

The reference PV power plant-based method

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Abstract

A new method has been developed by small scale power plants were built in a closely related place to estimate the power generation an any given time and give a short term forecast. This is called the reference power plant-based method. The essence of the method is a few references plants is under continuous monitoring, so an accurate estimation could prepare for the entire closely PV area in any time. It is possible, this method will able to forecasting. This could help while the balancing and the trading activity in the low voltage network. Thus, network integration of photovoltaic systems could be significantly facilitated.

Keywords: *Small scale photovoltaic, aggregator forecastind metode, clouds variability factor,*

1. Introduction

It is common that the photovoltaic power plants for predicting the clouds build solar radiation monitoring network (Bilionis et al., 2014). The application of similar solutions for the urban environment relatively could be more expansive and less accurate. In Hungary, the solar panels installed on rooftops rationally would be cover approximately 22.5% of the annual residential electricity consumption. For larger institutional buildings this number is nearly 8%. The technical potential is significant value, although the buildings are still typically not able to produce more power than consumed. In the event that available potential by 2020 is only 5% considered this, the expected target could be 555 GWh/year in the residential sector. This is approximately ten times bigger the total 2014 small scale PV production. In Hungary, the electricity network is basically centralized and not yet flexible enough to provide high VRE ratio will be available. The present study aims to provide a reference power plant based method to help the integration with the small-scale photovoltaic systems.

The PV GRID program showed the main network problems caused by the small scale photovoltaic systems and summarized the possible proposals for solutions. These solutions can be divided into five main groups from another own specific perspective:

- The surplus electricity production compared to consumer demand could be converted heat losses in the grid;
- Restricted effective photovoltaic electricity generation from the PV system (eg reactive power production, switch-off from the grid); avoid to actual overproduction ;
- Use some energy storage system with acceptance of the storage losses;
- In addition to making possible reversal of the current paths transformation losses with efficiency reduction by the larger power plants.

The important thing is the produced but also really consumed electricity production. The performance ratio (PR), for example, typically does not take into account as a negative quantity the produced, but not utilized energy. A system oriented new performance ratio value (PR_{net}) could be useful by the development and the optimization:

$$PR_{net} = \frac{(E_{pr} - E_{grl} + E_{grw} - E_{ow} - E_{st} - E_{bl})}{E_{us}} \quad (\text{eq. 1})$$

Where the PR_{net} is the system oriented performance ratio, E_{pr} is the net photovoltaic production [kW h^{-1}], E_{grl} is the transformation, distribution and other losses in the grid from the photovoltaic electricity production, E_{grw} is the total avoided grid losses due to the decentralized system near to the consumption. E_{ow} is the PV

power system losses (the system's own losses). E_{st} is the storage losses, if the battery option is available. E_{bl} is the blocked photovoltaic electricity production by the producer with automatic shutdown, reactive energy conversion, so on. E_{us} is the useful (really consumed part) energy.

So there is a need for indicators to characterize by complex way the photovoltaic systems and their grid integration quality. According to an IEA study (Müller, S. et al, 2014), the electricity price with a conventional fossil power plant portfolio could be expected between 86 and 94 USD/MWh. In the case when VRE (variable renewable energies) ratio could reach the 45% the electricity price would be higher (between 97 and 119 USD/MWh) with considering the additional network charges. In 2014 the EU supported "PV Parity" project modeled until 2030 to build 480 GW new photovoltaic power plants (PV Parity, 2013). According to the program the transmission grid cost can grow from the current costs from 0.5 euro / MWh to 2.8 euro / MWh up, but the distribution grid connected needs cause 9 EUR / MWh.

So by the integration ability one key component by the small scale photovoltaic systems is the reduction the variability and uncertainty with more accurate forecast. By these systems there is currently no cost-effective best practice method. In addition the forecasting tasks are complex challenges which are significantly differentiated:

- Planning, optimization, network assessment, cost - benefit analysis, evaluation of alternatives, verification by supports.
- 15 minutes schedule giving an electricity trader.
- Clarification of the planned schedule before the beginning of the relevant period.
- Clarification of the planned schedule within the relevant 15 minutes long period.
- Forecast for a very short periods (balancing) forecast, for example only 1 minute ahead.

