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Influence of the Monthly Solar Radiation Variations to the Performances of the Hybrid Photovoltaic-Diesel Systems

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Abstract – **Due to the stochastic nature of the solar radiation, the performances of the hybrid photovoltaic diesel systems vary. In this paper the solar radiation occurrence probability has been analyzed and modelled. The model is used for sensitivity analysis of a hybrid system performances. The variations affect the fuel consumption of the tested system, but the continuity of electricity supply is kept stabile.**

Keywords **– Solar Radiation, Occurrence Probability, Hybrid Photovoltaic Systems, Sensitivity Analysis.**

I. INTRODUCTION

Despite the intensive growth of the installed number of grid-connected photovoltaic (PV) systems, enabled by various incentives, in the following decades, the niche market of PV systems will remain in the field of stand-alone applications. In such applications, for enhancing economic and technical performances, usually are combined more electricity sources (incl. diesel gensets, wind generators, etc.) and energy storage components (batteries, fuel cells, etc.), creating a hybrid structure. However, such hybridization requires employing complex system component sizing along with selecting a proper dispatching strategy [1].

Hybrid PV systems are primarily driven by the incident solar energy on the PV panels, which has regular and stochastic variations. For quantifying the regular fluctuations, one needs to know the solar geometry rules [2]. However, many research efforts have been done to explore the stochastic (statistical and sequential) rules of the measured solar radiation datasets [3-6]. The findings are applied to create so called *Typical Meteorological Years* (TMYs), which are yearly synthetic hourly solar radiation datasets, consisting of data that recover the same statistical and sequential properties as the real (measured) solar radiation data [7]. TMYs are suggested and usually used for simulation purposes within the sizing procedures of hybrid PV systems [1,8,9]. Still, this approach does not give a complete reflection of the system's operation. Namely, as the weather changes from year to year, even for the same locations in the same months, the incident solar energy values fluctuate around the monthly means. Generally, this may lead to unexpected system behavior, such as variation of o&m costs, but in some cases may even lead to disrupting the continuous electricity supply.

Most of the regular variations of the solar radiation are removed when introducing the variable called clearness index, defined as a ratio of the solar radiation on a horizontal plane and extraterrestrial solar radiation [3-6]. In [3] is stated that the long-term probability distribution, on a monthly level, of the daily clearness index, depends only on their monthly mean value, but not of the location or of the month.

The analyses of yearly fluctuations on a monthly level basis are given in [8, 9]. As a result, the probability density distributions of mean monthly daily clearness index yearly fluctuations are obtained. These distributions are fitted with Gaussian probability density functions. Additionally, dependence between the total mean value of the daily clearness index and the standard deviation is revealed. This allows calculating of annual sets of mean monthly clearness indexes that occur with a specified probability. Some of this theory is presented here.

These analyses can be used for calculation of monthly mean daily clearness index values, which for a given location, occur with a specified probability. With these sets as inputs, synthetic hourly solar radiation data series can be generated. In this paper, these solar radiation data series are used to estimate the fuel consumption of the given hybrid PV system.

II. SOLAR RADIATION DATA ANALYSIS

In [8] was analyzed the database of the World Radiation Data Center (WRDC) [10], which is consisted of measured and calculated, monthly, daily and hourly values of the solar radiation components, from 1964 up to 1993 for locations all around the world. There was considered daily solar radiation data from 44 meteorological stations from the Balkans Region. For each year and location the monthly mean daily clearness index was calculated by:

$$\overline{K}_t(m,y,l)=\frac{1}{J}\sum_{j=1}^{J}K_t(j,m,y,l) \qquad (1)$$

where $K_t(j, m, y, l)$ is the daily clearness index, $j = 1, 2, \ldots J$ is the number of the day in the month m, J is the total number of days in the month, $y = 1963, \ldots 1993$ is the year and $l = 1, 2, \ldots 44$, denotes different locations.

