Usage of Cloud Tracking Solar Forecasting Methodology in Power System Operation

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ABSTRACT
The impact of intermittent power production by Photovoltaic (PV) systems to the overall power system operation is constantly increasing and so is the need for advanced forecasting tools that enable understanding, prediction, and managing of such a power production. Solar power production forecasting is one of the enabling technologies, which can accelerate the transition to sustainable energy environment. Short-term forecast information on the expected power production can assist existing forecasting techniques and enable efficient integration of renewable energy sources through the efficient energy trading, power system control and management of energy storage units.

The paper presents an approach to predict regional PV power output based on short-term solar forecasting by the use of ground-based camera and analyzes the benefits of such forecast to the power system operation.
In the proposed research, analysis of the commonly used forecasting methods with added precision of the short-term forecasting was made. Cost-effectiveness was calculated with different scales of a power plant. An overview of the benefits for the transmission system operator is given. This overview considers the ways in which short-term forecasting can improve the efficiency of power management in an electric grid.
A system cost-effectiveness analysis was carried out for electricity producers that can use this system to generate better forecasts for the production of electricity and thus reduce penalties for non-compliance with the anticipated production.

KEYWORDS
Short-term forecast, cloud tracking, PV integration, variable/renewable generation, power system control.

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**INTRODUCTION**

The negative climate impact of traditional energy sources leads to enhanced integration of renewable energy sources (RES) in the electric grid. The enhanced integration of renewable sources brings with it the uncertainties in the available generation. In particular, grid dependency on weather conditions grows as the share of RES in the grid increases, and in turn, that results with the more unpredictable electricity generation. The demand side of an electric grid is also weather-dependent not only as a result of the increase or decrease in the energy needed for the household heat management systems but also in turns of energy consumption increases to compensate for the reduction in local energy production.

To compensate for the changes in power consumption there is a need for the controllable energy sources. Some of the energy sources use technologies that can be scheduled. For fuel-based technologies, there is a possibility to manage the storage and usage of the resource, as is the case for most thermal and some hydropower generation technologies. But for other technologies, it is impossible to control the resource, as is the case for wind and solar photovoltaic technologies. In these cases, where the resource used for energy production cannot be controlled, other methods for controlling power plants power output are used. One of the ways to control power output is to not exploit the available energy potential i.e. curtailing power production. That means limiting the output of the renewable sources power plant to avoid excessive power production in the energy system. Another method is to forecast resource availability and prepare the grid for upcoming events in power production [1]. That is why forecasting has become a key component of power system planning, in order to cope with the uncertainty in the production and demand of electricity. It is used in several applications such as reserve planning and activation, operational planning, electricity trading, short-term power trading, congestion management, etc.

A solar photovoltaic (PV) system can operate in island mode or grid-connected. The islanded system normally consists of a micro power source (solar), battery storage unit and local loads. However, most of today PV installations are grid-connected systems composed only of PV panels and a grid-tied PV inverter. When connected to grid, the operating conditions of the grid are altered in either positive or negative way. Some of the examples of positive alterations are the reduction of transmission line loads and increased voltage stability while the negative alterations consist of unwanted frequency and voltage oscillations [2].

There has been rapid increase of grid connected solar PV power in rural, urban and city areas around the globe (e.g. Sweden, Germany, India and some parts of Africa) [3]. This is to enable solar PV systems to supply generated power locally and to other places through the existing transmission and distribution grid. This integration of solar PV power can result in improvements of the grids or can have negative impacts on the steady state system operation parameters.

Integration of solar power can have an impact on the power reliability due to variations in power production and this could, in turn, impact the voltage profile, voltage stability and protection of transmission and/or distribution grid [4].

In this paper, methods for predicting the production of solar panels are explained and an analysis of the annual solar energy production on a particular solar power plant is made. An analysis of two typical cloudy days is carried out and used to make an analysis of the economic viability of the short-term forecasting system.
WHY SHORT-TERM SOLAR FORECASTING?

