SZENT ISTVÁN EGYETEM

Autonomous and grid collaborative
photovoltaic system optimization

Thesis of PhD Work

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CONTENTS

1. INTRODUCTION, OBJECTIVES

The photovoltaic technology has become a main element of a sustainable energy supply in the future. So now the science and the engineering profession are facing many new complex challenges. The strategic and operational coordination between the centralized and the decentralized systems, the demand size management, the technological connection between the earlier separate sectors (electricity, heating and transport) have become key elements of the competitive, secure and sustainable energy supply in our days. The lack of reliable and short-term power prediction is currently an obstacle to the further development. There is huge demand for the creation virtually connected smart electricity systems and the establishing local communities of small scale energy producers and consumers, because of the common interests in a cost-effective decentralized energy generation, energy sales and the growing rate of the centralized system based consumption. There is also an increasing demand of the predictive control applications so it is necessary to develop new forecasting methods for the autonomous and grid photovoltaic technologies.

The installation modes of the PV systems also influence the frame of the grid integration possibilities of active solar systems also impacts, but the basic problem is the single aspirations for the maximum annual production without system level optimization, which causes tragedy of common situation. To achieve a higher share of solar renewable in the grid the overall coordination is necessary.

Renewable energy development goals also are typically not really based on the objective assessment of the social and environmental costs and benefits. Authoritative and objective targets are required which is capable of creating the greater understanding and cooperation. The main aim of the research is to promote the integration of the solar PV systems to the public grids or the autonomous networks. My aims are shown in the next points:

- Development of new photovoltaic power forecasting methods;
- Development and evaluation of an average power forecasting methods for a given fifteen minutes scheduled period during that period.
- Evaluation of the possibilities of the virtually photovoltaic power plants' group predictability depending on its homogeneity;
- Developing a new evaluation method for the different individual PV system installation solutions, what is suitable for qualification, classification and certification in views of the negative impacts on the stability of the public utility grid;
- Establishing a numerical optimization decision support method, this is suitable with a joint assessment of cost-effectiveness, the direct social and the environmental effects to determine an optimal renewable energy target structure.

2. MATERIALS AND METHODS

In this chapter I present the methods necessary to achieve the dissertation aims.

2.1. Short term performance prediction by the small scale power solar systems

The modeling the PV predictions could be based on the stochastic assessments. However, the variability of PV generation does not follow any well described distribution. The stochastic based models which use standard or other type distributions can be used only for several hours, or several days, or even longer period. Furthermore, not enough to know of the average external temperature conditions, because the PV system efficiency determined also other external parameter (e.g. the spectral light irradiation, temporary clouds effect, etc.), and the individual characteristics of the PV systems. For these reasons I applied the genetic algorithm method. A genetic algorithm approach is based on the observed mathematical regularities for genetic populations. Accordingly, the knowledge the observed capabilities (as a genetically determined values) in the starting position it can determine the possibilities of the every future capability in the probability space. Therefore it can precisely define that forecasted performance, which has the highest probability within a given set of possibilities.

The genetic method was performed with an encoding process in the sampling period and a decoding process in the forecasted period based on deviations between the typically expected and the measured real performance values. So the fundamental part of this forecasting methodology was the developing of the expected typical performances for every minute in the researched period with free of charge achievable physical based forecast. For getting the expected typical data I use more well-known equations with relatively few required information and some free available databases. Therefore for the every minutes of a year the expected performance values were determined in a reproducible manner (Table 1).

The test system was the FŐTÁV Ltd. solar power system, which is built on top of its central office building by 150 pieces PV panels with 250 W_P nominal rated capacities per units and eight inverters connect it to the public grid. One inverter maximum output capacity is 5 kW and in six cases there are a ten solar panel formed string and a nine solar panel formed string parallel-connected, and in two cases there are two parallel connected nine panel formed sting behind an inverter. Based on the measurement data by these eight inverters I could evaluate by eight independent systems. The types of PV modules: AS-250 W 60P ECO polycrystalline silicon solar cells. The orientations of PV modules are +10.7 degrees (SSW) and their tilt angles are 20 degrees. The nominal connection capacity of the whole PV plants to the grid is 40 kW.

Table 1. The selected testing days and these characteristics

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

The research experiments were carried out on seven different days based on a random sample. The different numbers of data were available on the different days, so I prepared 689-809 pieces/days performance predictions for every minute as an equivalent peak load hours. Besides the assessment of the whole day I also separately examined the intense radiation periods (between 10-16 hours) with 360 pieces/day predicted data.

2.2. Regular schedule compliance performance by the small scale power solar systems

I also made prediction method for the average performance in the scheduling periods partly based on the series of the given moments performance (in equivalent peak load hours) forecasts. During testing I always made the predictions five minutes before the end of the 15 minute. By this forecasting method I applied five measured and counted equivalent peak load hour data and ten predicted values to get the average equivalent peak load hour in the whole fifteen minutes period. The first forecast was made on every test days for those quarter-hour periods when the measured energy production was available in every minute in the period. Thus, for the each test day I made 45-52 pieces a quarter-hours predictions.