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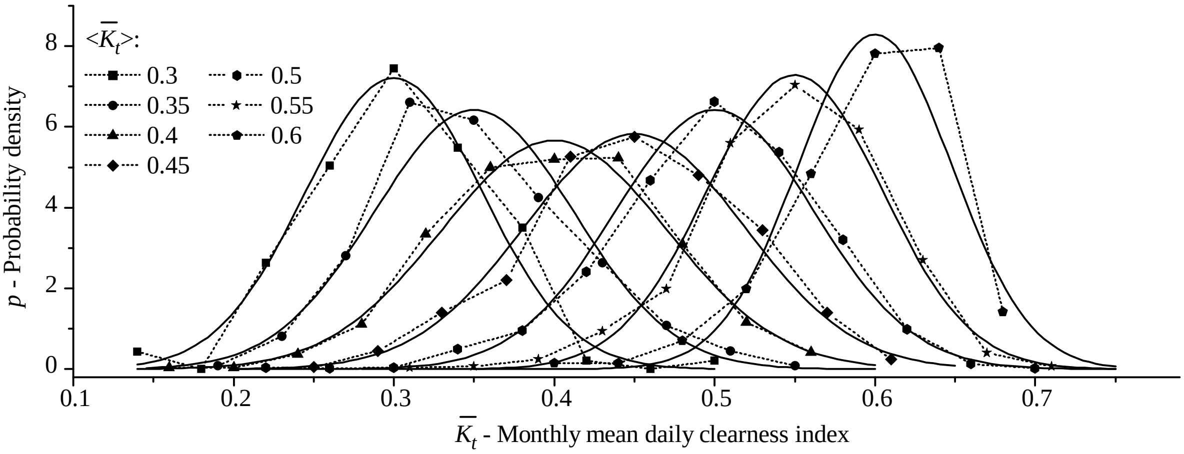

Fig. 1. Probability density distributions of K_t values and the fitting Gaussian functions

For each location l, the grand monthly mean daily clearness index, was calculated by:

$$<\overline{K}_t(m,l)> = \frac{1}{Y}\sum_{y=1964}^{1993}\overline{K}_t(m,y,l) \qquad (2)$$

where Y is the total number of years with having complete and regular $K_t(m, y, l)$. In the further text, for simplifying, $<K_t(m, l)>$ will be noted with $<K_t>$ and $K_t(m, y, l)$ with K_t.

Independent of location and month, sets of K_t values, having grand monthly mean daily clearness index $<K_t>$ that belongs to a narrow interval of ± 0.01 around the specified nominal clearness index, were grouped together. Because the intervals' length was 0.02, they overlap, thus one set of K_t values belongs to two neighbouring intervals.

The empirical standard deviation of all $K_t(i)$ belonging to the groups with a grand mean value $<K_t>$ was calculated by:

$$\sigma_{emp} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left[K_t(i) - <\overline{K}_t>\right]^2} \qquad (3)$$

where: $i = 1, ..., N$, N is the total number of $K_t(i)$ in a group.

For each group, the frequency distribution has been done. For all groups the bin length was $h = 0.04$. These distributions were then normalized, by dividing their values with the total number of the K_t-values in the groups. The normalized frequency distributions represent the occurrence probability $P(K_t, <K_t>)$ of K_t in a specified month for a given location, having grand monthly mean daily clearness index $<K_t>$.

In order to fit the empirical probability distributions with the theoretical probability distribution functions, it is more convenient to deal with the corresponding probability density distributions $p(K_t, <K_t>)$. Assuming that $p(K_t, <K_t>)$ is constant for the whole bin length h, it can be calculated with:

$$p\left(\overline{K}_t, <\overline{K}_t>\right) = \frac{P\left(\overline{K}_t, <\overline{K}_t>\right)}{h} \qquad (4)$$

In Fig. 1, with dotted lines, are shown 7 empirical probability density distributions with a range of $<K_t> = 0.30,.., 0.60$. As can be noted, the distributions are bell-shaped, which suggests a possibility to be fitted with the Gaussian probability density function. The theoretical probability density functions, when a random variable K_t, with mean $<K_t>$, has Gaussian distribution, are determined by:

$$p_{th}\left(\overline{K}_t, <\overline{K}_t>\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\overline{K}_t - <\overline{K}_t>}{\sigma}\right)^2} \qquad (5)$$

where σ is the standard deviation.