Most of the forecasting research that has been performed in the context of the power system planning and operation has focused on four key variables: electricity demand [5,6], electricity prices [7,8,9], wind-based generation [10,11], and solar-based generation [12]. These four quantities are arguably the most important for utility companies and transmission system operators.

For the transmission system operator, knowing the demand of electricity is paramount for power system planning, congestion management, reserves purchasing, and ensuring that costs are minimized while demand for electricity is ensured. Similarly, utility companies might also benefit from electricity demand forecasting in several ways, e.g. operational planning, optimized use of battery storage. Short-term forecasting can improve existing forecasting methods with the introduction of greater temporal precision.

With the increasing integration of RES, the volatility of electricity prices has surged. That is why accurate forecasting of electricity prices is of paramount importance to utility companies for successfully trading electricity, programming backups, and scheduling processes.

In the European Union, wind and solar-based generation respectively, represent the second and third largest share of RES, only after hydropower, which is not relevant in this case due to its relatively stable nature.

Local use of solar-based generation translates to the more unstable demand power curve with limited possibilities to forecast it. Short-term solar forecast based on cloud imaging can be used in a system that covers the entire city area and thus can more reliably forecast short-term drops in solar radiation and with it a correlating burst in energy demand.

As a result, accurate forecasting of solar generation is crucial for both the transmission system operator and utility companies. As before, the transmission system operator needs to forecast the solar generation in order to purchase reserves, anticipate possible congestions, scheduling power systems, etc. Likewise, for utility companies, these forecasts are essential in order to perform power trading and process planning.

The difference between long and short-term forecasting

Forecasting methods are typically divided into two groups considering the prediction horizon. Those groups are usually forecasts that are made for short-term horizons and forecasts for long-term horizons. Although this separation is present across the different forecasting fields, the meaning of short-term vs long-term does not have a standardized meaning.

Regardless, short-term forecasting typically implies prediction horizons that range from a day-ahead to nearly real-time, while long-term forecasting usually refers to months and years ahead. In addition, short-term forecasting is usually employed for day to day trading while long term forecasting typically involves strategic planning.

In contrast, when referring to solar generation, models used to predict the weather dictate the division between short and long-term forecast. Short-term forecasting is characterized by forecasting techniques based either on time series models using ground data or on cloud vector models using satellite images and by prediction horizons below 6 hours. When the prediction horizon is larger than 6 hours, the described techniques are no longer accurate, and with the new time frame, numerical weather-based models are also required. In particular, numerical weather-based models are employed to forecast solar radiance ranging from 6 hours to 1-2 weeks ahead.

Electricity price is an important signal for all participants of the electricity market and the motive behind most of their activities. Price forecast plays a major role in today's power markets and is the key input data for market participants. Companies that trade in electricity markets make extensive use of price forecast techniques either to bid or to hedge against volatility.
However, despite the importance of electricity price prediction, it is a complex signal for forecasting.

Power system frequency stability requires constant balance between generation and load. On short timescales, most users of electricity are unaware of or indifferent to its price. Moreover, on a short timescale, transmission bottlenecks may prevent free exchange among different regions. These facts lead to extreme price volatility or even price spikes in the electricity market. Besides, volatility in fuel price, load uncertainty, fluctuations in hydro-electricity production, generation uncertainty (outages), and behavior of market participants also contribute to electricity price uncertainty [1].

The electricity price signal features extreme jumps of magnitudes rarely seen in financial markets that also occur at greater frequency. Amjady and Hemmati have discussed how the uncertainty of hourly loads and some other stochastic signals, such as equipment outages and fuel prices, are combined resulting in a higher level of uncertainty in the electricity price [13]. Additionally, electricity price is a nonlinear time variant mapping function of its input features which nonlinearily changes with respect to variations in the inputs. For instance, load demand is an important driver for electricity price. However, load variations in low-load and high-load levels have different impacts on the electricity price. Moreover, its time-variant nature is related, for instance, to discrete changes of participants, strategies (e.g., agents decide to switch from a conservative behavior to a more aggressive or risky one) or to changes in market regulations. A discussion on the other characteristics of electricity price time series such as multiple seasonality (e.g., daily and weekly periodicities), high-frequency changes, and high percentages of unusual prices (outliers) can be found in Reference [13].