2.3. Virtual photovoltaic group joint performance predictability by the small scale power solar systems

The group forecast is based on the measurement and forecast data of a single system. I worked with two PV generator groups with different characters. The "homogeneous" group was the FŐTÁV photovoltaic system in the Kalotaszeg street as a whole (eight independent and measured inverter units). The heterogeneous group was partly from the homogeneous group: the number first, the number third (both 4750 W_P) and the number seventh (4500 W_P) inverters, but partly was consisted by two other small scale PV systems with different locations and products (both 2160 W_P).

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2.4. Experimental data on the small scale power solar systems qualification in view of the grid integration difficulties by the small scale power solar systems

The produced but not utilized electricity by the autonomous systems is an important parameter, but currently it is typically not yet used by the grid connected systems. I introduced the net power factor of the above with modification from the known relationship one. It is shown in the equation 1:

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

In this equation the directly generated electricity (E_{pr}), the photovoltaic system losses (E_{ow}), the achieved network losses reduction (E_{grw}), the storage losses (E_{bl}) and the produced to grid, but really unused electricity, which transforms to network losses (E_{bl}) are shown. The really useful production, which is really consumed by any grid connected consumer, is in the denominator (E_{us}). The difference between the new and the traditional performance ratio *(PR)* is the overload production, which causes increasing network losses or regulated interventions by inverters (e.g. switch-off, reactive compensation). So the net performance ratio shows the system-wide efficiency. The produced electricity is important, but the net performance ratio also should be for the harmony between the productivity and system level effectiveness. The new evaluation method based on the new PV system in the botanical garden Vácrátót.

In Vácrátót a new 7.75 kW PV system was set up. The annual productivity of this system is less than as is usual by this rated capacity, but the implementation way promotes the easier integration into the public grid. Two of the three separate units (string) of this system were built on the east roof surface and the other one was on the south-west roof surface:

- southeastern roof, upper row, 2 kW_p polycrystalline PV solar unit,
- southeastern roof, bottom row, 1 kW_p amorphous PV solar unit,
- southwest roof, 4 kW_p polycrystalline PV solar unit,

The causes of the "system-friendly style" installation are resulting from three specific characteristics of the installation. The PV fields contains both different orientated panels (SE and SW orientations), so the overall power output is different from the traditional bell curve by the whole installed systems and the daily peak power is less so high (peak cutting effect). The solar panels integrated into the top of the building without highlighting, so the performance curve is different from the curve of the systems with "ideal" tilt angle. The system is built with not only polycrystalline modules, which are able to uses the direct radiation greater efficiency, but smaller partly with amorphous silicon modules, which are less sensitive to shielding effect. Differences between Vácrátót and a Szentendre system are illustrated in Fig. 1-4.:
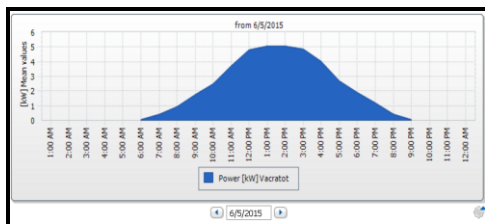
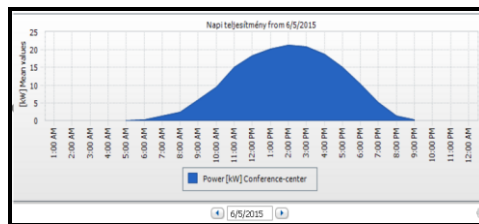Fig. 1. PV system Vácrátót hourly average power (6. June 2015.)

Fig. 2. PV system Szentendre hourly average power (6. June 2015.)
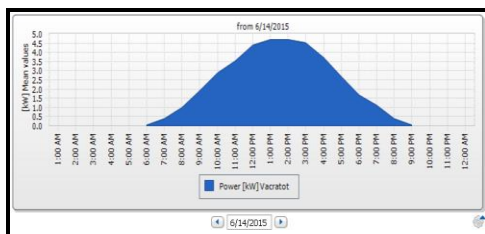

Fig. 3. PV system Vácrátót hourly average power (14. June 2015.)
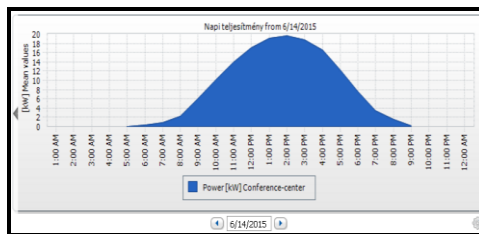

Fig. 4. PV system Szentendre hourly average power (14. June 2015.)

The data analyses were the period from May to August in 2014-15. I selected the sunny days, which matched the next criterion: All of the measured hourly performance data between 10-16 hours in any case exceeds the 75% of the maximum hourly average performance data, which were measured at same time in the current month. These are critical days in terms of the grid problems.