For fitting the empirical probability density distributions with a Gaussian probability density function, the widely used non-linear least square Levenberg-Marquardt method was employed. The standard deviation value σ_{LM} is chosen by finding a function given with Eq. (5), which optimally fits the empirical distributions. The fitting was done for the whole range of distributions, thus for each distribution, the parameter σ_{LM} was obtained. In Fig. 1, with solid lines, are also shown the Gaussian probability density functions that fit the corresponding empirical probability density distributions. Furthermore, it was approximated the dependence of the standard deviation to $<K_t>$, with the following expression:

$$\sigma_{fit} = -0.515 <\overline{K}_t>^2 + 0.436 <\overline{K}_t> - 0.026 \qquad (6)$$

When the probability density function of a random variable is known, the probability can be obtained by integrating the function given in Eq. (6). In this case:

$$P\left(\overline{K}_t, <\overline{K}_t>\right) = \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{\overline{K}_t} e^{-\frac{1}{2}\left(\frac{\overline{K}_t - <\overline{K}_t>}{\sigma}\right)^2} d(\overline{K}_t) \qquad (7)$$

Observing the measured data, all values of K_t belong to the range $0.05 < K_t < 0.8$. However, the significance of the above equation exceed this range from both sides. Still, the errors when using the Gaussian distribution in this case is the order of 10^{-7}, which is practically negligible.

The integral in Eq. (7) cannot be solved in exact form, and the solution is represented through error functions. On the other hand, in this paper, is required the inverse solution of the Eq. (7), i.e. the calculation of K_t for known $<K_t>$ and a specified probability $P(K_t, <K_t>)$. In order to easy the procedure of calculation of K_t, in this paper was not done

TABLE I

MONTHLY MEAN DAILY VALUES OF THE SOLAR RADIATION, CLEARNESS INDEX AND AIR TEMPERATURE

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
H [kWh/m^{2}day]	1.76	2.59	3.62	4.90	5.97	6.50	6.65	6.04	4.62	3.40	2.15	1.47
$\langle K_t \rangle$	0.449	0.473	0.489	0.516	0.544	0.560	0.586	0.596	0.560	0.552	0.495	0.422
T_a [°C]	0.1	2.6	5.7	11.2	16.0	19.1	21.0	21.3	17.4	12.1	7.5	2.2

TABLE II

MONTHLY MEAN DAILY CLEARNESS INDEX WITH A SPECIFIED PROBABILITY

Month	$\langle K_t \rangle$	σ_{fit}	Probability												
			0.001	**0.05**	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**0.95**	**0.999**
Jan	**0.449**	**0.066**	0.653	0.557	0.534	0.504	0.484	0.466	**0.449**	0.432	0.414	0.394	0.364	0.341	0.245
Feb	**0.473**	**0.065**	0.674	0.580	0.556	0.528	0.507	0.489	**0.473**	0.457	0.439	0.418	0.390	0.366	0.272
Mar	**0.489**	**0.064**	0.687	0.594	0.571	0.543	0.523	0.505	**0.489**	0.473	0.455	0.435	0.407	0.384	0.291
Apr	**0.516**	**0.062**	0.707	0.618	0.595	0.568	0.548	0.532	**0.516**	0.500	0.484	0.464	0.437	0.414	0.325
May	**0.544**	**0.059**	0.726	0.641	0.619	0.593	0.575	0.559	**0.544**	0.529	0.513	0.495	0.469	0.447	0.362
Jun	**0.560**	**0.057**	0.735	0.653	0.633	0.608	0.590	0.574	**0.560**	0.546	0.530	0.512	0.487	0.467	0.385
Jul	**0.586**	**0.053**	0.749	0.673	0.653	0.630	0.614	0.599	**0.586**	0.573	0.558	0.542	0.519	0.499	0.423
Aug	**0.596**	**0.051**	0.753	0.680	0.661	0.639	0.623	0.609	**0.596**	0.583	0.569	0.553	0.531	0.512	0.439
Sep	**0.560**	**0.057**	0.735	0.653	0.633	0.608	0.590	0.574	**0.560**	0.546	0.530	0.512	0.487	0.467	0.385
Oct	**0.552**	**0.058**	0.730	0.647	0.626	0.601	0.582	0.567	**0.552**	0.537	0.522	0.503	0.478	0.457	0.374
Nov	**0.495**	**0.064**	0.692	0.600	0.577	0.549	0.528	0.511	**0.495**	0.479	0.462	0.441	0.413	0.390	0.298
Dec	**0.422**	**0.066**	0.627	0.531	0.507	0.478	0.457	0.439	**0.422**	0.405	0.387	0.366	0.337	0.313	0.217

