EVALUATION OF PHOTOVOLTAIC SYSTEMS FOR VOLTAGE QUALITY

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ABSTRACT

EVALUATION OF PHOTOVOLTAIC SYSTEMS FOR VOLTAGE QUALITY

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Because of the governmental incentives and developing photovoltaic technology, the distributed photovoltaic systems are populating rapidly in power systems. This rapid population brings with concerns about voltage quality of the power systems. This thesis aims to evaluate the effects of those plants to the voltage quality of power systems in terms of voltage regulation and flicker. The thesis develops a statistical analysis method by developing metrics for a photovoltaic power plant located in Ankara, using power generation data. The generation data involves all uncertainty associated with weather conditions as well as environmental factors. Therefore, it provides a complete statistical analysis of the feasibility of photovoltaic systems at the considered region, and hence its effects to the voltage quality.

In the literature, researchers are investigating the photovoltaic system generation to forecast the generation assuming it depends on certain variables as temperature and humidity. Considering the inaccuracy of those models and unknown parameters such as air pollution, ground reflection, etc. the thesis employs historic power generation data for the analysis. Besides the developed analysis method, the thesis also presents a bad-data identification method to eliminate the erroneous and outlier data before the statistical analysis.

The study is conducted using historic data gathered from the photovoltaic system located at the Department of Electrical and Electronics Engineering. To validate the obtained results, reliability of the generation is investigated in simulation environment. The results are assessed using voltage regulation and flicker as considered metrics.

Keywords: Photovoltaic system, statistical analysis, bad-data identification, voltage quality, flicker.

ÖZ

FOTOVOLTAİK SİSTEMLERİN GERİLİM KALİTESİ AÇISINDAN DEĞERLENDİRİLMESİ

Şengül, Deniz
Yüksek Lisans, Elektrik ve Elektronik Mühendisliği Bölümü
Tez Yöneticisi: Yar. Doç. Dr. Murat Göl

Nisan 2018, 55 sayfa

Devletin verdiği tevşikler ve gelişmekte olan fotovoltaik teknolojisi ile birlikte, elektrik sistemlerinde dağıtık fotovoltaiklerin sayısı hızla artmaktadır. Bu hızlı artış güç sistemlerinde gerilim kalitesi ile ilgili kaygıları da beraberinde getiriyor. Bu tez çalışması, fotovoltaik sistemlerin gerilim regülasyonu ve titreşimi açısından sistemin gerilim kalitesine etkilerini değerlendirmeyi amaçlamaktadır. Tez, Ankara'da bulunan bir fotovoltaik enerji santralinin üretim verilerini kullanarak metrik değerler geliştirip, bunlarla istatistiksel bir analiz yöntemi oluşturmaktadır. Üretim verileri, hava koşulları ve çevresel faktörlere bağlı tüm belirsizlikleri içermektedir. Bu nedenle fotovoltaik sistemlerin fizibilitesinin düşünülen bölge için tam bir istatistiksel analizini sağlar ve dolayısıyla sistem güvenilirliğine etkilerini de bulur.

Literatürde araştırmacılar fotovoltaik sistem üretimini, üretimin sıcaklık ve nem gibi belirli değişkenlere bağlı olduğunu varsayarak üretim tahmini yapmak için inceliyorlar. Bu modellerin hatalı olduğu ve hava kirliliği, ışığın yerden yanması gibi bilinmeyen parametreleri göz önünde bulundurarak, tez tarihsel enerji üretim verilerini analiz için kullanmaktadır. Geliştirilen analiz yönteminin yanı sıra, tez istatistiksel analiz öncesinde hatalı ve aykırı verileri elimine etmek için bir yanlış veri tanılama yöntemi de sunmaktadır.

Çalışma Elektrik-Elektronik Mühendisliği Bölümü'nde bulunan fotovoltaik sistemden elde edilen tarihsel verileri kullanarak yürütülmektedir. Elde edilen sonuçları doğrulamak için, simülasyon ortamında üretimin güvenilirliği araştırılmaktadır. Sonuçlar, metrik olarak düşünülen gerilim regülasyonu ve titreşimi kullanarak değerlendirilmiştir.

Anahtar Kelimeler: Fotovoltaik sistem, istatistiksel analiz, yanlış veri tanılama, güvenilir sistem işletimi, gerilim kalitesi, titreme.

To My Parents

and To My Friends

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LIST OF ABBREVIATIONS

EAF	Electric Arc Furnace
ENTSO-E	European Network of Transmission System Operator
FFT	Fast Fourier Transform
HV	High Voltage
LV	Low Voltage
METU	Middle East Technical University
MILGES	National Solar Power Plant Development Project
MV	Medium Voltage
NRT	Normalized Residual Test
PV	Photovoltaic
RMS	Root Mean Square
TEIAS	Turkish Electricity Transmission Company
THD	Total Harmonic Distortion
VSC	Voltage Source Controller
WLS	Weighted Least Square

CHAPTER 1

INTRODUCTION

Solar energy is rapidly populating in recent years thanks to the increasing natural concerns and decreasing installation cost with developing photovoltaic (PV) technology. Moreover, governmental incentives supporting the renewable energy sources and effective utilization have considerable effect on this rapid grow all over the world [1].

