sinvert PVM17, and Sinvert PVM20 models) with multiple strings (PV module arrays). Most of the strings consist of 18 PV monocrystalline modules. Each string and module provide various raw data from their sensors. Also, ten additional devices for the whole plant are presented including an SR05 pyranometer for temperature and irradiation.

Digital Twin API [3-5] for module simulations is based on input telemetric data and module coefficients collected previously using average module calculations [5]. With these coefficients, raw input data could be compared with the simulated data and some short-term predictions could be made.

Initial data from June 2019 was used to calculate module coefficients; this month is used as the basic point for future simulation comparison. Data from July 2019 – November 2019 is used for simulations. Data was collected using Sunsniffer API.

Input data includes the following parameters: voltage, current, temperature, ambient temperature, irradiation, timestamp, and module id.

The output contains the following parameters: simulated parameters (voltage, current, max power, irradiation) together with raw input values for comparison and some calculated parameters (e.g. deviation between simulated and original max power).

The main idea is to compare simulated parameters with the original ones by each module and in general across the PV installation during the following 5 months to analyze the accuracy of simulations and find out the maximum possible period where the accuracy is enough for practical usage (targeting 6-month range).

Additional parameters were calculated based on simulation output results.

Delta params for max power, current, voltage, and solar irradiation:

$$P_{\Delta} = P_{sim} - P, \text{ W} \tag{1}$$

where P_{sim} – simulated max power, P – original max power.

$$I_{\Delta} = I_{sim} - I, \text{ A} \tag{2}$$

where I_{sim} – simulated current, I – original current.

$$U_{\Delta} = U_{sim} - U, \text{ V} \tag{3}$$

where U_{sim} – simulated voltage, U – original voltage.

$$G_{\Delta} = G_{sim} - G, \text{ Wh} \tag{4}$$

where G_{sim} – simulated solar irradiation, G – original solar irradiation.

Additionally, min/max/avg values were calculated for each valuable parameter:

– P: minP, maxP, avgP;
– P_{Δ}: min P_{Δ}, max P_{Δ}, avg P_{Δ};
– I_{Δ}: min I_{Δ}, max I_{Δ}, avg I_{Δ};
– U_{Δ}: min U_{Δ}, max U_{Δ}, avg U_{Δ};
– G_{Δ}: min G_{Δ}, max G_{Δ}, avg G_{Δ}.

Some of the devices are synchronized and provide data with exactly the same timestamps, and others may vary a bit, so mapping between different sources includes finding the nearest data points. On average, one new data point is acquired every 7 minutes.

Aggregated results for individual modules are passed to DT simulations API.

14144674 data points were analyzed. All parameters were calculated for each data point. Data dynamics were analyzed based on time periods and params changes between the strings.

For the next analysis resulting data points require filtering by various parameters, which was done during some filtering stages:

– filter points with $P < 20$ W;
– above filters + $G_{sim} < 300$ Wh and $G < 300$ Wh;
– above filters + $I_{\Delta} > 2$ A;
– above filters + $I_{\Delta} < -2$ A;
– above filters + $G_{\Delta} > 300$ Wh and $G_{\Delta} < -300$ Wh;
– above filters + $U_{\Delta} > 10$ V and $U_{\Delta} < -10$ V.

The accuracy was evaluated by normalized max power average delta parameter:

$$P_{\Delta accuracy} = \left| \frac{P_{\Delta avg}}{P_{avg}} \right|, \%. \tag{5}$$

With all filters applied, the accuracy would be compared between the non-filtered data and the 6th stage.

Simulations analysis.

Raw max power simulation results for Modules 1.1_1 and 2.3_10 during August are presented in Figures 1, 2.

For both modules simulated P_{max_sim} values stay very close to the real ones except some days. These days for Module 1.1_1 are August 3 – August 8, for Module 2.3_10 – August 5 – August 8. During these days DT simulations API provided approximated values that stay in the middle of the real data distribution and these approximated values still work quite well keeping similar performance output values with non-critical deviations.