2.5. A numerical complex decision support methods based on the social and the environmental effects, and the economic value of the various renewable technologies

The Hungarian National Renewable Energy Action Plan was developed in 2010 and currently it is approved strategic document. When it was prepared I created a new method for definition of goals. In the first step it is necessary by this to explore the energetic, economic and social characteristics of the different renewable energy technologies and it is need to determine the energy potentials. This is an expert team work. The next step is to prioritize technologies according to three different aspects. These the total unit cost of power generation, the large assessment of social impacts (local job creation, keeping income in region, etc.) and evaluation of some environmental impacts (carbon footprint, water consumption, etc.). By the technology assessment of the energy production costs of renewable technologies I followed the GREEN-X method which was developed by the University of Vienna with a consortium funded by the European Commission's Directorate-General for Research (DG available on the website Research). The description related to this cost evaluation methodology is available on the next website: http://www.green-x.at.

3. RESULTS

In this chapter, I present the results of my research supporting the achieved new scientific results.

3.1. The new dynamic solar power performance forecasting method

It was my aim during the research to find results which are independent from the PV generators, for his reason I made the forecasts with the equivalent peak load hours. Therefore the codes which are used in the genetic algorithms are developed from the expected equivalent peak load hours based on physical modeling by typical conditions.) The invented new method is a data driven determination system, when the physically modeled as an expected value in the forecasted time (t_0) is dynamically and continuously changing depend on the sets of measured data in the monitoring period before t_0 with Δt_1, Δt_2, ..., Δt_n durations.

This continuous changing is guided by the encoded metered data contents of the sampling period, which express also the currently unique and determinative effects for the electricity production. Therefore, the coding system is capable to capture the slightly or seriously unexpected behavior (the differences) in the sampling period as genetically deterministic properties. In this code system there are the unique properties stock defined and this give the approximately parental genetic material. So the most likely and valid in the following short time code can be determined.

All in all the probability of any next value can be calculated within the range which is designated by the recorded code set in the sampling period. This makes it possible to join different probabilities for different amounts of the future performances. However the chances still remain for the decisive changes in extreme weather conditions. These effects are considered as genetic mutation effects. The mutation gives so performance, which has zero probability based on the sampling period genetic material. The above is determined by the following equation (2):

$$H_i(t) = \frac{(h_i^*(t) - h_i(t))}{h_i^*(t)}, \tag{2}$$

where the expected equivalent peak load hours (h_i^*) are determined by the physical-based modeling and analysis. The real equivalent peak load hours (h_i) can be calculated from the measured performance value. The difference between these two values is the physical-based prediction error, from which I expressed the specific error (H_i). It may also be defined in accordance with equation (3) the past series of this specific in the sampling period (before t time moment, between n and m time moment). From these the average dH/dt change can be determined. In this equation the time is in seconds units according to SI system:

$$\frac{dH_i}{dt} \approx \frac{\Delta H_i}{\Delta t} = 60[\frac{s}{\min}]\frac{(H_i - H_{i-1}) + (H_{i-1} - H_{i-2}) + ... + (H_{m+1} + H_m)}{\Delta t_{n-m}} . \quad (3)$$

In the equation the time periods between H_i ... H_m are same long according to the equation (4):

$$t_i - t_{i-1} = t_{i-1} - t_{i-2} = ... = t_{m+1} - t_m . \quad (4)$$

Based on the above I determined the specific prediction for the error between the physically analyzed expected value and the real, measurable value at time t according to the equation (5):

$$H_t = H_{t-1}(1 + \frac{dH}{dt}) \approx H_i(1 + \frac{dH_i}{dt})^{\frac{\Delta t_{t-n}}{60[s/\min]}} \approx H_i(1 + \frac{\Delta H_i}{\Delta t})^{0,4\frac{\Delta t_{t-n}}{60[s/\min]}} . \quad (5)$$

The 0.4 multiplier exponent was the most favorable during the test in the equation (5). The reason is that the H specific errors during the sampling period are not fully independent from each other. Behind the variations of these specific error values more stochastic processes also can be assumed in the sampling period. The changing of the specific errors between the predicted value and the measured value from m till n period is made only partly by those natural effects, which occurs similarly after the t-n period in t time. So the predicted equivalent peak load hours (κ_t) can be made for t time at n time with the equation (6):