deeper analysis of the error functions. Instead, there was used the build-in function NORMINV from the Microsoft Excel®. It is a three-parameter (probability, $\langle K_t \rangle$ and standard deviation) function, which, as a result, gives the inverse solution of Eq. (7), i.e. K_t. This function applies numerical solving and some errors in the results are possible. The methodology has been validated for several locations from the Balkan region.

III. INPUTS AND SENSITIVITY ANALYSIS

The shown methodology was used to estimate the sensitivity of a hybrid PV system which was planned to be installed in a small rural village Vrbica in the R. of Macedonia (42.13°N, 22.25°E, altitude 800 m). For this location monthly mean global solar radiation values on a horizontal plane and the ambient temperature were obtained from the nearest meteorological stations (Table I). These values were used to calculate the mean monthly values of the daily clearness index. Since they are a result of long-term observations, we considered them as grand monthly mean daily clearness indexes $\langle K_t \rangle$. From those, we calculated the monthly mean of daily clearness index values K_t that appear with a specified occurrence probability, as previously shown (Table II). Then we calculated the mean monthly values for the global solar radiation on a horizontal plane. Further, using the software tool METEONORM [7], we generated the monthly sets of hourly solar radiation data, and they occur with a specified probability. On Fig. 1, for each month are given the solar radiation vs. probability diagrams. The diagrams can be read as follows: for example for September, with probability of 20 %, the global solar radiation on a horizontal plane is *equal or less than* 5.01 kWh/m^{2}day, or with 90 % probability – 4.02 kWh/m^{2}day. To note, that the values of the solar radiation given in Table I can be obtained for probability of 50 %.

The analyzed system is optimally sized to continuously supply several households in the mentioned rural area with the total average electricity consumption of 10 kWh/day. The optimization was done by using the techniques of genetic algorithms, and is elaborated in detail in [9, 11]. The system is consisted of PV generator – 1.68 kWp (fixed tilt angle of 40°), battery capacity – 13.2 kWh, diesel genset –2 kVA, inverter – 1.5 kVA. It uses a setpoint (SOC_{ON} = 0.398; SOC_{OFF} = 0.831) frugal (P_d = 817 VA) dispatching strategy [1, 9].

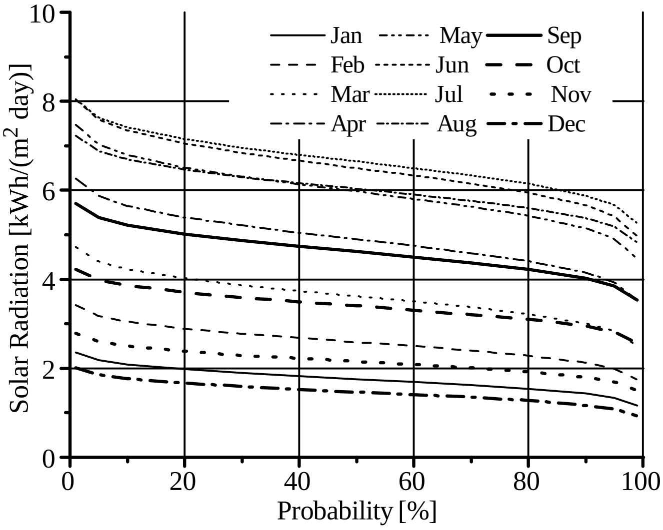

Fig. 1. Occurrence probability of the solar radiation

A year to year variations (for the same months) of the solar radiation, result with variations of the PV generator energy output. To ensure a continuous electricity supply, in case of shortage of PV energy, it is compensated by a prolonged diesel genset operation, i.e. with increased fuel consumption, and vice versa. The sensitivity of the fuel consumption in regard to different solar radiation input is obtained by a hybrid PV system simulation, using a software tool based on PVFORM [12], to which are implemented many modifications [9].