The average max power deviation across all non-filtered points is 5,01 W. avgP value is 46,21 W. All other calculated parameters would be compared below too. Now the accuracy should be estimated using the formula (5):

$P_{accuracy}$value before all the filtering = | -5,01 / 46,21 | = 10,8 %.

Such accuracy level is not applicable; therefore the filtering stages are required.

Filtered max power simulation results for Modules 1.1_1 and 2.3_10 during August are presented in Figures 3, 4.

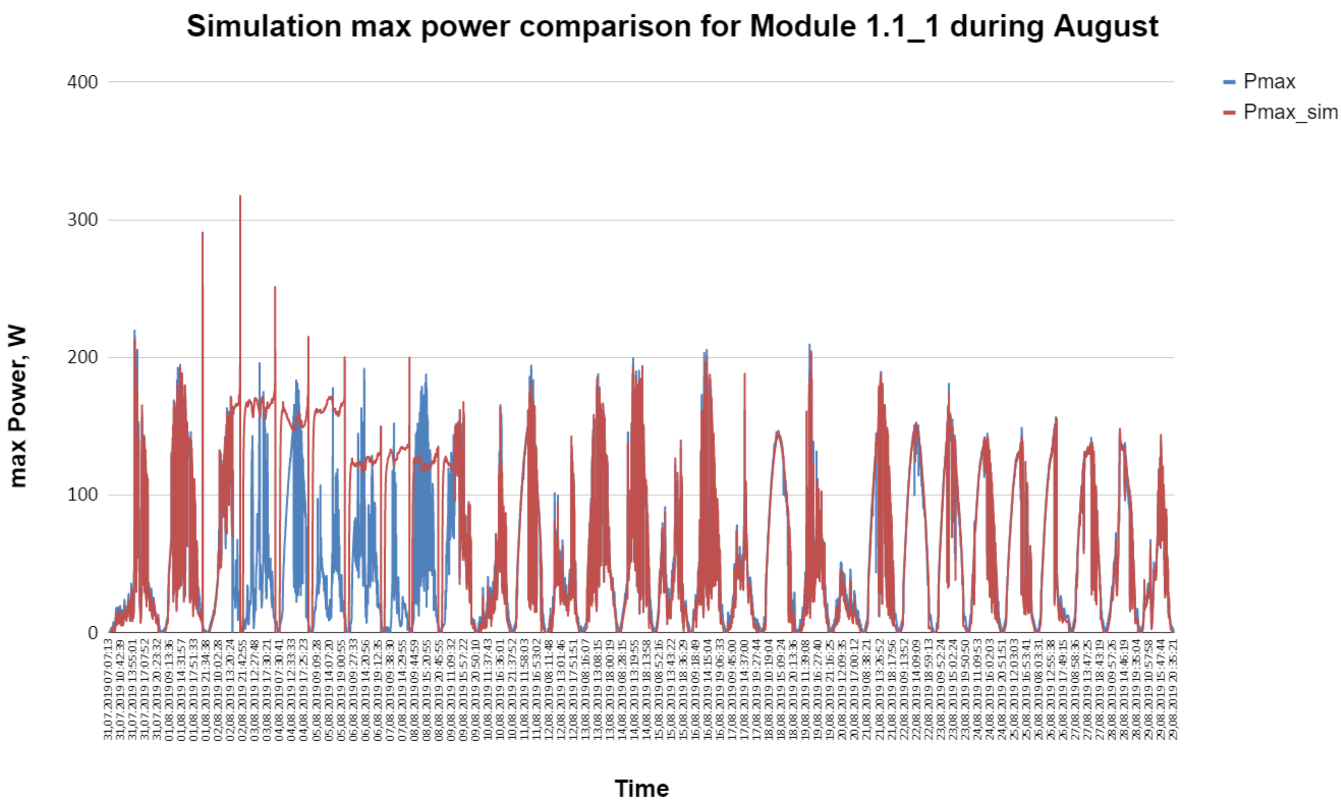

Figure 1. Comparison between simulated and real max power for Module 1.1_1 during August (figure 2.)

