UDK 004.42

DIGITAL TWIN FOR PV PLANT'S POWER GENERATION ANALYSIS



R.M. Asimov[1], *PhD, CEO of Sensotronica Ltd*

S.V. Valevich[3] *Graduate student BSUIR*

I. Kruse[2], *CEO of SunSniffer GmbH*

V.S. Asipovich[3] *PhD, associate professor BSUIR*

[1]Sensotronica Ltd, Kulman, 9, 373, Minsk, 220010, Republic of Belarus. E-mail: roustam.asimov@sensotronica.com
[2]SunSniffer GmbH & Co. KG, Ludwig-Feuerbach-Str. 69, Nuremberg 90489, Germany. E-mail: ingmar.kruse@sunsniffer.de
[3]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 degree in Engineering. In 2018 got 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 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. Summary. A method of PV array-based calculation has been proposed, implemented and tested. The results showed the following. Array-based calculation is able to provide quite accurate results in Pmpp values for array, but defective modules with some electrical issues in particular array could be identified only with some additional module-based analysis.

Key words: Digital twin, Photovoltaic, Photovoltaic Array Calculation, Defective Photovoltaic Modules.

Introduction

Global solar energy market growth resides around 30% per year. Under optimal conditions, the world's solar generation plant capacity could reach up to 1,270.5 GW by the end of 2022 [1].

For solar energy cost-effectiveness and predictable power generation play a key role in any PV installations. On the other hand, the same module will behave differently in another location, with various weather conditions, climate, dust and shadow conditions of a particular cell, and so on. It's quite hard to estimate how all these factors will affect the cell's lifetime and its efficiency. Also, some electrical issues may appear and it's almost impossible to predict them.

All of the above issues may be handled using monitoring via multiple sensors on PV module arrays, on cells, some external sensors, and systems that aggregate all the data. Monitoring helps to understand in a timely manner when anything on the plant requires maintenance, which will result in reduced operating costs.

Typical PV plant consists of multiple PV module arrays, and each module requires its own sensors, devices, and additional handling like regular cleaning procedures, especially for dusty areas [2]. Usually, PV equipment allows predicting plant's power generation using some maximum power point tracking (MPPT) methods combined with the raw data (temperature, irradiation, output params like the voltage, current, and power) from sensors located on each module.

The issue occurs when there's a lack of various equipment and sensors which may be suitable for remote monitoring and timely maintenance. It's true for most of the current active PV stations. Many existing papers and researches suggest methods which are suitable for single parameter or effect, so each individual plant needs to search and combine suitable devices, sensors and implement particular methods, while it would be great to have some platform which aggregates all params and effects together and provides extensive monitoring data. Digital Twin (DT) concept was proposed to fill this gap [3, 4]. 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

PV module actual state. For instance, publication [3] demonstrates the ability to diagnose module states using DT.

However, the following issue occurs: there are plants without required voltage and temperature sensors on each module. In this case DT analysis for each module becomes impossible. Nevertheless, most of the PV plants are equipped with sensors that allow measuring temperature and irradiation for the whole plant and sensors for voltage and current parameters of module arrays.

This paper is aimed at the DT system's ability to detect defective modules or any other issues during PV plant operation based on telemetric data from module arrays. Currently DT calculates params by each module in order to analyze the technical plant state, but it requires temperature and voltage sensors located on each module to gather and analyze all the data which increases the plant's overall cost, especially for large PV plants.

Average module calculation

PV plant in Nürnberg, Germany, named Südstadt-Forum is used for data aggregation and calculations in this paper. 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 SR05 pyranometer for temperature and irradiation.

In order to aggregate and prepare all the data software application written in Node.JS was used.

Digital Twin platform prepared API for module-by-module calculations based on input data. Input data includes the following parameters: voltage, current, temperature, irradiation from devices, temperature from devices, timestamp.

The output contains the following params: maximum power point (MPP), voltage and current at MPP, series and parallel resistance, short circuit current and open-circuit voltage params.

During the experiment, all the data from August 2018 was used; this month includes a lot of sunny days and provides more accurate results in the case of MPPT. Data was collected using Sunsniffer API.

The idea is to compare the results of calculations by each module and by each string (which is faster).

Input params for module-level calculation were: module voltage, string current, module temperature, and irradiation. The time alignment between the module readings and the SR05 pyranometer, made using the timestamps of the individual data points.