My PhD research in progress examines the possibilities by the last two points. Those solutions as the „Wavelet Variability Model” (Dyreson et al, 2014), which for multi-megawatt power plants are acceptable even for small scale sizes often not cost effective.

The reference PV power plant-based method is based on simple idea. In a given urban setting the individual systems will receive the similar environmental impacts (for example smog, air pollution, temperatures, or spectral distribution. In some cases it can be useful for making forecast.

2. Basic model description

By a monitoring the following two main tasks are given:

- Making analytical forecast for every minute performances.
- Improving the accuracy of these forecasts very shortly in advance.

The energy output of PV systems depends on more special effects, which hard and expensive to measure and evaluate in time, for example the solar radiation intensity, temperature or solar spectrum (Farkas, Seres, 2008). The reference value is the difference the expected performance which based on analytical analysis and actual measured power. In order that this error (difference) can be used as a reference value, several conditions must be met:

- to be a relative number, because a comparison of different systems output is the target;
- to characterize the various systems by a comparable manner with simple transparency.

The equivalent peak load hours are characterized by the energy-generating capacity in a given moment. It means if same amount of power will produced in one year, the equivalent peak load hours is equal the traditional peak load hours (Sharma, Tiwari 2012):

$$h_{ekv} = \frac{\xi_{real}}{I_p} \quad (\text{eq. 2})$$

where I_p is the current value of the global radiation intensity [kW/m²] and ξ_{real} is the total amount of solar energy production unit [kWh/m²]. If the performance is expressed as an equivalent number of hours, the expected value can be written as follows:

$$h_{ekv,t}(t) = \frac{(G_{pv}(t) \times \eta(t) \times A)}{I_p} \quad (\text{eq. 3})$$

Where G_{pv} is the amount of daily global radiation in [kWh/day], η is the reference efficiency [%] and A is the useful photovoltaic solar surface [m^2]. The equivalent peak load hours shows a reachable capacity at a given moment with dimension of the hour or kWh/kW. If the system is functioning at a given time at a specific equivalent peak load hours, then in an imagined year with equal continuous output power, same value would result for the peak load hours for that year. This value represents an actual capacity of the PV power plant, which is clear, meaningful and comparable.

During the measurement, therefore in different periods of time it were determined the expected and the measured equivalent peak load hours. The series thus produced error factor is adapted to be forecast and made suitable systems to estimate the combined capacity in the closely related place (the formerly analytical forecast could be more precise). Determination of the relative error factor can be seen in the next table (Table 1.):

Tab. 1: Determination of the relative error factor

t_0	Δt	$h_{equ,t0}^*$ (expected equivalent peak load hours)	$h_{equ,t0}^m$ (measured equivalent peak load hours)	$H_0 =$ $ (h^* - h^m) /h^*$ (error factor)	$h^{**}_t =$ $f(h^*_t, r_{t-k}, r_{t-k+1}, \dots, r_{t-k+n})$ (short time prediction)
t_1	$t_1 - t_0$	$h_{equ,t1}^*$	$h_{equ,t1}^m$	h_{t1}	h^{**}_{t1}
t_2	$t_1 - t_0 = t_2 - t_1$	$h_{equ,t2}^*$	$h_{equ,t2}^m$	h_{t2}	h^{**}_{t2}
t_3	$t_1 - t_0 = t_3 - t_2$	$h_{equ,t3}^*$	$h_{equ,t3}^m$	h_{t3}	h^{**}_{t3}
...
t_n	$t_1 - t_0 = t_n - t_{n-1}$	$h_{equ,tn}^*$	$h_{equ,tn}^m$	h_{tn}	h^{**}_{t4}
...
t_m	$t_1 - t_0 = t_m - t_{m-1}$	$h_{equ,tm}^*$	$h_{equ,tm}^m$	h_{tm}	h^{**}_{t5}

Based on the analytical model and real values $r_{(t-k)}, \dots, r_{(t-k+1)}, r_{(-1)}, r_{(0)}$ error factors are added. Based on $r_{(t-k)}, r_{(t-k+1)}, \dots, r_{(t-k+n)}$ error factors, and the results of the traditional analytical model forecast for the expected equivalent peak load hours in t time it could be improve h^*_t for h^{**}_t . So there are two main steps, first of all $h^*_{equ,t}$ have to be counted, than after a monitoring it could be improve sort time in advance.