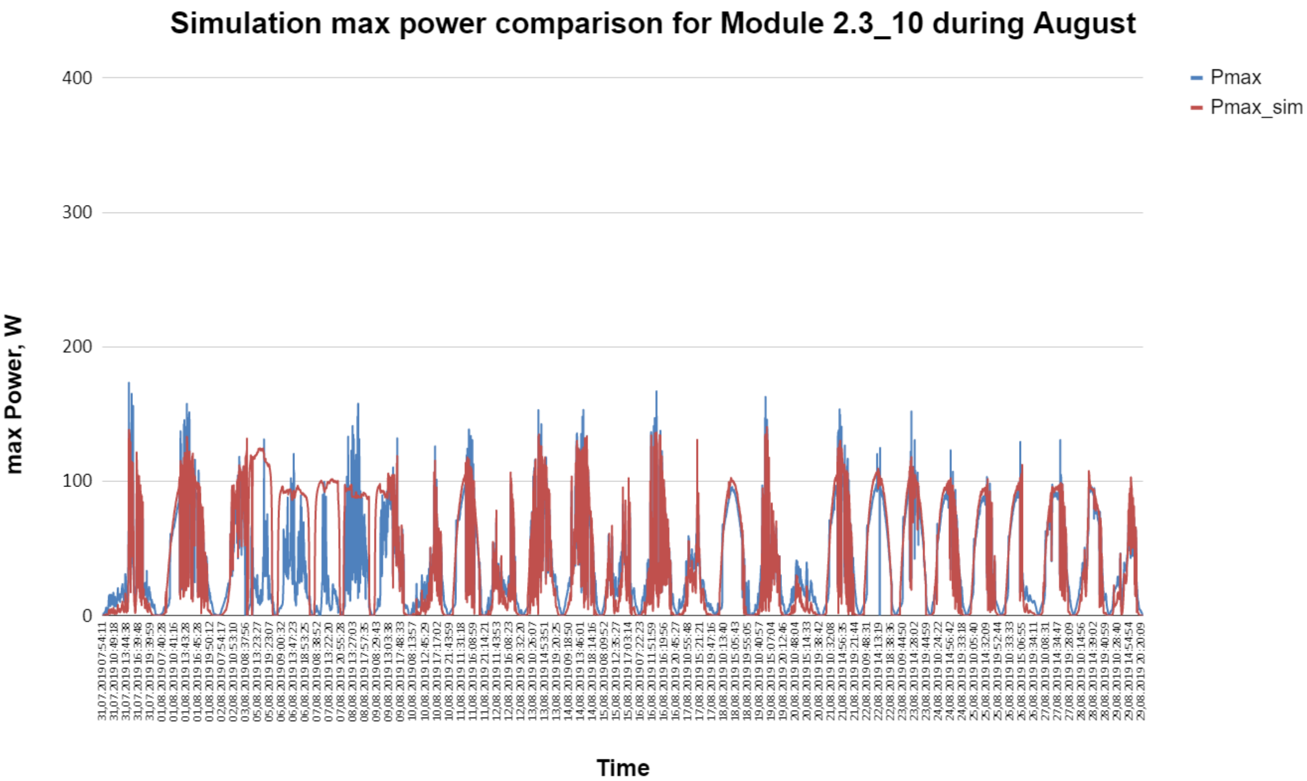

Figure 2. Comparison between simulated and real max power for Module 2.3_10 during August