Input params for average module calculation (based on string-level measurement) included average module voltage U_{avg}, string current, and average module temperature T_{avg} , temperature, and irradiation from SR05 pyranometer.

$$U_{avg} = \frac{U_s}{n},$$

where U_s – string voltage, n – count of PV-modules in this string.

$$T_{avg} = \frac{\sum_i^n T_n}{n},$$

where T_n – temperature of module, n – count of modules in this string.

Based on output params additional fields were calculated:

$$P_{mpp\ diff} = \frac{\sum_i^n P_{mpp\ module\ i}}{n} - P_{mpp\ string},$$

where $P_{mpp\ module\ i}$ – maximum power of module, $P_{mpp\ string}$ – maximum power of average string.

$$P_{mpp\ diff\ percentage} = \frac{|P_{mpp\ diff}|}{P_{mpp\ string}}\%$$

$$P_{Pmpp\ avg} = P_{month}\frac{n}{\sum_i^n P_{mpp\ module\ i}}\%,$$

where P_{month} – power, produced by string during the month.

$$P_{Pmpp\ string} = \frac{P_{month}}{P_{mpp\ string}}\%,$$

$$P_{percentage\ diff} = P_{Pmpp\ avg} - P_{Pmpp\ string}$$

All parameters were calculated once per month for each string and each module. Data dynamics were analyzed based on time periods and params changes between the strings.

For the next analysis and hypothesis verification some criteria were required in order to determine defective modules. The following parameters were introduced:

$$P_{mpp\ delta} = P_{mpp\ max} - P_{mpp\ min},$$

where $P_{mpp\ max}$ – maximum power, produced by module across the string during the month, $P_{mpp\ min}$ – minimum power, produced by module across the string during the month.

$$P_{mpp\ delta\ \%} = \frac{P_{mpp\ delta}}{P_{mpp\ max}}\%,$$

$P_{mpp\ delta}$ allows to find out if there're some defective modules in strings more precisely using max and min module power parameters.

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. For example, Module 1.1_1 has 3943 points during August after all the filtering on the app side. Most of the filtering stays inside DT calculation except some simple app-side preprocessing like removing points with invalid temperatures, points with missing parts of the data, and so on.

Aggregated results for individual modules, and average modules are passed to DT calculation API.

Calculation analysis

Diagrams of P_{mpp} distribution by modules during August 2018 are presented on figures 1, 2 (String 1.6 and String 2.2 for example).

On figure 2 it's clearly visible that String 2.2 distribution looks abnormal, we compared some valid string (String 1.6) with this one which has defective module (String 2.2).

For String 1.6 on string level average P_{mpp} = 173W, on module level average P_{mpp} across modules = 178W, min P_{mpp} = 174W. Difference between string and average module level P_{mpp} = 2.8%.

For String 2.2 on string level average P_{mpp} = 175W, on module level average P_{mpp} across modules = 181W, min P_{mpp} = 135W. Difference between string and average module-level P_{mpp} = 3.6%.