Therefore it is necessary to determine solar geometric data, the expected value of global radiation, and the characteristics of direct and diffuse radiation conditions. By the effective component of direct radiation it should be also considered the orientation of the solar panels. The ISES Pocket book gives the main equation (Martin, 2005):

$$H_{\alpha,\beta} = RB_{\alpha} + D \cos^2\left(\frac{\beta}{2}\right) + (D + B)\rho \sin^2\left(\frac{\beta}{2}\right) \quad (\text{eq. 4})$$

With the R factor in the equation 3 (solar panel tilt factor) at each moment it can be determined the perpendicular portion of the solar direct radiation reaching the surface depending on the inclination of the solar cell. The module temperature of the solar cell is important to estimate the cell efficiency. By the cell temperature estimation it was applied an approximate curve, which is considered as a typical for the relevant period (Figure 1.).

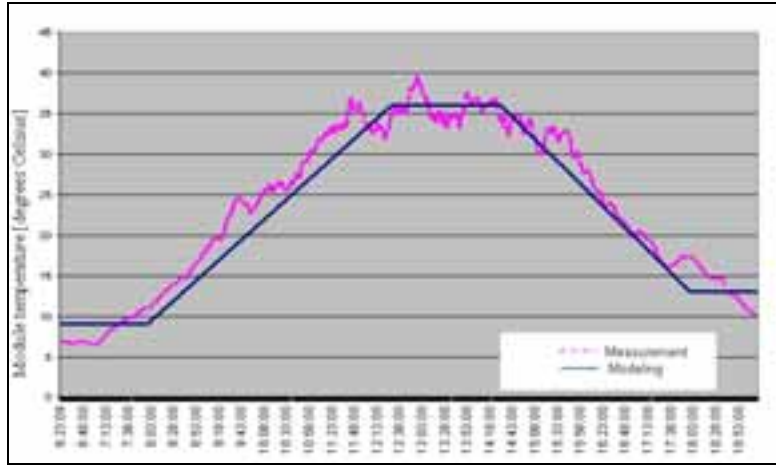


Fig. 1: Module temperature estimation

The other additional losses by determination of the electricity production were estimated according to the table. 2.

Tab. 2: The estimated electricity losses depending on the energy capacity of the effective part of the direct solar radiation

H [W m ⁻¹]	Losses in DC system	Installation uncertainties	Performance ratio of DC production	Inverter losses	Other losses in AC system	Expected losses barring service function by Inverter	Performance ratio
>500	6%	2%	92%	5%	3%	0.5%	84.46%
240 – 499	9%	2%	89%	4%	3%	0.5%	82.63%
120 – 239	12%	2%	86%	6%	3%	0.5%	77.43%
< 119	15%	2%	83%	9%	3%	0.5%	72.41%

Thus, according to the above, I calculated totally 15.5 - 27.6% losses. Therefore in every minute it may be obtained to get the expected equivalent peak load hours:

$$h_{equ,AC}(t) = \frac{P_{AC}(t)[W]}{(P_p[kW] \times 1000)} \times 8760, [h]. \quad (\text{eq. 5})$$

Where P_{DC} is the actual current PV performance to the grid and P_p is the nominal capacity of the PV system. From the differences between the observed (measured) and the expected equivalent peak load hours the error factors could be calculated according to the next equation:

$$H_{t-n} = \frac{(h_{t-n}^* - h_{t-n}^M)}{h_{t-n}^*}, [\%]. \quad (\text{eq. 6})$$