On Fig. 2, is given the PV generator output energy vs. its occurrence probability. Fig. 3 shows the dependence of the fuel consumption in regard to the occurrence probability of the solar radiation. The diagrams can be read on a following way: for example for December, when the mean daily solar radiation on a horizontal plane is 1.47 kWh/m^{2}day (for probability of 50 %), the total PV generator output energy equals to 124.6 kWh, while the fuel consumption is 85 liters. In 90 % of the time, the average value of the solar radiation is more or equal to 1.17 kWh/m^{2}day (20.4 % less than the average) and the PV output energy is more or equal to 90.2 kWh (27.6 % less) and the fuel consumption is at least 95 liters (11.8 % more than the average). In 10 % of the time, the solar radiation is more or equal to 1.77 kWh/m^{2}day (20.4 more than the average), the PV generator output is 158.4 kWh (27.12 % more) while the fuel consumption is at least 76 liters (10.6 less). In all considerations, no shortage of supply has been identified.

IV. Conclusion

This paper deals is presented the methodology for estimation of the solar radiation occurrence probability. Starting from the basic measurements, i.e. average monthly value of the solar radiation, the methodology enables to create hourly datasets of solar radiation that occur with a specified probability.

The variation of the solar energy has impact to the operation of the hybrid PV system. Lower values result with increased fuel consumption and vice versa. Hence, the methodology enables to quantify the expenditures and operation and maintenance costs and relate them to probability.

However, the proposed sensitivity analysis can give the answer if the designed hybrid PV system is able to supply the consumers without interruption.

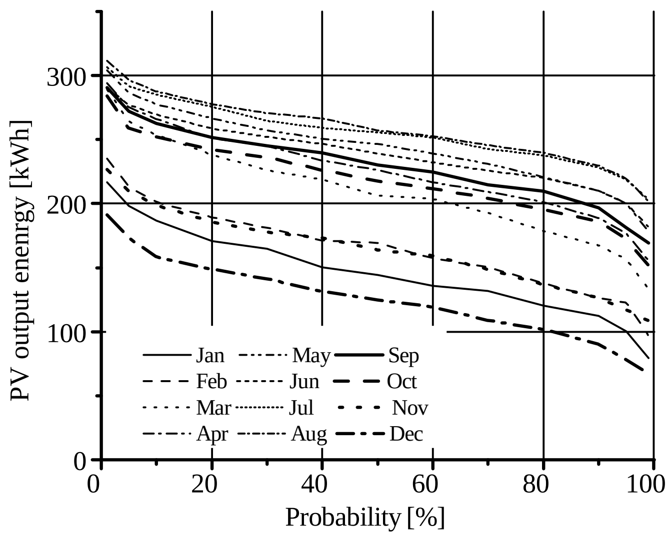

Fig. 2. Occurrence probability of the PV generator output energy

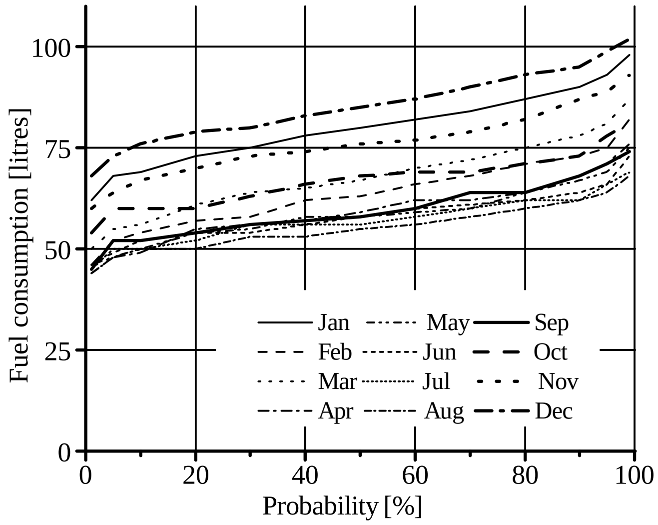

Fig. 3. Probability of the fuel consumption

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