Overview of Electricity Price Forecast Methods Importance and complexity of electricity price forecast motivate considerable research. For short-term price forecast, forecast step is usually from a fraction of an hour (e.g., 5, 15, and 30 min) to an hour. Its forecast horizon can be from 1 h ahead to 1 week ahead. However, the most common forecast horizon for short-term price forecast is the next day, used in day-ahead electricity markets. Due to the diverse nature of short-term electricity price forecast methods, a classification of these techniques can give a better insight about them. However, one point should be mentioned here before proceeding to the classification of the price forecast methods. An essential characteristic of the electricity markets is the pricing mechanism, which can be uniform or pay-as-bid pricing. Under the uniform pricing structure, the marginal bid block sets the market clearing price (MCP). In the presence of congestion in the power system, locational marginal price (LMP), which is the marginal cost of each bus, should be considered instead of MCP. However, in the pay-as-bid (discriminatory) pricing structure, every winning block gets its bid price as its income. The pricing mechanism can affect the competition, efficiency, consumer surplus, and total revenue of the players in the electricity markets, [1].

Classification of Price Forecast Methods A lot of forecast methods have been proposed for prediction of MCP or LMP of electricity markets in the literature. Some of these methods are basically the short-term load forecasting (STLF) methods. However, electricity prices are usually more volatile than hourly loads and so short-term price forecasting is more complex than STLF. In general, electricity price forecast methods can be divided into two main categories. Methods of the first category try to directly predict electricity price by analyzing the electricity market dynamics and effective parameters on the market price, such as production costs and strategic behavior of market participants. An important group of these methods is based on the game and auction theories. Another group consists of fundamental or structural
models, based on traditional cost models, which have been developed for centralized systems and adapted to liberalized markets. Methods of the second category try to forecast MCP without analyzing in detail the underlying physical processes. These methods, based on the black box models, analyze price evolution by means of statistical data. Methods of the second category, such as those based on the time-series techniques and neural networks, are more commonly used for electricity price forecast than those of the first category, due to greater flexibility, less input data is required, and adaptability is greater to the market participants' conditions. A similar and more detailed classification of electricity price forecast methods has been presented by Weron, where the methods are divided into six classes including production cost (or cost-based) models, equilibrium (or game theoretic) approaches, fundamental (or structural) methods, quantitative (or stochastic, econometric, reduced form) models, statistical approaches, and artificial intelligence-based techniques. Among these methods, artificial intelligence-based techniques have received more attention in recent years because of their high ability to tackle nonlinear complex input/output mapping functions with limited available data. For instance, Guo and Luh have discussed how neural networks are universal approximators and can approximate any continuous function, [1].

COLLECTION AND ANALYSIS OF DATA

Statistical information
In order to conduct an analysis of the economic viability of the system for the short-term photovoltaic forecast, the collection of the input data is required. Input data consist of the number of cloudy days per year and variations in the photovoltaic power generation during those cloudy days. Once the input data is determined, it is possible to calculate average daily energy that needs to be replaced by the use of other energy sources such as peaking power plants. Generation of electricity in such power plants is more expensive than the production of the same energy in the base power plants, which leads to an increase in electricity prices.

By analyzing the derivation of power production in time, data is collected on the number of power output changes during the day, as well as on the magnitude of each such change. With this information, it is possible to determine the amount of energy that needs to be compensated for by the addition of some other energy sources.