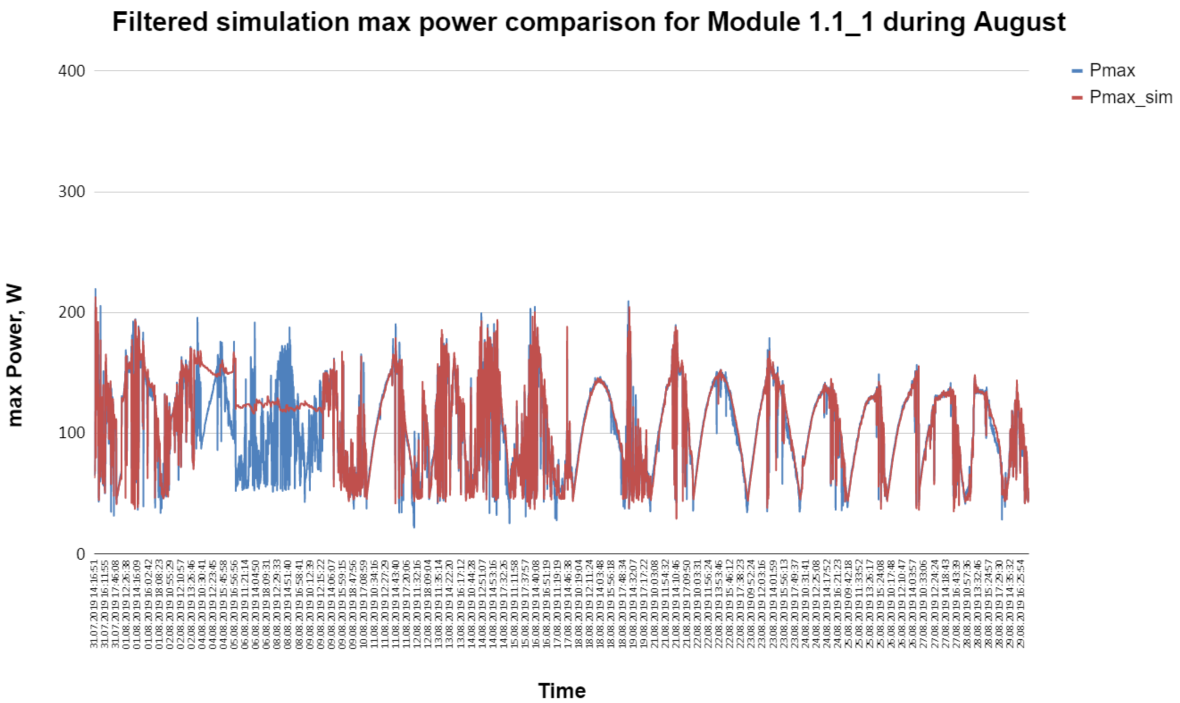

Figure 3. Comparison between simulated and real max power after filtering for Module 1.1_1 during August (figure 4.)