$$\kappa_t = h_t^* + H_t \times h_t^* = h_t^* \times (1 + H_t) . \quad (6)$$

The day (01 April 2014.) was the second least volatile one from the seven tested days, which was slightly cloudy, basically sunny and there was stable light conditions. Predictability is difficult for these types of weathers, because the bell curve is not clearly outlined and significant differences may occur compared to the expected values. However, the changes in the lighting conditions are less dynamic, which is favorable in view of the developed genetic algorithm methodology. So the relative errors of the prediction between 10 and 16 hours were only typically below 5%. Furthermore, I noticed that some major faults, which caused by short-acting dynamic changes, can incorporate into the forecasting and later cause an opposite distortion. In Fig. 5 the measured values and the experienced prediction errors of the equivalent peak load hours also are shown. The forecast distortion and oscillations are well-observed. For the oscillation damping it may be sufficient to use some real-time measurement of the typical conditions (light intensity, wind speed, spectral conditions), because of the real-time tracking could be useful to filter the 'mutations effects' with following there lifetime.
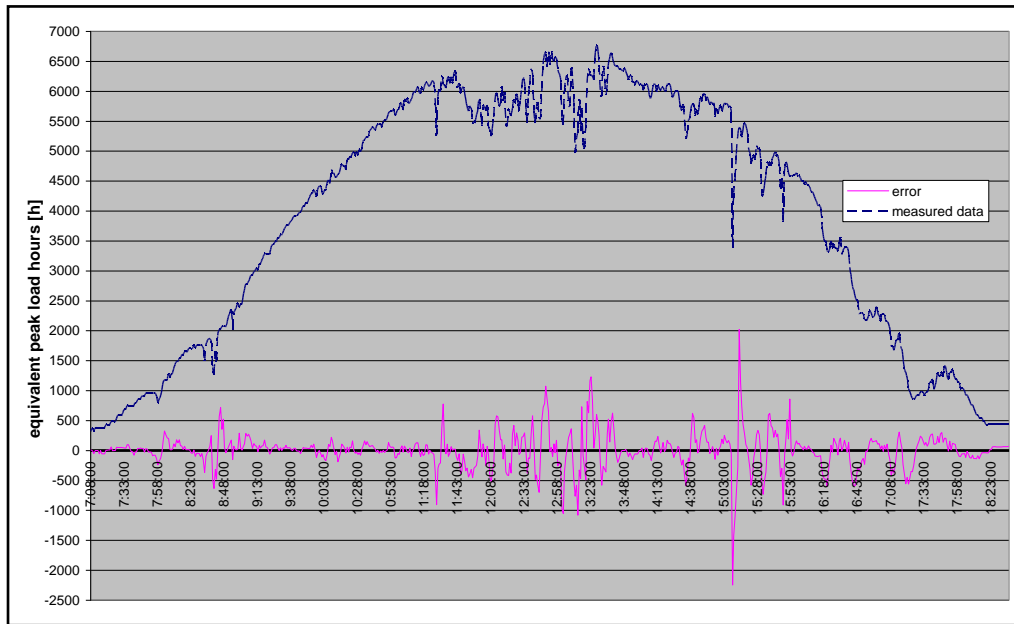
Fig. 5. Forecasts absolute errors and measured real values on 1 April, 2014

The relative errors of the series of experiments between 10-16 hours are shown in Table 2.

Table 2. Absolute values of the relative errors between 10 and 16 hours

Examined days in 2014	The mean absolute relative error, %	Error greater than 15% frequency, %	Error between 10%-15% frequency, %	Error between 5%-10% frequency, %	Error less than 5% frequency, %
IV.01.	4.34	4.43	5.26	19.11	71.19
IV.20.	20.68	30.47	13.02	16.07	40.44
V.01.	17.18	26.59	12.47	22.71	38.23
V.20.	34.56	15.51	0.55	4.16	79.78
VI.01.	28.74	54.85	12.19	13.57	19.39
VI.14.	55.75	47.92	5.54	12.47	34.07
VII.20.	3.87	3.60	1.39	4.99	90.03
Average	23.6	26	7	13	53

This 18.6% average error (and also the 23.6% average error between 10 to 16 hours) is too high value. But due to the above identified oscillation effects, these values can be improved. In addition, because the positive and negative alternately oscillations of the prediction errors, the forecast of a longer period will give a significantly lower relative errors. All in all, this prediction methodology is really applicable by the small scale photovoltaic systems.

For the forecast reliability the "mutations" frequency and variability of radiation conditions are determining. Therefore I created an indicator, which is characterized by a given period and its value express the variation frequency and size a complex way. I found the correlation between this indicator and reliability of the forecast method, so it was possible to determine the confidence interval between the indicator and reliability of the prediction method. This indicator is based on partly from the length of the given day or the period of day and secondly from the frequency of the dramatically high performance changes (as compared to previous minute) during the day or the given period of the day. The determination of the coefficient of variation is shown in Table 3.