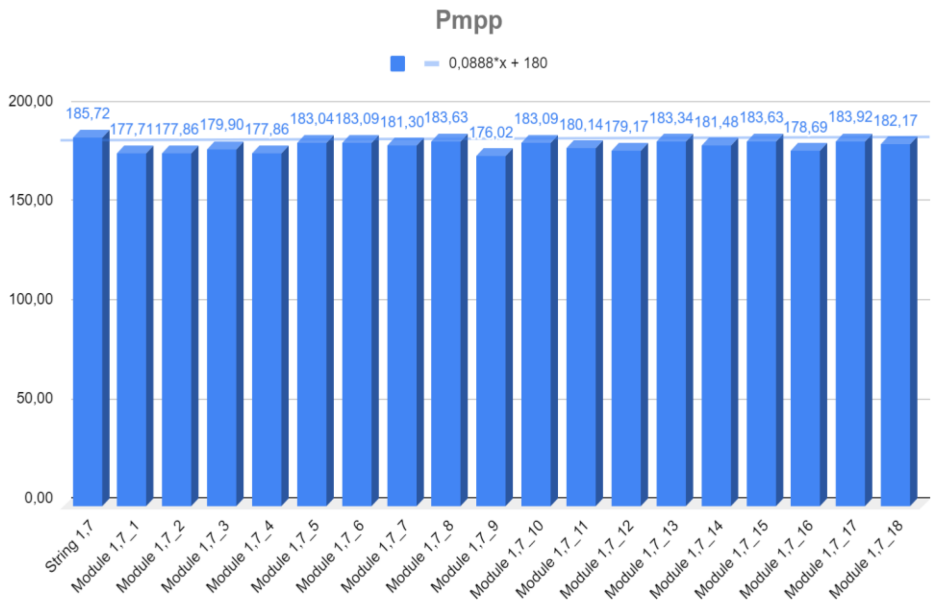

Figure *1*. – Distribution of String 1.6 module power in August, 2018

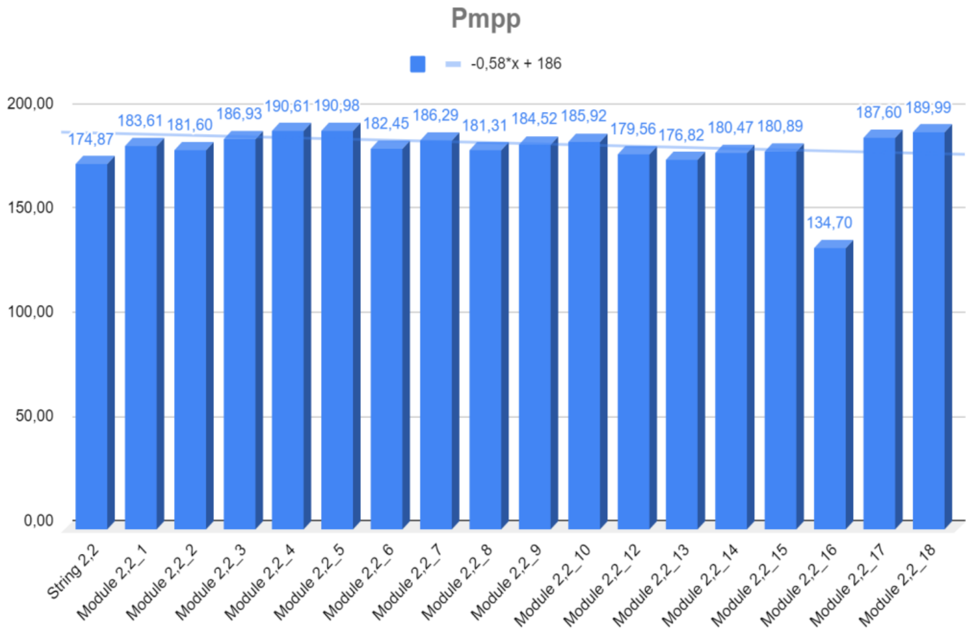

Figure *2*. – Distribution of String 2.2 module power in August, 2018

Statistical distribution is presented in figures 3 and 4 for String 1.6 and 2.2. For String 2.2 distribution appears more uniform and overall P_{mpp} is higher despite defective module, results of calculation on average string level correlate with it. Therefore the average string method allows estimating the strings's state adequately.