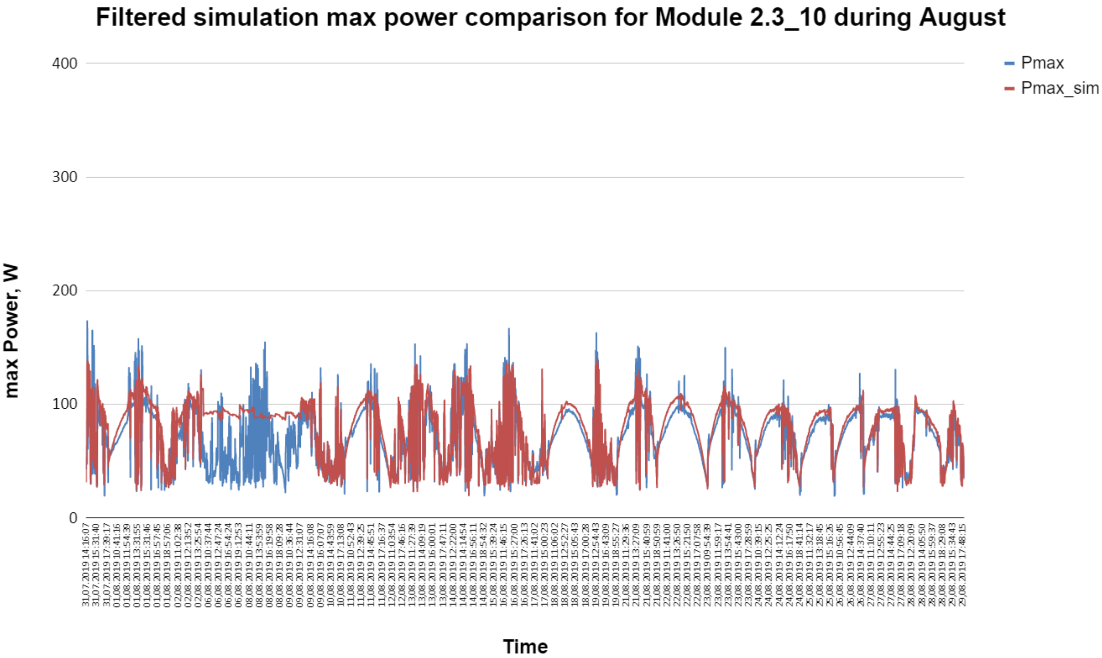

Figure 4. Comparison between simulated and real max power after filtering for Module 2.3_10 during August

Abnormal days for Module 1.1_1 are August 4 – August 8 (minus one day comparing with non-filtered points), for Module 2.3_10 – August 6 – August 8 (minus one day comparing with non-filtered points). Values during these days are still properly approximated.

The average max power deviation across all non-filtered points is 1,78 W. avgP value is 101,44 W. Now the accuracy for filtered points should be estimated using the formula (5):

$P_{\Delta accuracy}$ value on 6th filtering stage = | -1.78 / 101.44 | = 1,75 %.

With filtering accuracy improved by 6,17 times. Most of the outliers were removed and redundant early/late values which produce no power were removed from the calculations giving results related to the most valuable points simulation.

Full results for each filtering stage are given in Table 1.

Table 1. Filtering stages results

#	maxP	minP	avgP	$maxP_\Delta$	$minP_\Delta$	$avgP_\Delta$	$maxI_\Delta$	$minI_\Delta$	$avgI_\Delta$	$maxU_\Delta$	$minU_\Delta$	$avgU_\Delta$	$maxG_\Delta$	$minG_\Delta$	$avgG_\Delta$
0	233,88	0	46,21	164,2	-1265,66	-5.01	69,63	-4,3	0,14	25.13	-39.3	-5,71	42182,12	-990,71	-25,34
1	233,88	20	74,69	164,2	-209,72	-5.03	6,13	-4,3	0,14	22.1	-37.1	0,04	591,07	-776,5	-12,39
2	233,88	20	96,29	150,93	-209,72	-10.56	6,13	-4,05	0,3	22.1	-33.3	0,26	591,07	-776,5	-14,84
3	233,88	20	101,3	150,93	-102,95	-1.78	2	-4,05	0,03	22.1	-33.3	0,24	14,27	-776,5	-14,93
4	233,88	20	101,23	78,82	-102,95	-1.88	2	-2	0,04	22.1	-33.3	0,24	14,27	-776,5	-14,94
5	233,88	20	101,24	78,82	-102,95	-1.88	2	-2	0,04	22.1	-15.06	0,24	14,27	-67,34	-14,92
6	233,88	20	101,44	78,82	-96,52	-1.78	2	-2	0,04	10	-9.68	0,19	14,27	-67,34	-14,87

Stages filtering results.

1) Initial stage without filtering. Some obvious outliers are visible in many parameters. 14144674 points.

2) The first filtering stage filters points with P < 20 (most of the values during early morning and

night). 8153413 points left.

3) Second filtering stage, which filters points by solar irradiation with a level below 300 Wh (similar to the previous step, but using solar irradiation parameter). 5394372 points left.

4) Third filtering stage, which targets positive current deviation outliers (> 2 A). 4921193 points left.