In Turkey, there is a good solar potential as can be seen in Figure 1.1 [2], which is the solar energy potential atlas of Turkey. The Ministry of Energy and Natural Resources of Turkey gives incentives and takes regulations on licensed power generation, so it causes a rise above the average on population of PV systems in Turkish Electricity Grid. While installed capacity of PV power plants was 359 MW at the end of 2015, it increased up to approximately 3 times, 1048 MW and continues growing [3]. Furthermore, the ministry supports a project, which is National Solar Power Plant Development Project (Milli Güneş Enerjisi Santrali Geliştirme Projesi, MILGES), aiming to produce PV solar energy power plant equipment with its own national technology, and export this technology to the world. For this purpose, a 10-MW capacity PV power plant will be constructed as a pilot application for the necessary infrastructure [4].

With the rapid population of PV systems, researchers' interest is gathered on reliability and power quality issues, which can be either improved or worsen [5]. Power system reliability can be defined as a measure of the ability of a system, generally given as numerical indices, to deliver power to all points of utilization within acceptable standards and in amounts desired. It can be said that power quality is the fitness of generated electrical power delivered to user devices and equipment. Because the deviations from an ideal sinusoidal with a constant frequency case (interruptions, sags, swells, flicker and harmonics) are the power quality parameters, voltage quality can be accepted equivalent to power quality [6].

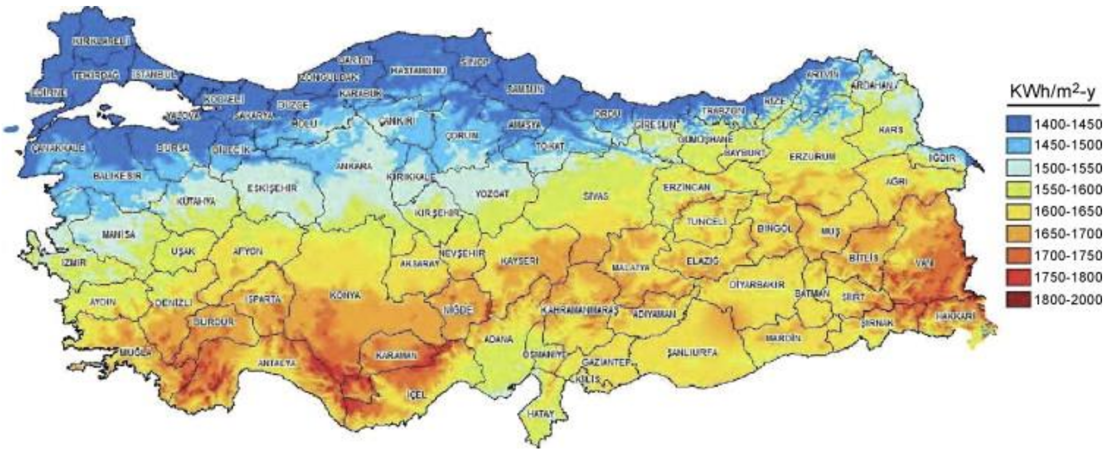


Figure 1.1 Solar map of Turkey

1.1. Scope of the Thesis

Although, evaluation of photovoltaic in terms of voltage quality is mainly investigated in this thesis, primarily it includes researches on photovoltaic power generation data. In the literature, there are not many standards and metrics for examining photovoltaic daily power data. In this context, it is aimed that some metrics can be determined to use for analyzing the reliability of system operation. Before the determination, there is a need to be sure if the data is correct due to problems that may occur in recording device or because of outlier effects such as maintenance of the panels.

This thesis, firstly, focuses on bad-data problem. After removing the bad-data from the dataset, it concentrates on investigation of the data as statistical methods to characterize the power generation of a PV system in Ankara region. For a PV power generation, continuity and predictability of power generation, and frequency and magnitude of variations in power output are seen as important variables. In the literature, there are some feasibility methods to find these variables with the forecast methods. The forecast methods use the certain variables like temperature, humidity to estimate these variables. However, these methods do not include uncertainty of weather conditions. In other words, some unexpected weather conditions like cloud passage or air pollution, which can be significantly effective on PV generation, is not a part of these methods. Therefore, the thesis intends to find some metrics to give information about these variables and use them in the evaluation of PV systems for reliable system operation with using historical PV generation data.

The evaluation of PV systems for reliable system operation is one of the hot topics in recent years with the increasing population of PV systems [7]. For this purpose, reliable system operation assessment is supported by investigating the effects of PV systems on the system reliability and power quality. Power quality can be accepted equivalent to voltage quality because its parameters are the variations from an ideal sinusoidal with a constant frequency (flicker, harmonics, sags, swells and interruptions) [6]. The effects of PV systems are generally accepted as adverse due to uncertainty of weather conditions [8].In this thesis, it is focused on the limits of variation of generation which may not meet the standards in terms of the reliability of the system, if variation of weather conditions within a specific time is bounded. Therefore, a serious feasibility analysis, considering historical data, gains importance to assess the effects of PV systems. The two metrics developed in this thesis are utilized for the evaluation purposes.

1.2. Thesis Outline

This thesis consists of five chapters. In the first chapter, the background and motivation is introduced. The populating PV systems and the reasons of this population in the world and Turkey are stated. Researchers’ concerns about the effects of the population to electricity grid is also mentioned.

Chapter 2 includes a bad-data identification method applied to PV data obtained from Ayasli Research Center. The reasons why a bad-data identification is needed for a PV data are described. Normalized residuals test method, that is one of the bad-data identification methods, is briefly explained. The method is adapted to the data from PV system and its thresholds are determined to find the suspicious data. The verification of NRT method is stated, and consequently the validation of NRT method is made day by day.