Number of overcast days
Daytime is the period of the day during which the observed location experiences direct sunlight. The length of the daytime depends on the geographical location and the time of year. Using that information and the weather information for certain regions it is possible to get the average number of sunshine duration in hours per year. Figure 1 shows a map of Europe with a chart showing the sunshine duration in hours per year in different parts of Europe.
In this paper, the sunshine duration of the city of Rijeka, Croatia, is used. The data is collected from the site Current Results/weather and science facts [15] that provides useful summaries of published data and research papers regarding weather data.

Table 1 gives yearly averages of how much sunlight urban areas get in the Republic of Croatia. The table gives three distinct values as a “measure of sunlight” for selected cities. The parameter “% Sun” represents the usual percentage of daylight hours during daylight. “Hours” gives the total hours of sunshine annually. “Days” is the typical number of days on a per year basis when clouds covered the sun for no more than 20% of the time. The weather data presented in Table 1 is calculated on the basis of data collected during the period from the year 1971 to the year 2000. Data shown in the table suggests that sunshine duration varies greatly among cities in a relatively small region. In this paper data measured at the meteorological station shown in Figure 2, which is located on the main building of the Faculty of Engineering, University of Rijeka, 80 meters distant from the solar power plant whose data is used in further analysis.

Table 1. Meteorological data for selected cities in the Republic of Croatia [15]

<table>
<thead>
<tr>
<th>City</th>
<th>Rijeka</th>
<th>Hvar</th>
<th>Zagreb</th>
<th>Varazdin</th>
<th>Osijek</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Sun</td>
<td>55</td>
<td>65</td>
<td>47</td>
<td>51</td>
<td>45</td>
</tr>
<tr>
<td>Days</td>
<td>76</td>
<td>124</td>
<td>49</td>
<td>56</td>
<td>72</td>
</tr>
<tr>
<td>Hours</td>
<td>2190</td>
<td>2738</td>
<td>1898</td>
<td>2008</td>
<td>1898</td>
</tr>
</tbody>
</table>
Analysis of data collected by the meteorological station suggests that during 2018 there were 145 cloudy days at the location of the solar power plant. This data will be used for further analysis although the number of cloudy days during the year varies with respect to the observation site and the year for which the data were collected. The total yearly number of cloudy days was determined by comparing the produced energy for each day of the year with the produced energy of the first adjacent day for whom recorded data suggest clear sky weather, therefore maximum possible production. If the energy produced on that day was less than 50% of the nearest sunny day energy production, it was assumed that the day was cloudy.

**PV plant’s power output fluctuation during cloudy weather**

The dynamic nature of the analyzed system requires a high data-sampling rate in order to observe all transients in power production. Such data is used to determine the frequency of occurrence of changes in production, the absolute value of that change and the speed at which the PV plant power output changes. The data-set used for the analysis was obtained from measurements performed at the Riteh-1 PV power plant, located in front of the Faculty of Engineering, University of Rijeka shown in Figure 3. The rated power of the PV plant is 3.5-kilowatt (kW). The PV panel are mounted on a dual-axis solar tracker system [16], which can be seen in Figures 4 and 5. The data was measured with a 45-second time interval from 22/03/2019 to 13/04/2019. The data measurement period is suitable for analysis since there was a large diversity in weather conditions within a relatively short period of time. Of the 22 days for which the data were measured at the high temporal resolution, 14 days were partially cloudy, which is a sufficient data-set in order to perform the analysis.
For the calculation two characteristic weather-condition days are used. The first characteristic day was a day with clear sky and occasional clouds casting shadow on the power plant, and the other one was an overcast day with occasional sunlight reaching the power plant. Graphs that show power production on these two “characteristic days” are shown in Figures 4 and 5. The number of clouds passing above the solar power plant varies considerably from day to day, therefore for the research purposes in this paper, the number of clouds passing for the characteristic days of 28/03/2019 and 3/04/2019 will be used. On the 28/3/2019 there has been a large number of small clouds passing over the PV plant, which results in a large number of significant changes in energy production with each individual change having a short duration. The graph presented in Figure 4 shows numerous changes in power production for the selected day.