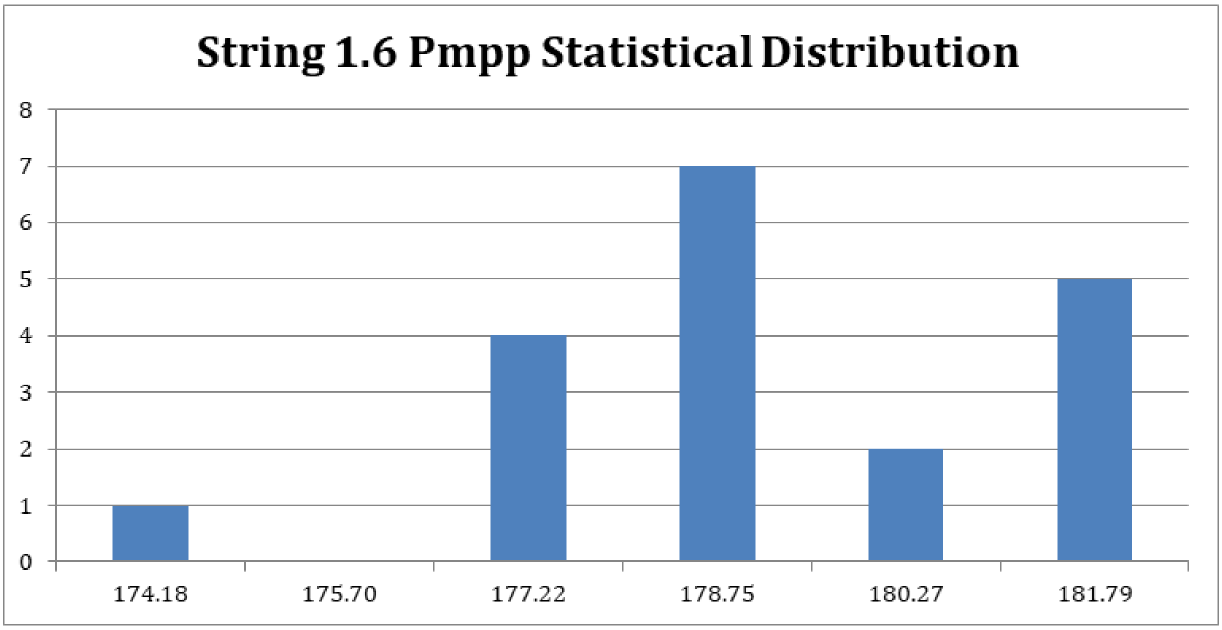

Figure *3*. – String 1.6 power statistical distribution in August 2018

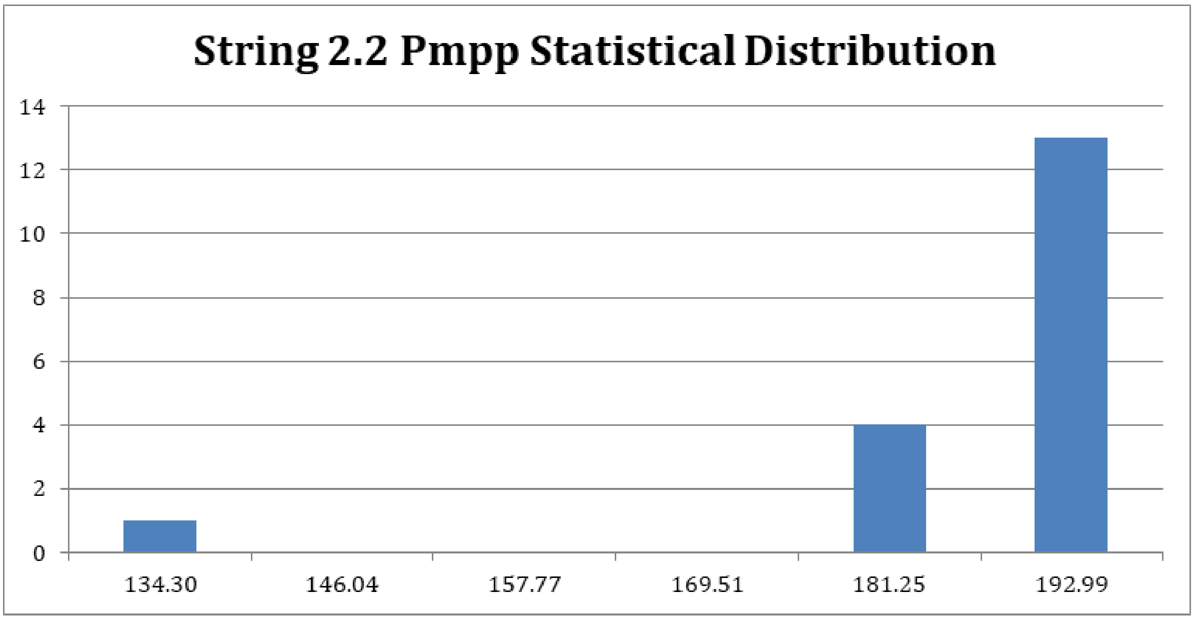

Figure *4*. – String 2.2 power statistical distribution in August 2018

More detailed analysis of Module 2.2_16 which contains voltage dynamics for this module is presented on figure 5.

It is clearly visible that the voltage on Module 2.2_16 falls to zero. That is an indication that module underperforms, and the bypass diodes activated under high current conditions. Either shadowing or defective module can cause such behavior.

Additional analysis showed that for Module 2.2_16 R_p = 50, R_s = 1.7 while valid modules have values around R_p = 400, R_s = 0.5.

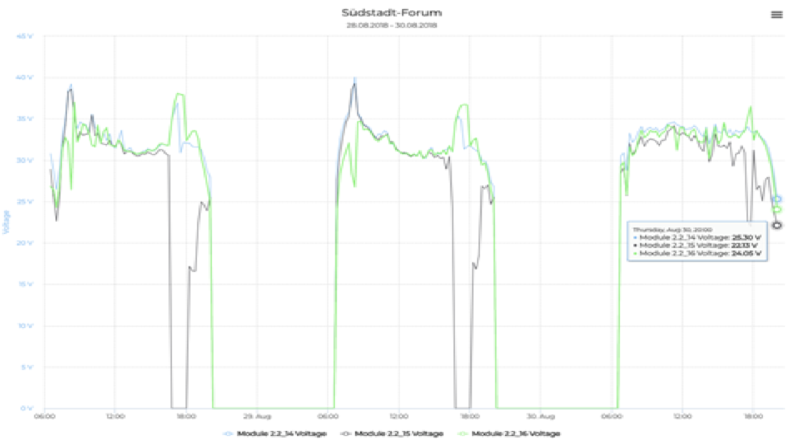

Figure 5. – String 2.2 Module voltages at DT calculation day (29.08.2018)

DT calculation results show that Module 2.2_16 has significantly higher series and lower parallel (shunt) resistance. That is an indication of an electrical defect of the module.