Chapter 3 consists of statistical analysis of solar power data, which is made suitable by applying bad-data identification in the previous chapter. The statistical analysis are performed in terms of mean of total change rate in a day when PV system is accepted as a deterministic power generator, total variation in a day, and total number and frequency of power generation irregularities in a day. These metrics are investigated with 3 methods, which are relative change, total generation distortion and sign change of derivative methods respectively. With these metrics, it is aimed to evaluate generation regime of solar power generation in Ankara to get information, and if the output is proper, such that PV investment is feasible. Because of the fact that the solar power generation curves in the literature have been investigated just for forecasting considering certain variables like temperature, radiation, humidity and slope of the PV systems, it is not enough to asses a regime about the changes in solar power generation properly. Therefore, the generation regime of solar power generation is obtained by these metrics using historical data, and some monthly and seasonal histograms are given to better understanding.

In Chapter 4, the effects of PV systems on system voltage quality are investigated with the variation of PV system generation. For this purpose, a sample radial power system, which consists of two residential loads, two industrial loads, source, and a PV system, is modeled. With the increasing variation of the PV system generation obtained from the Chapter 3, the effects are investigated in terms of flicker and voltage variation. Moreover, the effects of load characteristic on reliability are also investigated in terms of flicker and voltage variation with different load scenarios. The flicker and voltage variation results are used to find numerical outputs for the reliability assessment.

Finally, in the Chapter 5, the conclusion of the thesis is represented and the future works are stated.

CHAPTER 2

BAD-DATA IDENTIFICATION

In this chapter, a bad-data identification method is proposed for the PV system generation data. The generation data set can contain outliner data based on gross error or unexpected operation of the PV system such as malfunction or maintenance of inverters and recording device. Hence, the method is proposed to eliminate this type of data for obtaining more accurate data set, which will be used for statistical analysis.

2.1. Introduction

At the roof of Ayasli Research Center, Department of Electrical and Electronics Engineering, Middle East Technical University, there is a distributed PV system with 50 kWp generation capacity. This photovoltaic system consists of 10 separate inverters, and is connected to a commercial monitoring device. This system has worked for 5 years, but the recording device malfunctioned and stopped recording data in March 2017. Although the generation data recorded by commercial monitoring devices is accessible in appropriate data format when the devices are running properly, it is observed that recorded data or its data format can be corrupted due to a failure of the device. This corruption is also observed in the data obtained from Ayasli Research Center. When several of the data was investigated, it has been determined that some data can be inaccurate in terms of magnitude and shape. It is not possible to check the correctness of the data taken for a long time one by one, and hence the proposed method is developed for fast detection and identification of bad data.

There are a few bad data identification methods in the literature as mentioned in [9]. Those methods detect and identify the bad data by comparing the estimated values with the measurements statistically. Among those methods normalized residuals test (NRT) is reported to be one of the most effective methods [10]. NRT normalizes residuals between the measurements and state estimate with respect to the corresponding residual standard deviation, and assesses the statistical properties of those values to detect the corrupted data. In this work, weighted least squares estimator (WLS) is employed to determine the system states, as it is the best linear unbiased estimator (BLUE) under Gaussian noise [10] – [12]. Note that, noise associated with the solar data is assumed to be Gaussian and independent of the other errors, while bad data is defined as gross error, such that an error that is beyond the standard deviation of the considered measurement.

The daily generation curve of solar energy varies according to sunbathing in different months of the year. While it has an uninterrupted pattern on a totally sunny day, it is running intermittently on a cloudy day. In particular, a reference signal is needed to make sure that the curves in the cloudy days of the winter months are correct. Obtained daily production curves resembled a cosinusoidal curve when it is normalized to the highest generated power of the day because the motion of the earth around its axis leads to a sunbathing curve resemblance of a sinusoidal sign. Note that the location on the earth may cause inaccuracy in the behavior, but the inaccuracy is negligible as the aim is not to determine the exact generation of the solar generation system. In the method presented in this part, identification process was performed by comparing this reference cosine curve with measured daily generation curves.

In this part, the proposed normalized residual test method is explained in detail. The data obtained from Ayasli Research Center is investigated based on the proposed method by applying the method in Matlab environment, and some examples of daily generation curves are given to illustrate to bad-data and the correct ones. Furthermore, the data is controlled day by day and the validation of the proposed method is made.

2.2. Normalized Residuals Test

The relationship between measurements and states in a linear system can be expressed as:

$$z = Hx + e \tag{1}$$

In (1), z (mx1) is used as the measurement vector, x (nx1) expresses the state vector. H (mxn) refers to the linear relationship between states and measurements. Finally, e (mx1) represents the measurement error vector.

The measurement errors are assumed to be independent of each other and Gaussian because the power generations from different days can be accepted as independent observations. Hence, the state estimations can be found using the weighted least squares (WLS) estimators. The most important advantage of the WLS estimator is that it is the best linear unbiased estimator (BLUE) when only Gaussian errors present in the measurements [12]. In this context, the vector of state estimation problem is equal to the solution of the following relation.

$$\hat{x} = \left(H^T R^{-1} H\right)^{-1} H^T R^{-1} z \tag{2}$$

In (2), R (mxm) represents the measurement covariance matrix. In view of (2), the relationship between the residuals (r) and measurement errors (e) can be found as follows.

$$\begin{aligned}
r &= z - H\hat{x} \\
r &= \left(Hx + e\right) - H\left(H^T R^{-1} H\right)^{-1} H^T R^{-1}\left(Hx + e\right) \\
r &= e - H\left(H^T R^{-1} H\right)^{-1} H^T R^{-1} e \\
r &= \left(I - H\left(H^T R^{-1} H\right)^{-1} H^T R^{-1}\right) e \\
r &= Se
\end{aligned} \tag{3}$$

The expected values of the residuals and the covariance matrix are defined as follows.