The second characteristic day, 4/03/2019 shown in Figure 5 is a day that was completely cloudy but had periods in which there were short breaks in the cloud layer leading to spikes in production. That day is also used for the analysis in the scenario when there is not only a decay in power production but also a sudden increase.

The second graph in Figures 4 and 5 shows the time derivative of power production that gives changes in production for characteristic days. The time differential $\Delta t$ is 45 seconds, the same time that is used for capturing the data. The graphs show a large number of changes in power production level that have a large amplitude compared to production before and after the change.
Figure 4. Power generation and its time derivative on a partly cloudy day
Figure 5. Power generation and its time derivative on an overcast day

The threshold values of power production magnitudes, used in further analysis, are shown in Table 2. The second row gives relative values of the threshold values. Various applications such as electricity generation forecasting, energy storage requirements calculation, rotating reserve level selection, and voltage stability calculations use different amplitudes of power change as the lower limit of input data. For this reason, production changes are classified according to different values so that the obtained results can be used in different applications such as reserve planning and activation, operational planning, electricity trading, short-term power trading, congestion management, etc.

Table 2. Thresholds used in calculations

<table>
<thead>
<tr>
<th>Power (W)</th>
<th>2500</th>
<th>2000</th>
<th>1500</th>
<th>1000</th>
<th>700</th>
<th>350</th>
</tr>
</thead>
<tbody>
<tr>
<td>P / Pn (%)</td>
<td>71.43</td>
<td>57.14</td>
<td>42.86</td>
<td>28.57</td>
<td>20.00</td>
<td>10.00</td>
</tr>
</tbody>
</table>

Table 3 shows the number of transients in electricity production level recorded for the solar power plant during the two characteristic days described above. The first column shows the amount of power change within 45 seconds while the second and third column shows how many times that change occurred on a given day. The second column depicts the data for case A, a partially cloudy day (data recorded on 28/03/2019), while the third column depicts the data for case B, an overcast day (data obtained on 3/04/2019).
Table 3. The number of transients in case A and B

<table>
<thead>
<tr>
<th>Change in power production ($\Delta P$)</th>
<th>Case A ($n$)</th>
<th>Case B ($n$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta P &gt; 2500W$</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>$2000W &lt; \Delta P &lt; 2500W$</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>$1500W &lt; \Delta P &lt; 2000W$</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>$1000W &lt; \Delta P &lt; 1500W$</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>$700W &lt; \Delta P &lt; 1000W$</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>$350W &lt; \Delta P &lt; 700W$</td>
<td>18</td>
<td>4</td>
</tr>
<tr>
<td>$-700W &lt; \Delta P &lt; -350W$</td>
<td>16</td>
<td>12</td>
</tr>
<tr>
<td>$-1000W &lt; \Delta P &lt; -700W$</td>
<td>5</td>
<td>16</td>
</tr>
<tr>
<td>$-1500W &lt; \Delta P &lt; -1000W$</td>
<td>12</td>
<td>2</td>
</tr>
<tr>
<td>$-2000W &lt; \Delta P &lt; -1500W$</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>$-2500W &lt; \Delta P &lt; -2000W$</td>
<td>11</td>
<td>1</td>
</tr>
<tr>
<td>$-2500W &lt; \Delta P$</td>
<td>13</td>
<td>0</td>
</tr>
</tbody>
</table>

To compare the energy levels for periods in which changes occur, it is necessary to calculate the total production energy and the lack of production compared to the last produced energy of the solar power plant when the day was cloudless. The values in Table 4 are compared to the threshold of the minimum change in energy production, and the calculated values refer to the positive, negative and absolute change in production. Input values for the next analysis come from data used to generate graphs shown in Figures 4 and 5.
Table 4. Energy levels during the transients