Also, it is clearly visible that the parameter of the virtual module that describes string level data, does not allow us to detect the electrical failure within the string.

Further analysis of average string parameters dynamics during the half-year period from June till November was carried out.

The following parameters were gathered during the calculations for each separate month: $P_{mpp\ diff}$, $P_{mpp\ diff\ percentage}$, $P_{Pmpp\ avg}$, $P_{Pmpp\ string}$, $P_{percentage\ diff}$, $P_{mpp\ delta}$, $P_{mpp\ delta\ \%}$. $P_{mpp\ diff\ percentage}$ and $P_{percentage\ diff}$ values are presented in Tables 1, 2. N/A values (String 1.4) used when data isn't available for this period. November results look less accurate due to low temperatures during this month.

Table 1. – $P_{mpp\ diff\ percentage}$ values

	June	July	August	September	October	November
String 1.1	1,08%	2,35%	1,89%	6,70%	0,95%	4,47%
String 1.2	2,43%	2,75%	2,41%	0,06%	1,73%	11,19%
String 1.3	4,45%	2,76%	2,57%	3,88%	3,11%	27,30%
String 1.4	0,15%	1,39%	N/A	13,81%	N/A	N/A
String 1.5	3,08%	4,03%	3,69%	7,22%	4,12%	23,21%
String 1.6	3,14%	1,51%	2,57%	2,62%	0,42%	0,75%
String 1.7	5,35%	1,88%	3,16%	2,06%	3,74%	4,03%
String 1.8	2,74%	1,16%	2,66%	2,12%	3,57%	6,6%
String 1.9	1,73%	2,76%	0,22%	0,35%	0,07%	4,01%
String 1.10	3,10%	2,45%	1,67%	3,36%	4,78%	5,40%
String 1.11	1,27%	3,25%	2,74%	2,51%	3,60%	1,59%
String 1.12	3,19%	2,17%	3,55%	2,96%	2,93%	4,41%
String 2.1	0,88%	1,20%	2,53%	1,37%	1,48%	2,88%
String 2.2	3,00%	2,25%	3,64%	1,47%	1,44%	1,30%
String 2.3	1,73%	1,90%	2,81%	2,27%	5,93%	1,59%
String 2.4	3,67%	2,44%	3,18%	5,15%	0,19%	6,55%

Table 2. – $P_{percentage\ diff}$ values

	June	July	August	September	October	November
String 1.1	-0,51%	-0,79%	-0,72%	-3,77%	-0,69%	-8,49%
String 1.2	-1,16%	-0,92%	-0,92%	-0,03%	-1,14%	18,37%
String 1.3	1,95%	0,86%	0,90%	1,91%	2,06%	45,57%
String 1.4	0,21%	0,45%	N/A	-7,33%	N/A	N/A
String 1.5	1,35%	1,24%	1,27%	3,36%	2,39%	36,69%
String 1.6	1,45%	0,49%	0,94%	1,31%	-0,27%	-19,49%
String 1.7	-2,72%	-0,64%	-1,25%	-1,10%	-2,53%	-7,42%
String 1.8	-1,36%	-0,40%	-1,04%	-1,13%	-2,41%	-21,36%
String 1.9	0,82%	-0,95%	-0,08%	-0,18%	0,04%	-6,97%
String 1.10	-1,51%	-0,83%	0,63%	-1,78%	-3,14%	-9,44%
String 1.11	0,59%	1,02%	0,97%	1,22%	2,10%	2,44%
String 1.12	-1,55%	-0,73%	-1,35%	-1,53%	-1,83%	-7,01%
String 2.1	-0,68%	-0,41%	-0,96%	-0,71%	-0,90%	-4,48%
String 2.2	1,41%	0,74%	1,35%	0,75%	0,87%	1,97%
String 2.3	0,83%	0,63%	1,04%	1,14%	3,44%	2,34%
String 2.4	-1,83%	-0,84%	-1,21%	-2,93%	0,12%	-11,56%

Table 3 includes additional data about specific month (August for example), e.g. produced power for each String, all P_{mpp} values. All result params are combined together for better view. Figure 6 presents $P_{percentage\ diff}$ values from the table.