It can be defined a specific series of error factors between $t-n$ and $t-m$. From this the current characteristics of their changes (dH/dt) can be deduced:

$$\frac{dH}{dt} \approx \frac{\Delta H_{n-m}}{\Delta t_{n-m}} = \frac{(H_{t-n} - H_{t-n-1}) + (H_{t-n-1} - H_{t-n-2}) + \dots + (H_{t-m+1} - H_{t-m})}{n - m}, [\% \text{ min}^{-1}] \quad (\text{eq. 7})$$

where are true, that

$$t_{t-n} - t_{t-n-1} = t_{t-n-1} - t_{t-n-2} = \dots = t_{t-m+1} - t_{t-m} \quad (\text{eq. 8})$$

Thus, the error factor prediction is described here:

$$H_t = H_{t-1} + \left(1 + \frac{dH}{dt}\right) \approx H_{t-n} + \left(1 + \frac{dH}{dt}\right)^n \approx H_{t-n} \times \left(1 + \frac{\Delta H_{n-m}}{\Delta t_{n-m}}\right)^{0.4n}, [\%].$$

(eq. 9)

Under the average conditions the 0.4n exponent has formed to be approximately an optimal value during by measurements. View of the above the revised forecast comes according to next equation:

$$h_t^{**} = h_t^* + H_t \times h_t^* = h_t^* \times (1 + H_t), [h].$$

(eq. 10)

The parameters, which were used during the analysis and the measurements, are shown in Table 3.

Tab. 3: The main parameters of the tests

The duration of the predicted period	$t_n - t_{n-1}$	n	m
1 minutes	1 minutes	5 minutes	15 minutes

Therefore during the measurement and analysis the series of h_t^{**} was available in 5 minutes before time t. This gave the opportunity to give other forecast for the average performance in every full quarter-hour with 5 minutes before the end of the period. During the test the prediction for average performance (equivalent peak load hours) in 15 minutes periods based on 5 minutes measured data and 10 minutes predicted data with get from the presented method.. The method of determining is illustrated with nest equations.

$$h_{15 \text{ min}}^m = h_{t-14} + h_{t-13} + h_{t-12} + h_{t-11} + h_{t-10}$$

(eq. 11)

$$h_{15 \text{ min}}^{\text{exp}} = h_{t-9}^{**} + h_{t-8}^{**} + h_{t-7}^{**} + h_{t-6}^{**} + h_{t-5}^{**} + h_{t-4}^{**} + h_{t-3}^{**} + h_{t-2}^{**} + h_{t-1}^{**} + h_t^{**}$$

(eq. 12)

$$h_{t,15 \text{ min}}^{**} = \frac{h_{15 \text{ min}}^m + h_{15 \text{ min}}^{\text{exp}}}{15}$$

(eq. 13)

The significance of the error factor is stronger in these times when the radiation is more intensive, so the period between 10:00 – 16:00 were also separately analyzed.

3. The reference PV power plant model description

The reference PV power plant-method is based on the presented forecast which is extended to a whole photovoltaic plant area. Continuous monitoring system works only by the reference power plant and the basic data from others is known. There are two approaches are conceivable:

- forecast for balancing purpose;
- virtual smart grid group (aggregator) forecast for a 15 minute average performance.

So based on the analytical expected equivalent peak load hours ($h_{1,t}^*$) and these modified forecasts with the monitoring ($h_{1,t}^{**}$) for the reference power plant, as well as expectations for a second pv system ($h_{2,t}^*$) without monitoring the new modified values ($h_{2,t}^{**}$) also could it be estimated:

$$\frac{h_{1,t}^{**} - h_{1,t}^*}{h_{1,t}^{**}} \approx \frac{h_{2,t}^{**} - h_{2,t}^*}{h_{2,t}^{**}} = 1 - \frac{h_{2,t}^*}{h_{2,t}^{**}}$$

(eq. 14)

Consequently $h_{2,t}^{**}$ could be counted with the next equation:

$$h_{2,t}^{**} \approx \frac{h_{2,t}^*}{1 - \frac{h_{1,t}^{**} - h_{1,t}^*}{h_{1,t}^{**}}}$$

(eq. 15)