<table>
<thead>
<tr>
<th>Power output ramp rate</th>
<th>ΔP &gt; 350</th>
<th>ΔP &gt; 700</th>
<th>ΔP &gt; 1000</th>
<th>ΔP &gt; 1500</th>
<th>ΔP &gt; 2000</th>
<th>ΔP &gt; 2500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute (W)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔP &gt; 10</td>
<td>2692</td>
<td>2460</td>
<td>2304</td>
<td>1995</td>
<td>1564</td>
<td>908</td>
</tr>
<tr>
<td>ΔP &gt; 20</td>
<td>76.93</td>
<td>70.29</td>
<td>65.83</td>
<td>57.01</td>
<td>44.69</td>
<td>25.95</td>
</tr>
<tr>
<td>ΔP &gt; 29</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔP &gt; 43</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔP &gt; 57</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔP &gt; 71</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Case A

Overall change in power production:

| Absolute | 2692 | 2460 | 2304 | 1995 | 1564 | 908 |
| Relative | 76.93 | 70.29 | 65.83 | 57.01 | 44.69 | 25.95 |

Ramp up:

| Absolute | 1334 | 1223 | 1149 | 1014 | 817 | 471 |
| Relative | 38.11 | 34.96 | 32.82 | 28.98 | 23.35 | 13.45 |

Ramp down:

| Absolute | 1359 | 1237 | 1155 | 981 | 747 | 438 |
| Relative | 38.82 | 35.34 | 33.01 | 28.02 | 21.34 | 12.51 |

Case B

Overall change in power production:

| Absolute | 445 | 249 | 183 | 47 | 27 | - |
| Relative | 12.71 | 7.12 | 5.23 | 1.34 | 0.78 | - |

Ramp up:

| Absolute | 198 | 130 | 87 | 19 | - | - |
| Relative | 5.64 | 3.71 | 2.48 | 0.56 | - | - |

Ramp down:

| Absolute | 247 | 119 | 96 | 27 | 27 | - |
| Relative | 7.07 | 3.41 | 2.76 | 0.78 | 0.78 | - |

Power generation data recorded on the 31/03/2019, depicted in Figure 6 are used to calculate the total energy produced by the PV power plant. The calculated energy corresponds to a maximum possible daily energy output for the period of the year in which both characteristic days are present, i.e. the weather conditions were ideal regarding the lack of cloudiness.
Losses due to power limitations
In order to mitigate the adverse effect of unpredictable changes in PV power plant production, the output limitation method can be used. By this method, the power output is limited to a value with a small difference compared to the power before the increase in production. This in turn would mean that in a partially cloudy day the power is limited to the amount of a local minimum produced power, which significantly reduces the produced energy through that day. In the other case, the power production on an overcast day, in moments when the clouds clear up over the PV power plant, is retained to the last stable value. Figure 7 shows data of available and produced energy for both cases.

Figure 6. Power generation data for 31/3/2019
Figure 7. Power output with and without implementing the power output limitation method

Available energy, limited output energy, and lost energy, which is a difference between available and lost energy, are shown in table 5. The lost energy is also shown as a relative value which one enables to use it as a guideline for calculating gained and lost energy in PV power plants of different size (rated power). In case of larger power plants, losses can be lower due to the larger surface area they cover, and thus slower power production changes of such power plants. On the other hand, larger power plants produce more energy that has a greater impact to the power system and gives greater economic losses due to lost power (energy).

Table 5. Available energy, limited output energy, and lost energy

<table>
<thead>
<tr>
<th></th>
<th>Available energy (Wh)</th>
<th>Limited output energy (Wh)</th>
<th>Lost energy (Wh)</th>
<th>Lost energy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case A</td>
<td>22724</td>
<td>15434</td>
<td>7290</td>
<td>67.92</td>
</tr>
<tr>
<td>Case B</td>
<td>7819</td>
<td>5822</td>
<td>1997</td>
<td>74.46</td>
</tr>
</tbody>
</table>
From the results presented in Table 5, it can be observed that considerable energy is lost if the output energy is limited. The use of energy storage would solve this problem, but high investment costs associated with energy storage technology is the most important limiting factor preventing its stronger integration in today’s power systems. Reduction of energy losses is also possible by short-term forecasting of energy production for power plants where there is no control over the input resource (solar and wind energy). Short-term forecasting can foresee an upcoming change in production for up to 10 minutes ahead and enable the power system operators to prepare for the imminent RES power change. Therefore, the power system operator can redispatch other dispatchable power plants. Likewise, if there are battery packs installed in the system, they can be prepared for an upcoming rise in available energy or lack of one so that they deplete or refill their storage in order to free up space or store energy for the upcoming energy surplus or deficit.