Table 3. Determination of the coefficient of variation

	Number of the AC performance changes compared to previous minute, piece/day								The coefficient of variation V_{day}, unit/day
	Reduction				Increase				
	Over 55%	Bet-ween 35%-55%	Bet-ween 15%-35%	Bet-ween 5%-15%	Over 55%	Bet-ween 35%-55%	Bet-ween 15%-35%	Bet-ween 5%-15%	
2014.	a_1	a_2	a_3	a_4	b_1	b_2	b_3	b_4	**Daytime**
IV/01.	0	1	2	55	0	0	9	51	131
IV/20.	8	8	40	71	16	11	40	76	460
V/01.	2	6	21	68	5	4	19	65	271
V/20.	11	6	10	47	19	3	10	34	268
VI/01.	3	7	34	108	12	9	38	106	466
VI/14.	20	19	29	61	35	10	29	54	538
VII/20	2	0	7	26	3	0	6	23	95

Determination of the coefficient of variation is shown in the equations (7) and (8). I used the specific coefficient of variation for the evaluation of the reliability of the new predictive methodology, which means the hourly average value of the coefficient of variation.

$$V_{nap} = 4a_1 + 3a_2 + 2a_3 + a_4 + 4b_1 + 3b_2 + 2b_3 + b_4, \tag{7}$$

$$V_{nsz} = 4a_{1'} + 3a_{2'} + 2a_{3'} + a_{4'} + 4b_{1'} + 3b_{2'} + 2b_{3'} + b_{4'}. \tag{8}$$

3.2. Predictability of the average 15 minutes period performance by the small scale power solar systems

I prepared five minutes before the end of each 15 minutes period for the average AC performances of this period. I used only five pieces measured data (the first five minutes performances) and ten predicted performance data (from 6. to 15. minutes on the period) based on the new performance forecasting method according to previous (3.1.) point. The results of a very variable day can be seen in Fig. 6.
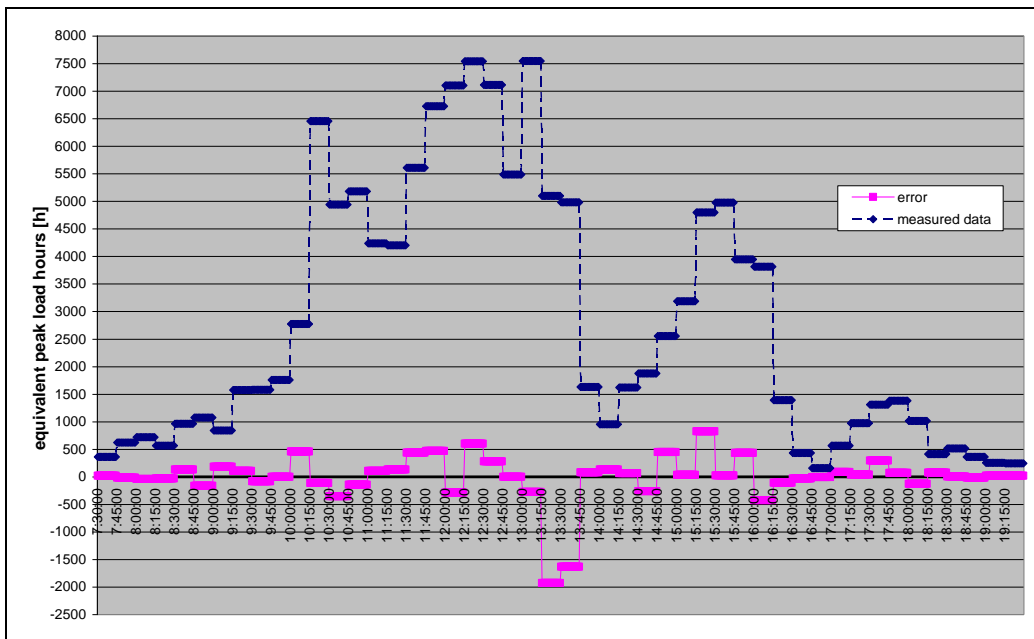
Fig. 6. Prediction errors by the dynamic schedule keeping performance forecasts and the measured values (1. June 2014)

During the researched seven day the average relative error was below 6%. In three days of the seven all errors by each period between 10 and 16 hours were below than 10%. On average of these seven days, the predictions errors remain below 5% with 65% probability. I have proved if the specific coefficient of variation is 23.65 unit/hour, then the average error of the forecast is between 3.54-6.46%. And it has been also proved that if the specific coefficient of variation is 16.61 unit/hour or less, then the average relative error of the predictions is less than 5%. I have also proved that the average relative error of the forecast is below 5% in significant part between 10 and 16 hours and it can be achieved that the average relative error is between 5-7% by this invented new method.

3.3. Group level forecast based on Power plants' performance

One of the main basic of the group level forecast is the new short term prediction method for the performances of the PV system as before. Secondly, the errors between the new dynamic forecasted performance and the expected from physical models forecast is largely the unusual result of more unexpected outside physical impacts (the error as a genetic-based property can be detected). The third assumption is that those external impacts reach the nearly similar systems closely in the same period and it can be caused similar effects.