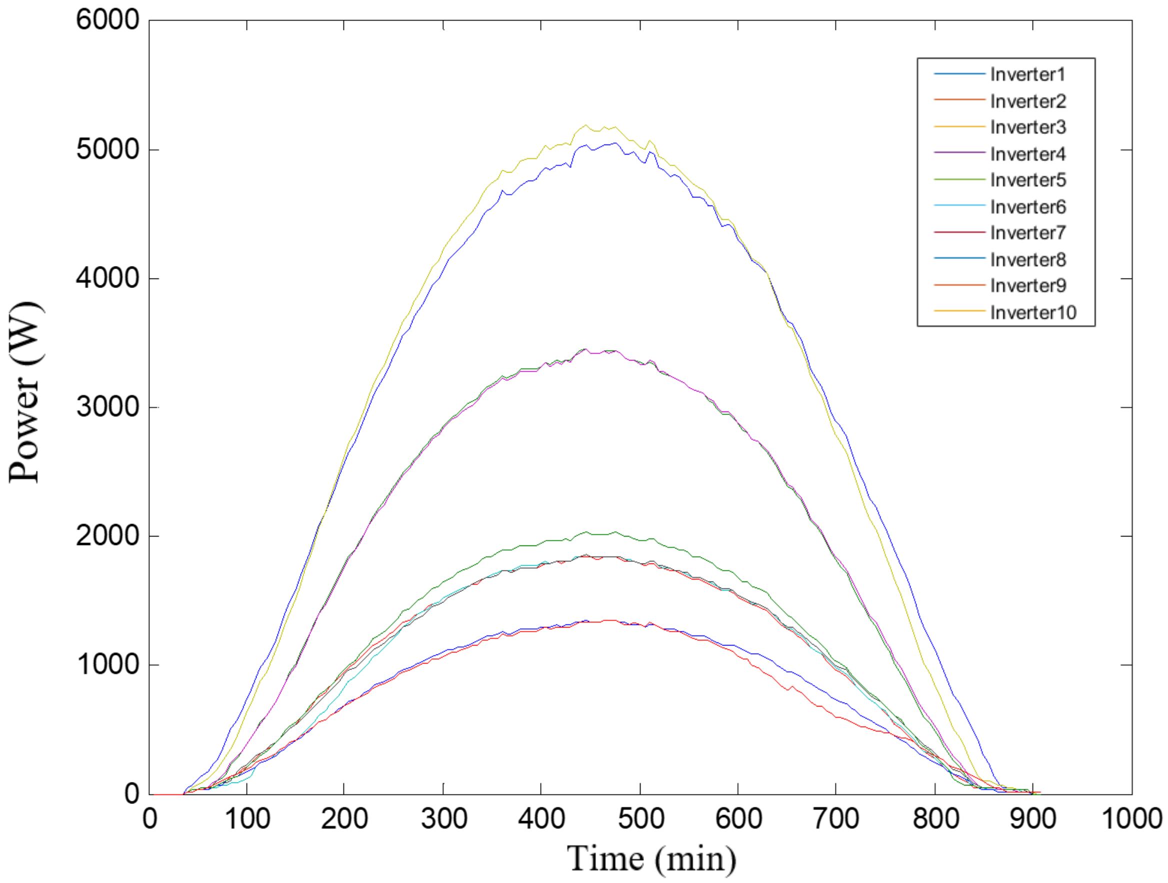
$$\begin{aligned}
&\mathrm{E}[r] = \mathrm{E}[Se] = S\mathrm{E}[e] = 0 \\
&\mathrm{cov}(r) = \mathrm{E}\left[rr^T\right] = S\mathrm{E}\left[ee^T\right]S^T = SRS^T = \Omega
\end{aligned} \tag{4}$$

The residual covariance matrix (w) cannot be reversed, as it is a singular matrix. Therefore, only the diagonal elements (residual variances) are involved in the analyses used [9], assuming variance of the residuals are more effective compared to the covariance values between the residuals. Each residue is normalized with respect to the corresponding residual standard deviation, and those normalized residuals exceeding a pre-determined threshold refers to the presence of erroneous. The largest of the normalized residues are marked as erroneous data.