As noted above, in addition to the analysis of a reference power plant it also could be prepared the forecasts

for the 15 minute average performance ($h_{2,t,15m}^{**}$) by other nearby plants (which based on 5 minute measurement data from the reference system due to equation 13):

$$h_{2,t,15m}^{**} \approx \frac{h_{2,t,15m}^*}{1 - \frac{h_{1,t,15m}^{**} - h_{1,t,15m}^*}{h_{1,t,15m}^{**}}} \quad (\text{eq. 16})$$

4. Data and methods

The research examined reference power plant owned by the Budapest District Heating Co. Ltd. (Főtáv Zrt.). The PV plant is located in the company' headquarter (Budapest, Kalotaszeg 31.) in the top of the 'D' building. The reference power plant was considered only one part of the whole (the one inverter part form the 8). With the same orientation and the same angle 19 panel units has a single inverter. The main data of the plant:

- Location: Latitude: 47.4584°, Longitude: 19.045°;
- PV module type: AS-60P 250 W ECO;
- Rated power of a panel: 250 W_p;
- The number of solar panels installed: 150;
- Position: +10.7 degrees (SSW) (as determined by measuring from map),
- Angle of inclination: 20 degrees
- Number of inverters: 8;
- The PV Power Plant nominal connection capacity: 40 kW.

The main site of research is shown in Figures 2.



Fig. 2: The examined reference power plant

The eight independent inverters have enabled to forecast from one continuously measured inverter data to others, so the reference PV power plant model can be test in optimal situations (the systems are very close each others in the same position). This will be also tested another two system is located within a 10 km. The research analyzes data from seven different days which was randomly selected (Table 4. and Table 5.).

Tab. 4: The test days and characteristics

Number	Dates	The serial number of the day (d_n)	Sunrise (GT+1)	Sunset (GT+1)	Azimuth at sunrise (AZI_{SRT})	Azimuth at sunset (AZI_{SST})	Potential sunshine duration (N_0) [h]
1.	1 April 2014.	91	6:23:09	19:13:13	-97.58°	97.89°	12.84
2.	20 April 2014.	110	5:46:32	19:39:56	-108.07°	108.37°	13.89
3.	1 May 2014.	121	5:27:32	19:55:15	-113.55°	113.89°	14.16
4.	20 May 2014.	140	5:01:25	20:20:01	-121.36°	121.58°	15.31
5.	1 June 2014.	152	4:50:58	20:32:51	-124.80°	124.96°	15.69
6.	14 June 2014.	165	4:46:12	20:42:09	-126.86°	126.91°	15.93
7.	20. July 2014.	201	5:07:10	20:32:34	-122.58°	122.38°	15.42

Tab. 5: Characteristic of the analyzed days by the reference power plant

Dates	Throughout the day		Between 10:00 and 16:00		Solar irradiation characteristics
	Average equivalent peak load hours	Maximum equivalent peak load hours	Average equivalent peak load hours	Maximum equivalent peak load hours	
	hour	hour	hour	hour	
1. 04. 2014.	3889	6766	5633	3427	sunny, slightly cloudy, stable light conditions
20. 04. 2014.	3047	9360	4245	1187	Cloudy volatile, rarely sunny
1. 05. 2014.	2604	8310	4609	1522	almost uniformly cloudy but periodically clear
20. 05. 2014.	4227	7679	6348	802	variably cloudy or clear sky, rapidly changing light conditions
1. 06. 2014.	2717	9528	4606	761	volatile cloudy typically, it is rarely sunny
14. 06. 2014.	4032	9089	5515	757	strong variably, cloudy or sunny wether
20. 07. 2014.	4252	7031	6261	1557	sunny, cloud drift infrequently, but otherwise stable

5. Validation results

To evaluate the reliability of the model it was introduced a special indicator that is able to characterize the variability of the particular days. This indicator is the variability factor, it signs with V . Determine of this value is deepen on the numbers of the bigger changes of the measured average AC power within one minute. The definition is shown with the equation 16 and 17 and is illustrated in the table 6 and 7. This indicator is unique in that the connected weight values larger when the sudden change is bigger.