In the case of a monitored, reference power plant, I determined the differences between the new dynamic way forecasted and the physical model expected performances. Based on these differences by reference system and the physical modeled expected performances by other system, I anticipated the predicted error of the static physical based modeling error. Then I have delayed the forecast for the foreseeable mistake of modeling and I made a dynamic forecast for other systems without monitoring. By aggregating them I got to group level projections. The group level forecasts were analyzed for two different composition-type groups. The 5 minute prediction errors are given in Table 4 This shows the evaluations of the forecast methodology for the schedule keeping with five minutes before the end of the fifteen minutes periods. In order to make comparisons I show also the errors of the own performance predictions for the reference system alone.

Table 4. PV group level evaluation of the forecast methodology for schedule keeping

2014	Evaluated period	The average of the absolute values of deviations with equivalent peak load hours, h			The average of absolute relative errors, %		
		Refe-rence system	Homo-geneous group	Hetero-geneous group	Refe-rence system	Homo-geneous group	Hetero-geneous group
IV/01	7:08-18:36	73	79	89	2.64	3.01	3.42
	10:00-16:00	87	90	102	1.55	1.60	1.77
V/20	6:25-19:09	189	473	331	5.26	9.78	9.51
	10:00-16:00	260	665	466	4.36	9.65	7.67
VI/01	7:34-19:14	242	273	429	9.00	11.28	19.55
	10:00-16:00	397	402	567	9.29	8.94	14.81
VII/20	6:32-19:14	104	61	161	4.03	1.86	4.78
	10:00-16:00	175	80	214	3.87	1.31	3.47
Ave-rage	**All daytime**	**152**	**222**	**253**	**5.23**	**6.48**	**9.32**
	10:00-16:00	**230**	**309**	**337**	**4.77**	**5.38**	**6.93**

3.4. Qualification of photovoltaic systems network integration authority

I used publicly available and easily accessible data to create the indicators for the qualification system. The assessment is based on the fixed hourly performance data and the daily data on the AC electricity generation with the knowledge of the systems' rated data. I have defined the following indicators:

- peak time variability;
- linearity;
- peak height;
- peak cuts efficiency.

The results of the testing the indicators are summarized in Table 5.

Table 5: The inerrability indicators

Indicators	Explanations	PV system in Vácrátót	Units
Peak time variability	standard deviation of the hourly average performances and the nominal PV (peak) power ratio (May-August)	35	W/kW_P
Linearity	Linear gradient of the hourly AC performances with linear regression at absolute value (May – August)	13	$W/kW_P/h$
Peak height	The height of the triangle formed on the basis of the maximum hourly AC power and its preceding and following hourly powers (May - August).	44	W/kW_P
Peak cuts efficiency	The quotient of the difference of the specific daily yields by clear sky in June between the certified system and a reference system and the differences of the Peak height between the certified system and a reference system. The reference system is an existed PV system installed (first of all by optimal orientation and tilt angel) for the maximum annually energy production)	7.70	kWh/ kW/d

The result of the study is the creation of a new methodology, which can evaluate and qualify in a transparent way the different construction solutions of the PV systems according to the grid integration. So this PV architecture certification can define the system-friendly photovoltaic system installation methods. Indicators can be verified by measurements and the results can be generalized. Therefore the indicators are suitable for the objective and comparable certification of each PV installation type solution.

3.5. A numerical complex decision support methods for the optimization of the target by renewable structure

By developing a renewable energy target structure for strategy or political aims it requires to make choice between different renewable energy technologies and sources. This choice can be made through several approaches and it is often the result of political weighting and non-objective, non-transparent evaluation. To address this problem, I developed a numerical optimization method based on more fixed and transparent decision-making criteria and weights.

The numerical task is to combine the three, earlier presented extreme versions to produce a large number of variants, modelling the effects of these variants and eventually ranking them based on the expectable output (result) indicators. I defined five different parameters for the combination procedure. Three of these parameters always show the proportions, what percentages were taken into account in the combination. Their sum is one.

The remaining two parameters show the ratio, how the two combining methodologies are used in the combination. So their sum is also one. Following the one type of combination transformation, all the technologies already accepted which was earlier in any extreme versions. But earlier the whole achievable energy potentials of the accepted technologies were the aims in the extreme versions, after the transformation the individual technology goals are reduced proportionately. During another type of transformation some technologies with lower priority in the extreme version, which earlier have been accepting, fall out from the aims. But what could remain, it remains at its full achievable potential value.

The results of each transformation can be written in matrix form. Before the versions are finalized it also needs attention to the accumulations and the discreetly dependent on the numbers of the highest capacities technologies. By accumulated analysis with the characteristics and the impact indicators of each technology it can be generated the impact matrix behind the alternative variations. Knowing this impact matrix and create some selected result indicators each version can be evaluated and ranked.

The numerical transformation is illustrated in Table 6.