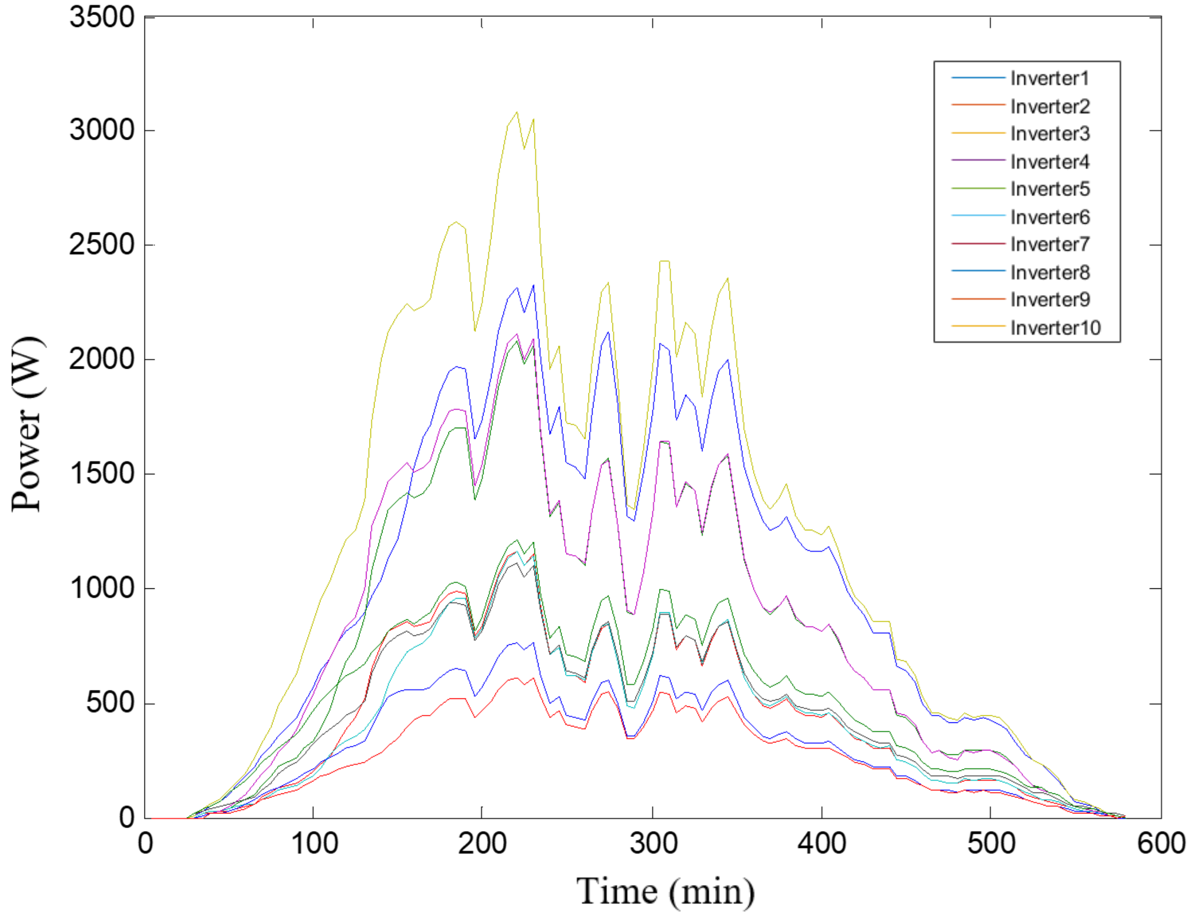
2.3. Identification of Suspicious Files

In this part, it is aimed to determine the files bearing the error of solar energy generation data based on the normalized residual test. The considered system records the data of 10 parallel inverters installed at METU - Ayaslı Research Center. Each file contains solar energy generation for a given day. Figure-2.1 shows the production data recorded under various seasonal conditions for different inverters.

At the end of the examinations made, it is seen that the change of generation on time in a sunny day is similar to a cosine function. In Figure-2.2, it is seen that the generation curves normalized with respect to the peak point are compared with the cosine function.