So the variability factor for the all day:

$$V_{day} = 4a_1 + 3a_2 + 2a_3 + a_4 + 4b_1 + 3b_2 + 2b_3 + b_4 \quad (\text{eq. 17})$$

And for the period between 10:00 - 16:00:

$$V_{10-16} = 4a_1 + 3a_2 + 2a_3 + a_4 + 4b_1 + 3b_2 + 2b_3 + b_4 \quad (\text{eq. 18})$$

These factors in the investigated date are in the next: The confidence indicator correlates to the period considered as a unit specific value is shown in the table 8.

Tab. 6: Determination of variability factor for the measured days

Dates	Changes in average AC power within 1 minute								Variability factor V_{day} [unit/ day]
	Down				Up				
2014	Above 55%	Between 35%-55%	Between 15%-35%	Between 5%-15%	Above 55%	Between 35%-55%	Between 15%-35%	Between 5%-15%	Day
	a_1	a_2	a_3	a_4	b_1	b_2	b_3	b_4	
1.04.	0	1	2	55	0	0	9	51	131
20.04.	8	8	40	71	16	11	40	76	460
1.05.	2	6	21	68	5	4	19	65	271
20.05.	11	6	10	47	19	3	10	34	268
1.06.	3	7	34	108	12	9	38	106	466
14.06..	20	19	29	61	35	10	29	54	538
20.06..	2	0	7	26	3	0	6	23	95

Tab. 7: Determination of variability factor for the measured days between 10-16 hours

2014	Changes in average AC power within 1 minute								Variability factor V_{10-16} [unit/ 6 hours]
	Down				Up				
	Above 55%	Between 35%-55%	Between 15%-35%	Between 5%-15%	Above 55%	Between 35%-55%	Between 15%-35%	Between 5%-15%	10:00 –
	a_1	a_2	a_3	a_4	b_1	b_2	b_3	b_4	
01.04.	0	1	1	17	0	0	2	18	44
20.04.	5	3	15	21	9	4	17	24	186
01.05.	2	6	12	22	5	3	10	28	149
20.05.	7	4	2	5	12	1	2	8	112
01.05.	2	6	23	54	9	8	21	61	289
14.06.	19	18	13	28	32	6	9	22	370
20.07.	2	0	1	8	3	0	1	8	40

Tab. 8: Determination of the specific variability factors

	Variability factors	Length of the period	Specific variability factors
<u>2014</u>	V_{day} [unit/day]	Δt_{day} [hour]	$v_{\text{nap}} = V_{\text{day}} / \Delta t_{\text{day}}$ [unit/hour]
01.04.	131	12,84	10,20
20.04.	460	13,89	33,12
01.05.	271	14,46	18,75
20.05.	268	15,31	17,51
01.05.	466	15,69	29,71
14.06.	538	15,93	33,78
20.07.	95	15,42	6,16
	Variability factors	Length of the period	Specific variability factors
<u>2014</u>	V_{10-16} [unit/6 hours]	Δt_{10-16} [hour]	$v_{10-16} = V_{10-16} / \Delta t_{10-16}$ [unit/hour]
01.04.	44	6	7,33
20.04.	186	6	31,00
01.05.	149	6	24,83
20.05.	112	6	18,67
01.05.	289	6	48,17
14.06.	370	6	61,67
20.07.	40	6	6,67

The results of the forecast are demonstrated in Figure 3 and 4 for a one day (2014.04.01). Figure 3 shows the relative error according to prediction with the equation 9, where the forecast is for a one minute equivalent peak load hour and it was made 5 minute earlier. Figure 4 shows the relative error according to prediction with the equation 12, where the forecast is for a 15 minutes average equivalent peak load hour and it was made also 5 minutes earlier, than the end of the period.