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Table 6. Combination possibilities between the extreme optimal versions

Rank	Number of the technology	The achievable energy potential	Recommended target by an extreme optimal versions	The remaining goals after the α type combination	The remaining goals after the β type combination
1.	N_1	P_1	P_1	αP_1	P_1
2.	N_2	P_2	P_2	αP_2	P_2
...	...	...	...	...	...
H	N_h	P_h	P_h	αP_h	λP_h
I	N_i	P_i	P_i	αP_i	0
...	...	...	...	...	...
M	N_m	P_m	μP_m	$\alpha\mu P_m$	0
N	N_n	P_n	0	0	0
...	...	...	...	...	...
Z	N_z	P_z	0	0	0

During the research and development in 2010 I used the following result indicators to evaluate the various versions:

- Total support needs by 2020;
- Financial feed-in framework for the operation maintenance support in 2020;
- All job creation by 2020;
- Total greenhouse gas reductions by 2020.

4. NEW SCIENTIFIC RESULTS

The scientific results of my research can be summarized as follows:

1. New dynamic performance prediction method of solar photovoltaic systems

I developed a new performance forecasting method for short-term forecasting of solar power systems, which I called a dynamic error signal driven forecast. The method uses a genetic algorithm approach to produce predictions from performance data during a previous sampling period. Differences between the measured and the expected performances on the basis of the physical model show the complex unusual, unexpected circumstances and processes. Therefore the dynamic error series in the sampling period illustrates complex effects, as the potential for genetically encoded features for the future. The statistical evaluation of the error series allows the determination of possible errors of the physical-based predicted performance values at a nearby future time. By decoding the most likely error value the dynamic performance prediction can be made. I have defined the following relationship for the most probable value of the specific error of the physical-based expected performance in the future (at t time) expressed by equivalent peak load hours:

$$H_t = H_{t-1}(1+\frac{dH}{dt}) \approx H_i(1+\frac{dH_i}{dt})^{\frac{\Delta t_{t-n}}{60[s/\min]}} \approx H_i(1+\frac{\Delta H_i}{\Delta t})^{0,4\frac{\Delta t_{t-n}}{60[s/\min]}}. \quad (9)$$

2. Predictability of the average power of a solar PV system in a given period

I worked out a new dynamic data driven forecast method for an average PV system performances in a given fifteen minutes scheduled periods with using partly by measuring and partly by predicted data for the average performance. I have proven that, under suitable conditions, the prediction can be made with a relative error of less than 5% at five minutes before the end of the period with five measured and ten predicted performance data. Furthermore I have also justified that, the average relative error is close to 9% even by the strong variable light conditions. I introduced a new parameter to test the reliability of the forecast, which I called the specific coefficient of variation factor:

$$v_{day} = \frac{V_{day}}{\Delta t} = \frac{(4a_1 + 3a_2 + 2a_3 + a_4 + 4b_1 + 3b_2 + 2b_3 + b_4)}{\Delta t}. \quad (10)$$

This factor expresses the volatility of the solar PV operation and the predictability of solar power during a given period of time. I verified the strong correlation between the average relative error of the forecast and the specific coefficient of variation factor by 95% confidence.

3. Group level forecasting based on real-time monitored reference PV system and group level real-time monitoring reliability

I have verified by my research that a reliable forecast can be made for a physically or only virtually connected solar PV system groups with a real-time performance monitoring of a single reference PV power system and with the application of my developed new dynamic data driven forecasting method. In addition, I have found that good real-time value for the performance can be calculated for a PV system group based on the reference PV plant with the errors between the real-time monitored performances and its expected values from the new dynamic data driven forecasting method. Furthermore, I proved that the reliability of the new forecasting and the new real-time monitoring methods for the PV system groups depends on the homogeneity of the group.

4. Qualification of network integrity of photovoltaic systems

With changing the inclination angels or the orientations by the installed PV panels it can be created a more favourable system (grid) level state, which is different from the local optimum of the individual electricity production. I have made an objective rating system for the construction solutions of each photovoltaic system with developing and testing an integration-friendly PV system. This is suitable for classifying the installation variants in view of the negative impacts on the stability of the public network system.

I introduced the F_4 peak cuts efficiency index, which evaluate the technical cost of integration-friendly PV systems installation solutions:

$$F_4 = \frac{\overline{E}_R - \overline{E}_{PV}}{F_{3,R} - F_{3,PV}} \; . \tag{11}$$

This is a new indicator, which is suitable for the comparable determination of the technical costs of cutting the peak power in kW/kW_p dimension. So this indicator is suitable for qualifying the architectural solution which was used because of the improvement of the integrability of PV system to assess the specific decrease of electricity production ability.

5. Numerical decision support system for optimizing the target for renewable energy

I have worked out a new decision-support numerical optimization method, which is able to assess together with the cost-effectiveness, the direct social impacts (job creation) and the environmental aspects (greenhouse gas emission reduction). This method is suitable for defining an optimum renewable energy targeting structure in accordance with the open, transparent and predictable weights of each decision-making aspect (preferences).