(a) - Generation data for a sunny day



(b) - Generation data for a cloudy day

Figure 2.1 Generation data recorded under various seasonal conditions

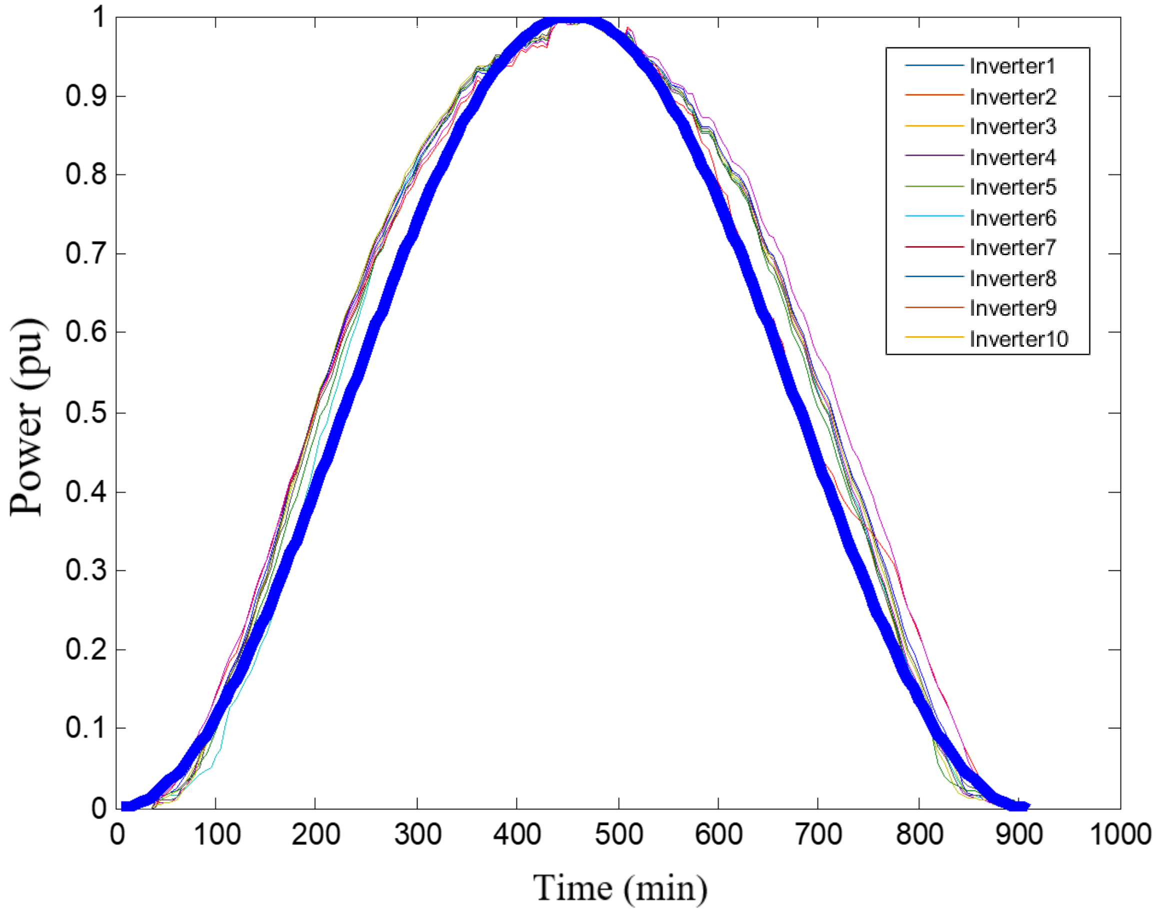


Figure 2.2 Comparison of the generation curves normalized to the peak point with the cosine function (cosine sign is drawn in bold)

Based on the similarity shown in Figure-2.2, the mathematical relationship between expected solar energy generation and measurements is modeled as follows.

$$z = x + v \tag{5}$$

In (5), z represents received measurements and v represents the deviations in energy generation due to changes in weather conditions. These deviations may be negligible, but they may also cause the expected cosine characteristic to deteriorate, as shown in Figure-2.2.

Regardless of the magnitude of the deviations due to the weather conditions, these deviations show different characteristics than of bad-data, as seen in the comparison given in Figure-2.3. In this context, by comparing the ratio of the residuals of each file to the mean residual variance with a certain threshold value, the files containing bad-data can be detected. The mean residual variance can be calculated as follows.

$$\sigma_i^2 = \frac{1}{N}\sum_{k=1}^{N}\left[z(k) - x(k)\right]^2$$
$$\sigma_{mean}^2 = \frac{1}{T}\sum_{i=1}^{T}\sigma_i^2 \tag{6}$$