**The estimated cost of lost energy**

The electricity price on the electric energy market changes every hour, which excludes the possibility to calculate economic losses with one particular electric energy price. For this reason, the results of the following calculations are used as a framework value that can be used to estimate the actual savings that would be achieved with the electricity forecasting system that would make possible a greater use of available renewable energy sources.

The electricity price used in the following calculations was rounded to 50 € / MWh, using the data set by the European Commission [17].

Table 6 shows the values of annual economic losses caused by missed opportunity to sell electric energy by not using the available renewable sources. Economic losses are shown for some typical PV plants with rated power of 3.5, 10, 100, 500 and 1000 kW. Those values are used to present the data in a usable way for feasibility calculations. Input data used to calculate the economic losses shown in table 6. was explained earlier in the paper. These input data are - energy price, yearly number of cloudy days and daily energy loses of 4.64 kWh, as a mean value for the two characteristic days shown in this paper.

<table>
<thead>
<tr>
<th>Nominal power (kW)</th>
<th>3.5 kW</th>
<th>10 kW</th>
<th>100 kW</th>
<th>500 kW</th>
<th>1000 kW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic losses (£)</td>
<td>34</td>
<td>96</td>
<td>962</td>
<td>4810</td>
<td>9619</td>
</tr>
</tbody>
</table>

The results show that the use of a relatively low-cost solar forecasting system based on security cameras described in [18] and shown in Figure 8 would pay itself in only one year in the case of larger solar power plants.
CONCLUSION

Short-term solar forecasting gives the opportunity to power system operators to prepare the system for upcoming changes in the production level of solar power plants. This tool greatly helps in days when solar power production is characterized with sudden changes in output power. Apart from giving the system operator enough time margin to prepare for upcoming changes in solar production level, adequate solar forecasting makes possible maximum utilization of solar energy potential.

With increased share of solar power plants in the electricity generation pool, problems that unpredictable renewable energy sources bring also increase. It is necessary to prepare the system for greater integration of not only large solar power plants but also those with relatively small rated power. Such small PV power plants are usually on the consumer side, which the transmission system operator cannot directly manage, but in theory, prediction of their power production can be made by predicting solar radiation in a specific geographical area.

On the other hand, the negative impact of renewable energy sources can be reduced by limiting the output power and thus obtaining more stable output power. Nevertheless, the limitation of output power has its own shortcomings. If the production of a solar power plant is limited due to major changes in its production, loss of energy is introduced that otherwise would be produced from a clean, renewable energy source. Therefore, it is necessary to predict with a great level of certainty near-future levels of solar electricity generation to limit the amounts of lost energy to the power system from RES.

In cases where the photovoltaic energy output is not limited, but that energy is released into the system, other power plants in the power system must reduce their output in order to make the overall balance of the produced and consumed power in the system. The use of high ramp rate
power plants not only results in an increase in electricity prices but also in the increase of harmful emissions. High ramp rate power plants are considerably lower in efficiency, and because of the type of fuel most commonly used, less favorable for the environment.

To conclude, the paper presented empirically gained knowledge upon the scale of changes in photovoltaic power production due to cloud dynamics and the magnitude of associated energy losses. Additional research will be focused on a dynamic short-term forecasting model constructed with the use of the neural network trained with a mix of volumetric cloud movement simulations and real photogrammetry data captured with the low-cost security cameras.

REFERENCES

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