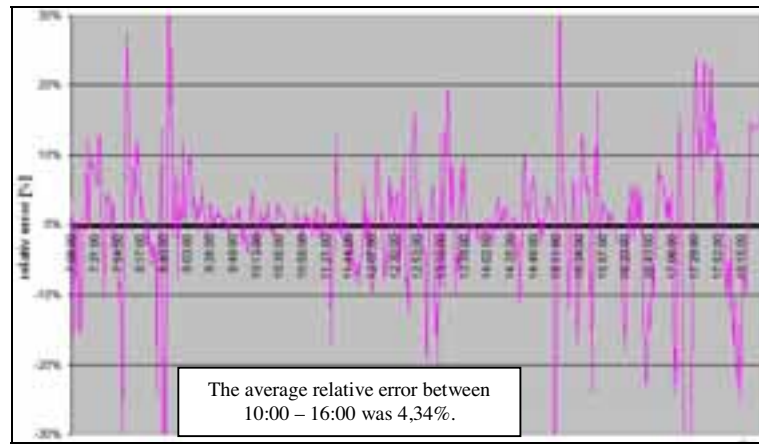


Fig. 3: Prediction with the equation 10 (AC relative error of the forecast, 01.04.2014)

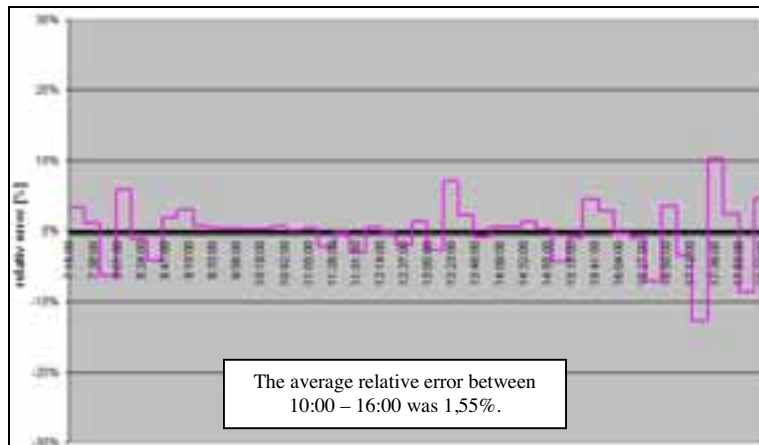


Fig. 4: Prediction with the equation 13 (AC relative error of the forecast, 01.04.2014)

Based on the differences between the monitoring forecasted values and the measurement data it was determined in both the absolute and relative errors for each minutes with the next equations..

$$\Delta h_t = |h_{ekv,t} - h_t^{**}|, [\text{hour}] \quad (\text{eq. 19})$$

$$h_h = 100 \times \frac{\Delta h_t}{h_{ekv,t}}, [\%]. \quad (\text{eq. 20})$$

The results of the prediction for the reference power plant are shown in the table 9 and table 10.

Tab. 9: One-minute' forecast performance data between 10:00 and 16:00

	Absolute errors (equivalent peak load hour)				Relative errors				
	Average error	Above 200 hour	Between 100 and 200 hour	Under 100 hour	Average error	Above 15%	Between 10% and 15%	Between 5% and 10%	Under 5%
01. 04.	235	37,95%	20,22%	41,83%	4,34%	4,43%	5,26%	19,11%	71,19%
20. 04.	885	55,68%	13,85%	30,47%	20,68%	30,47%	13,02%	16,07%	40,44%
01. 05.	693	55,40%	24,38%	20,22%	17,18%	26,59%	12,47%	22,71%	38,23%
20. 05.	798	29,64%	17,73%	52,63%	34,56%	15,51%	0,55%	4,16%	79,78%
01. 05.	1 203	80,33%	9,97%	9,70%	28,74%	54,85%	12,19%	13,57%	19,39%
14. 06.	1 880	72,58%	13,02%	14,40%	55,75%	47,92%	5,54%	12,47%	34,07%
20. 07.	175	12,19%	16,90%	70,91%	3,87%	3,60%	1,39%	4,99%	90,03%

Tab. 10: Fifteen-minute' forecast performance data between 10:00 and 16:00 (5 minutes before the end of the period)