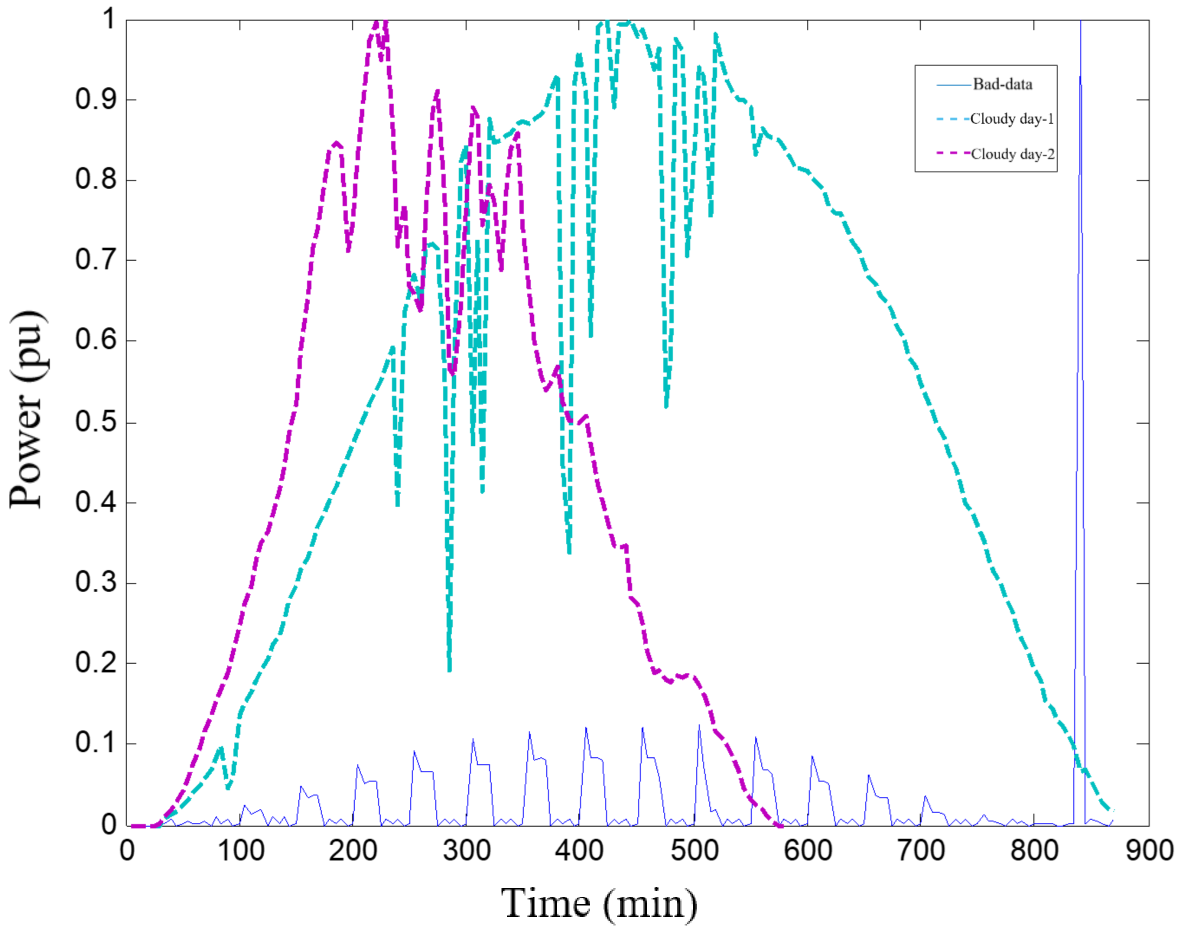


Figure 2.3 Comparison of generation curves of two cloudy days with bad-data (Dashed lines represent the data from cloudy days).

In (6), σ_{mean}^2 represents the mean residual variance. N is the total number of data in a file, and every day varies from file to file for the duration of sunbathing is different. T is the total number of files and corresponds to the number of days taken. As mentioned earlier, if there is more than one inverter in the system of interest, the variance of each inverter is calculated in each file, and the largest one is taken as the variance of that file. When calculating σ_{mean}^2, a file group containing both cloudy and sunny days is used, which does not contain erroneous data.

2.4. Validation of the Method

The data used for validation are taken from 10 different inverters with a total rated value of 50 kW installed in METU Ayaslı Research Center. The data files contain 1652 days from 01.01.2012 to 31.12.2016 during which the system has been working on. In this study, suspicion threshold value was chosen 5 because the reference half-wave cosine curve does not exactly fit a PV power generation curve in a cloudless smooth day. σ_{mean}^2 is calculated as 0.19.

Figure-2.4 shows the calculated normalized residuals for each file. The files of 158 in day 1652 are marked as bad-data by the proposed method. Examples of bad-data marked files are given in Figure-2.5 and Figure-2.6. Figure-2.5 shows the data taken on 21.06.2012 in full scale and zoomed. The first part of the curve has been observed to be the bad-data estimate of the data originating from the wrong transformation, the fact that the file cannot be used as a whole even if the last parts of data is correct. In Figure 2.6, an example is given which is thought to be bad-data originated from the record, which is also evident from the shape of the curves and the power ratings. The generation curve for the cloudy day given in Figure-2.1.b is not marked as bad-data by the method as it is due to the oscillations in the generation.