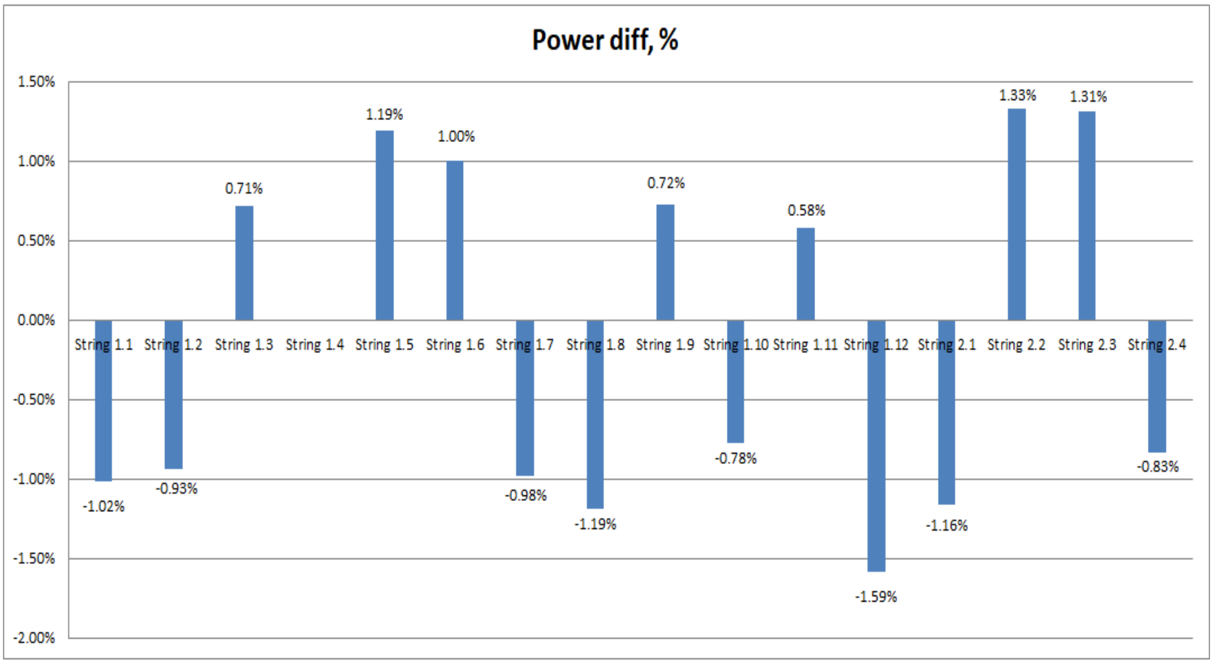

Figure 6. – Diagram of the difference between power's produced by String for August division by two P_{mpp} types (by modules and average by strings)

For Figure 6, there are top 3 strings - 1.5, 2.2, and 2.3. The two highest values belong to 2.2 and 2.3, which have defective modules 2.2_16 and 2.3_10 (clearly visible by P_{mpp} diagrams for each String above).

Table 3. – Calculation results compared together with power produced by each String during the August

String name	String power, kWh	$P_{mpp\ avg}$ by modules	P_{mpp} string	P_{mpp} diff	$P_{mpp\ diff}$ percentage	$P_{Pmpp\ avg}$	P_{Pmpp} string	$P_{percentage}$ diff
String 1.1	491.61	176.3	181.3	-5	-2.76%	35.86%	36.88%	-1.02%
String 1.2	503.17	180.2	184.9	-4.7	-2.54%	35.81%	36.75%	-0.93%
String 1.3	519.13	180.8	177.1	3.7	2.09%	34.83%	34.11%	0.71%
String 1.4	504.16	179.6	N/A	N/A	N/A	35.62%	N/A	N/A
String 1.5	520.69	179.6	173.4	6.2	3.58%	34.49%	33.30%	1.19%
String 1.6	490.81	178	173.1	4.9	2.83%	36.27%	35.27%	1.00%
String 1.7	490.71	180.9	185.7	-4.8	-2.58%	36.86%	37.84%	-0.98%
String 1.8	480.34	177.6	183.3	-5.7	-3.11%	36.97%	38.16%	-1.19%
String 1.9	483.16	177.6	174.1	3.5	2.01%	36.76%	36.03%	0.72%
String 1.10	489.91	178	181.8	-3.8	-2.09%	36.33%	37.11%	-0.78%
String 1.11	516.682	182.6	179.6	3	1.67%	35.34%	34.76%	0.58%
String 1.12	516.617	182.8	191	-8.2	-4.29%	35.38%	36.97%	-1.59%
String 2.1	515.51	184.7	190.7	-6	-3.15%	35.83%	36.99%	-1.16%
String 2.2	488.85	181.4	174.9	6.5	3.72%	37.11%	35.78%	1.33%
String 2.3	481.531	176.2	169.9	6.3	3.71%	36.59%	35.28%	1.31%
String 2.4	517.342	185.1	189.4	-4.3	-2.27%	35.78%	36.61%	-0.83%