5) Fourth filtering stage filters negative current deviation outliers (< -2A). 4915248 points left.

6) The fifth filtering stage affects solar irradiation deviation outliers (both positive and negative, + – 300 Wh). 4915109 points left.

7) And sixth filtering stage targets voltage deviation outliers (both positive and negative too, + – 10V). 4896551 points left.

After all the above stages most of the outliers by each parameter were removed from the dataset and, additionally, values with near-zero performance due to no sunlight during early/late hours were filtered too. 9248123 points were filtered. Therefore only valuable points which produce most of the power were left for future comparison and accuracy analysis.

Also, results by separate month for the 6th final filtering stage are presented in Table 2.

Table 2. 66th filtering stage by months

Month	maxP	minP	avgP	$maxP_{\Delta}$	$minP_{\Delta}$	$avgP_{\Delta}$	$maxI_{\Delta}$	$minI_{\Delta}$	$avgI_{\Delta}$	$maxU_{\Delta}$	$minU_{\Delta}$	$avgU_{\Delta}$	$maxG_{\Delta}$	$minG_{\Delta}$	$avgG_{\Delta}$
July	233,88	20	108,9	78,48	-96,5	-2.70	2	-2	0,07	10	-9.46	0,16	14,27	-46,77	-3,93
August	226,1	20	104,3	78,82	-93,2	-2.98	2	-2	0,07	10	-9.68	0,23	1,63	-63,09	-11,46
September	212,72	20	100,61	75,51	-79,7	-0.17	2	-2	-0,01	10	-9.48	0,21	0,25	-52,36	-20,21
October	201,54	20	88,64	74,16	-85,7	0.12	2	-2	-0,02	10	-9.35	0,18	-0,75	-65,5	-29,49
November	148,97	20	76,05	73,01	-80,5	-3.02	2	-2	0,07	10	-8.5	0,07	-2,86	-67,34	-34,94

$P_{\Delta accuracy}$ values by months: July – 2,5 %; August – 2,86 %; September – 0,17 %; October – 0,14 %; November – 3,97 %.

Results by separate months display that simulations accuracy depends mostly on the climate conditions (September and October provide the most accurate results with 0,14 – 0,17 % deviation accuracy range by the whole PV installation, while July and August give 2,5 – 2,86 % deviation accuracy despite standing close to the original start data from June).

Even separated by months, results during the whole 5 months of predictions stay quite accurate, the accuracy range is 0,14 – 3,97 %. General accuracy (whole 5 month predictions) calculated above is 1,75 %.

Conclusions.

Digital Twin can simulate PV parameters with 0,14 – 3,97 % even for cold months. General deviation accuracy for the whole installation during 5 months prediction is 1,75 %. It could be used during PV site choosing or in the PV fault detection field.

Filtering is critical for the accuracy of the results, with all filter stages enabled accuracy increased by 6,17 times and was able to achieve a 1,75 % level for the whole installation.

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ИСПОЛЬЗОВАНИЕ ЦИФРОВОГО ДВОЙНИКА СОЛНЕЧНОЙ ПАНЕЛИ ДЛЯ АНАЛИЗА ПАРАМЕТРОВ СИМУЛЯЦИЙ

Р.М. Азимов ***С.В. Валевич*** ***И. Круз*** ***В.С. Осипович***

Аннотация. Предложен, реализован и протестирован метод симуляции параметров с использование цифрового двойника. Результаты симуляции были собраны, обработаны и была проведена оценка точности симуляции на основе сравнения реальных данных и полученных в ходе симуляции значений. Результаты показали следующее: результаты симуляции могут быть использованы для краткосрочных прогнозов (использовался период в 6 месяцев, 14144674 точек с данными было рассчитано для 300 PV модулей) с точностью 1,75% в рамках всей солнечной инсталляции (и с точностью в пределах 0,14 - 3,97% для отдельных месяцев).

Ключевые слова: Цифровой двойник, фотоэлектрический, симуляции, точность модели.