	Absolute errors (equivalent peak load hour)				Relative errors				
	Average error	Above 200 hour	Between 100 and 200 hour	Under 100 hour	Average error	Above 15%	Between 10% and 15%	Between 5% and 10%	Under 5%
01. 04.	87	12,50%	25,00%	62,50%	1,55%	0,00%	0,00%	4,17%	95,83%
20. 04.	302	37,50%	16,67%	45,83%	6,63%	12,50%	0,00%	29,17%	58,33%
01. 05.	256	37,50%	29,17%	33,33%	5,92%	12,50%	8,33%	25,00%	54,17%
20. 05.	260	29,17%	8,33%	62,50%	4,36%	8,33%	8,33%	4,17%	79,17%
01. 05.	397	58,33%	20,83%	20,83%	9,29%	20,83%	12,50%	20,83%	45,83%
14. 06.	694	75,00%	8,33%	16,67%	13,09%	37,50%	12,50%	16,67%	33,33%
20. 07.	56	8,33%	4,17%	87,50%	0,93%	0,00%	0,00%	8,33%	91,67%

The average relative error examining the relationship between Specific variability factors Student's t-test were performed. The square of the correlation coefficient by the fifteen-minute' forecast performance was 0.9854 between 10:00 – 16:00, so this mens a strong linear relationship. The confidence intervals for this tested case are summarized in Table 11.

Tab. 11: The forecast errors' critical values in the 95% confidence level (5 minutes earlier prediction before the end of the 15 minutes period)

Specific variability factors [unit/hour]	Average relative error [%]
23.65	$5 \pm 1.46 = [3.54; 6.46]$
47.85	$10 \pm 1.47 = [8.53; 11.47]$
$23.65 \pm 7.04 = [16.61; 30.69]$	5
$47.85 \pm 7.28 = [40.57; 55.13]$	10

So, using the developed forecasting methodology for a 15-minute average performance in five minutes earlier to predict between 10 and 16 hour, when a specific variation factors are met 23.65 unit/h, with 95% confidence level true that the relative error of the forecast between 3.54% and 6.46% in Hungary. Furthermore, if the specific peak loads variation is less, than 40.57 unit/hour, it can be sure with a 95% confidence that the mean relative error of the forecast is less than 10%. If specific variability factors are less, than 16.61 unit/hour, the average relative error is better than 5%. The average value of the indicator during the tests was 28.3 unit/hour. This is very close to the 23.65, so it could be estimated an annual average of between 5-7% accuracy available between 10:00 -16:00.

Further analyzes are still in progress, but it is already clear that in some cases from the monitoring by only the inverter 1. No. a good prediction could be made for example with a relative error of 1.6% of the full power (inverter 8) performance between 10 and 16 hour.

6. Conclusions

The reference power plant-based method seems to be suitable for simultaneous modeling of the whole electricity energy production of more pv system in a low-voltage distribution grid with a smart grid, for short-term predictive modeling (balancing activity) and for prediction to keep the 15 minute schedule (trading activity).

The main research results so far:

- To establish a new factor (indicator);
- Anew analysis of the accuracy of forecast
- Analysis of other systems for the accuracy of forecast

7. References

Bilionis, I., Constantinescu, E. M., Anitescu, M., 2014. Data-driven model for solar irradiation based on satellite observations. *Solar Energy* 110, pp. 22-38.

Dyreson, A. R., Morgan, E. R., Monger, S. H., Acker T. L., 2014. Modeling solar irradiance smoothing for large PV power plants using a 45-sensor network and Wavelet Variability Model, *Solar Energy* 110, pp. 482-495.

Farkas, I., Seres, I., 2008. Operational experiences with small-scale grid-connected PV system, *R&D in Mechanical Engineering Letters*, Vol. 1, pp. 64-72.

Martin, C.L. and Goswami, D.Y., 2005. *Solar energy pocket reference*, International Solar Energy Society

Müller, S. /Ed/ (2014): *The Power of transformation*, OECD/IEA

PV Parity (2013): *Cost and Benefits of PV Grid Integration*, <http://www.pvparity.eu/results/cost-and-benefits-of-pv-grid-integration/>, downloaded: 2015.04.14.

Sharma, R., Tiwari, G.N., 2012. Technical performance evaluation of stand-alone photovoltaic array for outdoor field conditions of New Delhi, *Applied Energy*, 92. pp. 644-652.