For more accurate detection of defective modules additional params were used: $P_{mpp\ delta}$ and $P_{mpp\ delta\ \%}$ (tables 4, 5).

Table 4. – $P_{mpp\ delta}$ values

	June	July	August	September	October	November
String 1.1	7,55	7,66	8,77	25,67	12,71	20,06
String 1.2	15,08	18,89	9,11	9,9	14,87	16,86
String 1.3	8,94	17,94	7,17	7,08	14,52	27,69
String 1.4	12,81	13,41	12,1	9,57	N/A	N/A
String 1.5	9,62	15,98	8,69	8,62	9,7	19,35
String 1.6	12,02	6,31	6,06	7,26	9,6	14,98
String 1.7	15,71	10,48	6,8	5,36	9,22	11,5
String 1.8	9,9	12,73	11,95	8,36	12,39	11,7
String 1.9	8,79	5,07	6,04	5,91	13,85	20,41
String 1.10	8,51	12,04	4,72	5,77	13,84	11,86
String 1.11	13,74	10,94	9,64	7,83	7,86	101,41
String 1.12	6,98	11,58	8,05	5,08	9,68	95,64
String 2.1	44,12	11,38	13,05	10,85	13,17	11,67
String 2.2	12,72	61,67	58,7	9,73	9,25	22,91
String 2.3	54,32	51,2	25,55	40,01	55,3	65,8
String 2.4	3,99	11,95	8,74	9,82	9,95	9,38

Table 5. – $P_{mpp\ delta\ \%}$ values

	June	July	August	September	October	November
String 1.1	4,24%	4,31%	4,87%	14,05%	6,87%	10,76%
String 1.2	8,26%	10,09%	4,96%	5,29%	7,96%	9,11%
String 1.3	4,91%	9,61%	3,88%	3,80%	7,64%	13,69%
String 1.4	7,11%	7,26%	6,51%	5,13%	N/A	N/A
String 1.5	5,31%	8,62%	4,77%	4,68%	5,22%	10,87%
String 1.6	6,64%	3,55%	3,33%	3,91%	5,12%	7,80%
String 1.7	8,48%	5,74%	3,69%	2,85%	4,91%	6,09%
String 1.8	5,48%	6,97%	6,53%	4,52%	6,78%	6,27%
String 1.9	4,87%	2,88%	3,35%	3,24%	7,27%	11,08%
String 1.10	4,78%	6,59%	2,61%	3,16%	7,50%	6,39%
String 1.11	7,33%	5,86%	5,14%	4,23%	4,25%	55,42%
String 1.12	3,82%	6,21%	4,29%	2,72%	5,18%	51,63%
String 2.1	20,02%	5,99%	6,77%	5,67%	6,83%	6,09%
String 2.2	6,76%	32,04%	30,43%	5,16%	4,87%	11,92%
String 2.3	30,42%	28,64%	14,19%	21,83%	29,91%	36,37%
String 2.4	2,20%	6,27%	4,63%	5,23%	5,23%	4,95%

Based on the analysis of tables 4, 5 defective strings were identified. Additional verification of DT calculation using internal electrical parameters for each module confirmed existing of defective modules and allowed to create the following list.

List of known strings with defective modules during June - November period:

1) June - String 2.1 (Module 2.1_11, P_{mpp} = 220,38W, $P_{mpp\ diff\ percentage}$ = 0,88%, R_p = 1000, R_s = 0,9);

2) June - String 2.3 (Module 2.3_10, P_{mpp} = 124,26 W, $P_{mpp\ diff\ percentage}$ = 1,73%, R_p = 95, R_s = 2,49);

3) July - String 2.2 (Module 2.2_16, P_{mpp} = 130,8 W, $P_{mpp\ diff\ percentage}$ = 2,25%, R_p = 95, R_s = 1,89);

4) July - String 2.3 (Module 2.3_10, P_{mpp} = 127,6 W, $P_{mpp\ diff\ percentage}$ = 1,9%, R_p = 185, R_s = 2,09);