I have verified that these extreme versions developed according to the selected main priorities can be combined numerically and with this combination based on systematic changing of some input indicators it can be create a wished number optional targeting variations. These different versions are able to evaluated and ranked by the decision weights based on result indicators from the modelling data. This requires that the maximum and minimum values of the E_{tg} values will be determined independently of the decision support system. I set the following target function for the optimization procedure depending on the input indicators:

$$E_{tg} = \alpha_1(P_1^I + P_2^I + .. + \mu^I P_m^I) + \alpha_2(P_1^{II} + P_2^{II} + .. + \mu^{II} P_m^{II}) + \alpha_3(P_1^{III} + P_2^{III} + .. + \mu^{III} P_m^{III}) +$$
$$+ (P_1^I + P_2^I + .. + \lambda^I P_h^I) + (P_1^{II} + P_2^{II} + .. + \lambda^{II} P_h^{II}) + (P_1^{III} + P_2^{III} + .. + \lambda^{III} P_h^{III}).$$

$$(12)$$

The developed optimization method is suitable for finding optimal and objective strategic goals for each renewables energy technology based on their technical characteristics at regional, national or international level. The decision support system is objective and transparent, because it does not allow the arbitrarily determinations of the technological targets. Only the predefined boundary conditions and clear preferences are the determinants.

5. CONCLUSIONS AND SUGGESTIONS

The results of my research provide solutions and directions for further progress. My suggestions and conclusions are divided into three parts.

The genetic algorithm approach, the predictive dynamic data driven forecasting techniques are becoming more and more accepted today. However rare is this solution, which does not have a large and expensive numbers of measured or long term empirical parameters which has to be used by the dynamic models. I think this is a good solution by forecasting used only the expected data from a simplified typical meteorological year with only approximate punctuality and based on real-time performance measurements only by one selected reference PV plant. Thus, it can be avoiding the determination the typed conditions with using costly available, huge numbers (15 to 20 parameters generally) historical data. During my research, I have also mentioned so directions that would improve the further applicability and reliability of the new researched forecasting methodology according to the above approach. From these directions, the real-time measuring the radiation intensity by reference system seems to be a good direction, in which the degree and frequency of dynamic changes in intensity are essential information to improve the forecasts. So it seems that in the case of short-term forecasts, only the real-time meteorological measurements can already be sufficient and cost-effective solutions. According to similar principles, the developed predictions of individual photovoltaic systems can help to implement predictive controls, but the reference system based group level forecast can be a cost-effective solution for smart grid systems

To further define the integration-friendly classification of smaller photovoltaic systems for the public utility network, further studies are desirable. The various typable technical and architectural solutions needed to evaluate. After this the better installation solution types can be evaluated and facilitated.

A transparent definition of economic, social and environmental goals is a major demand by the different renewable technologies at the international, national and regional level, too. By the application of the developed numerical decision support system they cannot be dispensed the details definitions of the potentials, costs, social and environmental impacts of relevant renewable technologies. With these the rational, transparent and optimal targeting can be ensured. The numerical optimization process proved to be ready and applicable in the elaboration of the Hungarian Renewable Energy Action Plan in 2010.

6. SUMMARY

The technological development of photovoltaic systems reached a new level from the former marginal position with their increasing weight in the world's electricity production. The high potential of solar energy and their almost everywhere possible applicability projects that the future importance of PV's will grow even more. The dissertation shows that this intensive process to effect complex positive social and environmental aspects. In addition to the highly variability together with the wind energy is a major challenge for the stabile and safe operation of the electricity network. It shows why the network integration difficulties are perhaps the greatest barrier to the further expansion of PV technology. Therefore a key factor is the forecasting possibilities of the variable energy production. The dissertation presents the main types of various forecasting techniques and also shows a variety of possible forecasting purposes. I also discuss the basic knowledge for the analytical determination of the solar energy potential.

My presented research strongly connected to the issue of solar integration. I examine this problem of integration of the three sides. On the one hand I deal with smart, efficient use of forecasting options. Secondly, I research in the area of the application installation of photovoltaic systems in order to reach a bigger PV produced electricity ratio in a given grid. Thirdly, I deal with the use of transparent social and environmental benefits to decision-making processes

The dissertation presents a new dynamic data driven forecasting method, which is created for a very short period prediction to the performance of small PV systems. The method is developed and applied not only for a performance prediction, but also for the scheduling periods with their average performances. For the variability new indicators are created. I can evaluate the reliability of the forecast method context with this new indicator. The presented measurements and evaluations were performed for individual systems, but I also extended these to a two different groups of PV systems.

By a presented pilot project the research purpose was to create a small PV system to reach a more grid favourability. Measurement data of this sample small plan is compared to a typical reference system. Based on this comparison the scientific framework of a new assessment method is defined. The usability of this evaluation method was proved and in addition a new index was created to measure the cost-effectiveness of system friendly solutions.

Furthermore, in the dissertation I present a created numerical optimization mathematical method with the economic, social and environmental aspects.

In my work, I present the research locations, the methodologies, the results and my established thesis as described above.

7. THE MOST IMPORTANT PUBLICATIONS RELATED TO THE THESIS

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