5) August - String 2.2 (Module 2.2_16, P_{mpp} = 134,2 W, $P_{mpp\ diff\ percentage}$ = 3,64 %, R_p = 95, R_s = 1,69);

6) August - String 2.3 (Module 2.3_10, P_{mpp} = 154,56 W, $P_{mpp\ diff\ percentage}$ = 2,81 %, R_p = 95, R_s = 1);

7) September - String 2.3 (Module 2.3_10, P_{mpp} = 143,25 W, $P_{mpp\ diff\ percentage}$ = 2,27 %, R_p = 500, R_s = 1,69);

8) October - String 2.3 (Module 2.3_10, P_{mpp} = 129,6 W, $P_{mpp\ diff\ percentage}$ = 5,93 %, R_p = 140, R_s = 2,68);

9) November - String 1.11 (Module 1.11_15, P_{mpp} = 71,59 W, $P_{mpp\ diff\ percentage}$ = 1,59 %, R_p = 50, R_s = 4,56);

10) November - String 1.12 (Module 1.12_11, P_{mpp} = 89,61 W, $P_{mpp\ diff\ percentage}$ = 4,41 %, R_p = 95, R_s = 4,17);

11) November - String 2.3 (Module 2.3_10, P_{mpp} = 115.14 W, $P_{mpp\ diff\ percentage}$ = 1,59%, R_p = 95, R_s = 3.57).

Values from Table 1 for these defective strings ($P_{mpp\ diff\ percentage}$) look like average values across all strings (especially for String 2.3 which was defective during all 6 months) and cannot definitely identify string with a defective module.

However, with additional analysis for each module or with $P_{mpp\ delta\ \%}$ parameters defective modules could be easily identified (yellow values from table 5).

Dynamics analysis for $P_{percentage\ diff}$ and $P_{mpp\ diff\ percentage}$ values (tables 1, 2) in comparison with $P_{mpp\ delta}$ and $P_{mpp\ delta\ \%}$ (tables 4, 5) shows that the relationship between these parameters and defective modules is not clear.

Conclusions

Digital Twin estimates the string's state with 0,6 – 3,5% variation. It could be used during analysis of the actual PV plant's state by comparing real parameters with those calculated from DT.

However, the parameter of the virtual module that describes String level data does not allow us to detect the electrical failure within the string.

References

[1.] M. Schmela, A. Beauvals // Global Marker Outlook For Solar Power 2018-2022 // SolarPower Europe, Brussels, 2018

[2.] S.A. Sharaf, M.S. Abd-Elhady, H.A. Kandil // Feasibility of solar tracking systems for PV panels in hot and cold regions // Renewable Energy, Volume 85, 2016, pp. 228-233.

[3.] Asimov R.M., Valevich S.V., Kruse I., Asipovich V.S. Virtual laboratory for testing of solar power plants in big data analysis // Collection of materials of the V International Scientific and Practical Conference «BIG DATA and ADVANCED ANALYTICS», March 13–14, 2019, Minsk, BSUIR, pp. 61–65.

[4.] Osipovich V.S., Asimov R.M., Chernoshey S.V. Digital twin in the Analysis of a Big Data // Collection of materials of the IV International Scientific and Practical Conference «BIG DATA and ADVANCED ANALYTICS», May 3–4, 2018, Minsk, BSUIR, pp. 69–78.

ИСПОЛЬЗОВАНИЕ ЦИФРОВОГО ДВОЙНИКА СОЛНЕЧНОЙ ПАНЕЛИ ДЛЯ АНАЛИЗА ВЫРАБОТКИ ЭЛЕКТРОЭНЕРГИИ СОЛНЕЧНОЙ ЭЛЕКТРОСТАНЦИЕЙ

Р.М. Азимов
Директор
Sensotronica Ltd

С.В. Валевич
Магистрант
кафедры ИПиЭ

И. Круз
Директор
SunSniffer

В.С. Осипович
Доцент кафедры
ИПиЭ

Аннотация. Предложен, реализован и протестирован метод расчета на уровне массива панелей. Результаты тестирования показали следующее. Расчет на уровне массива панелей позволяет получить достаточно точные результаты по значениям P_{mpp} для массива, но для определения дефектных панелей с какими-то электрическими неисправностями в конкретном массиве необходим дополнительный анализ на уровне конкретных панелей

Ключевые слова: Цифровой двойник, фотоэлектрический, расчет для фотоэлектрического массива, дефектные фотоэлектрические панели.