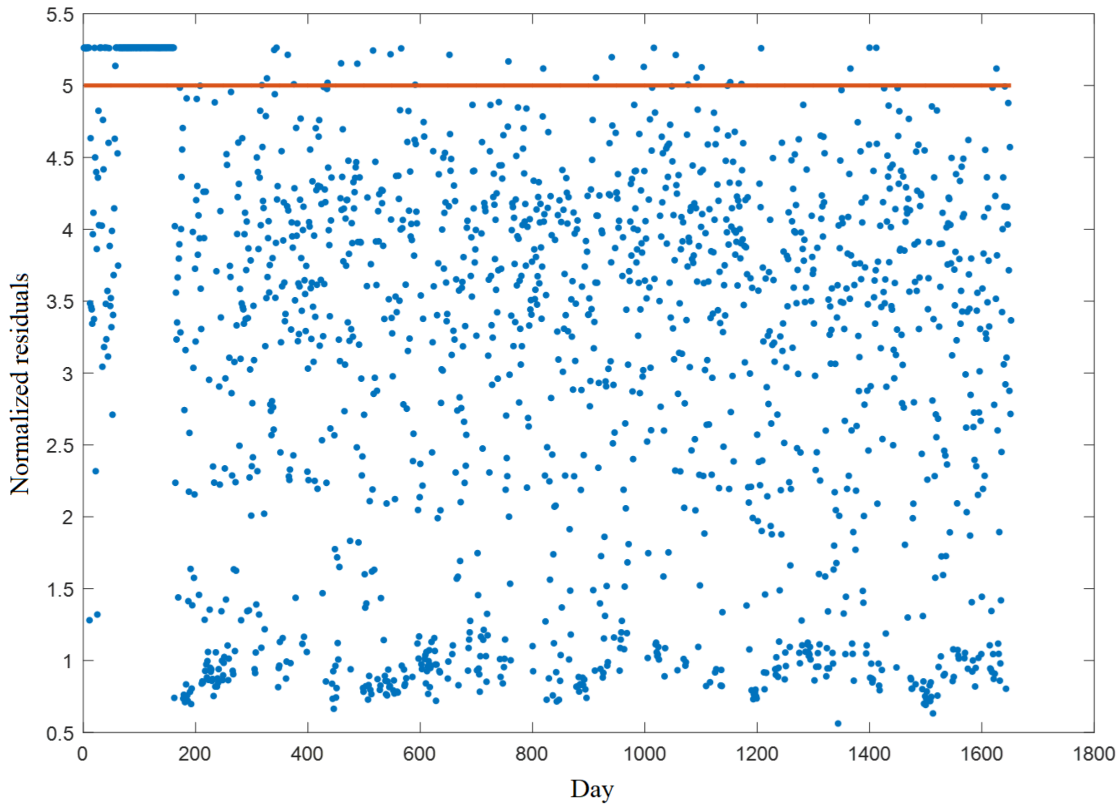
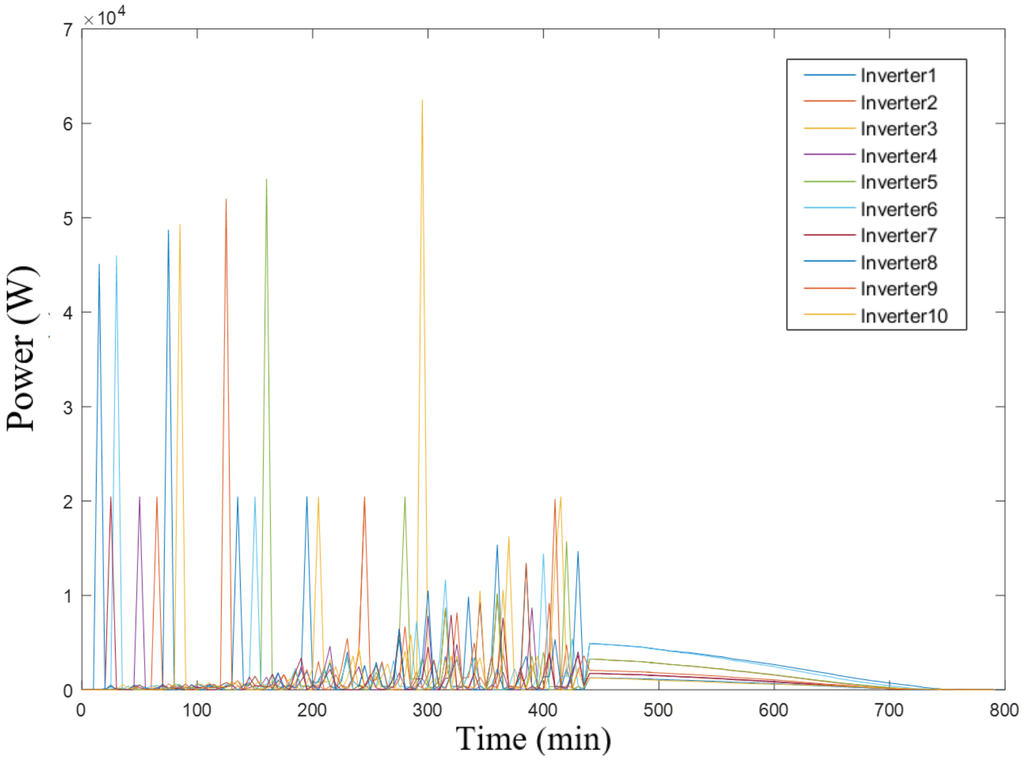
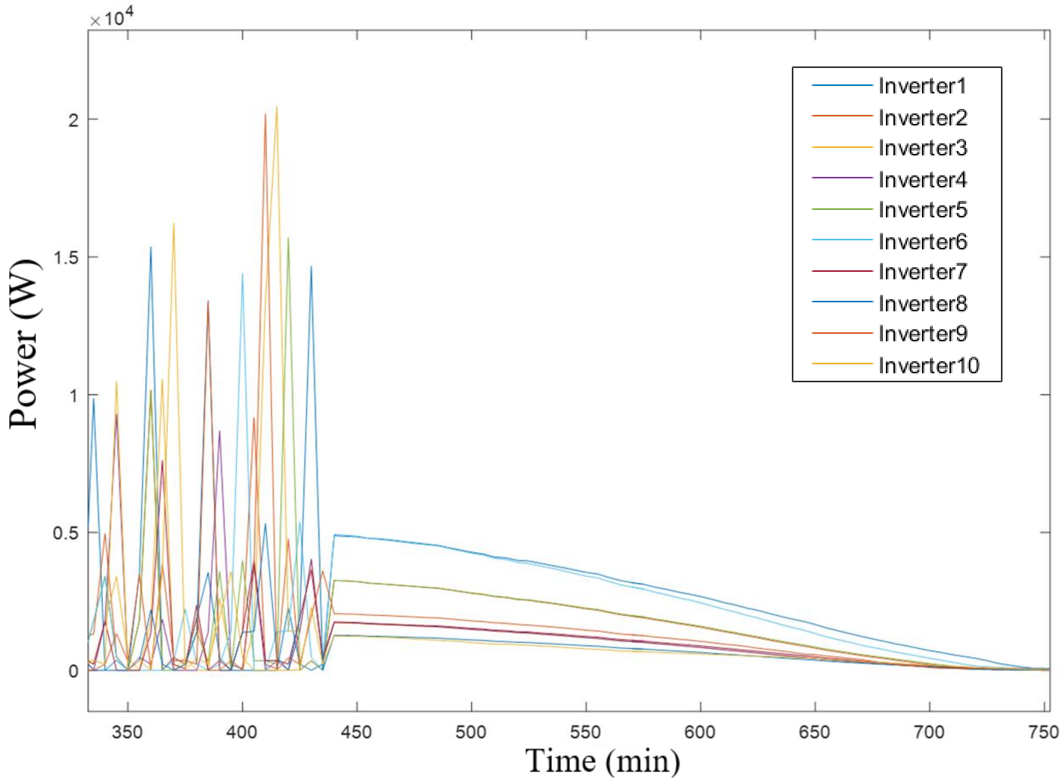


Figure 2.4 Normalized residuals' data collected for each day

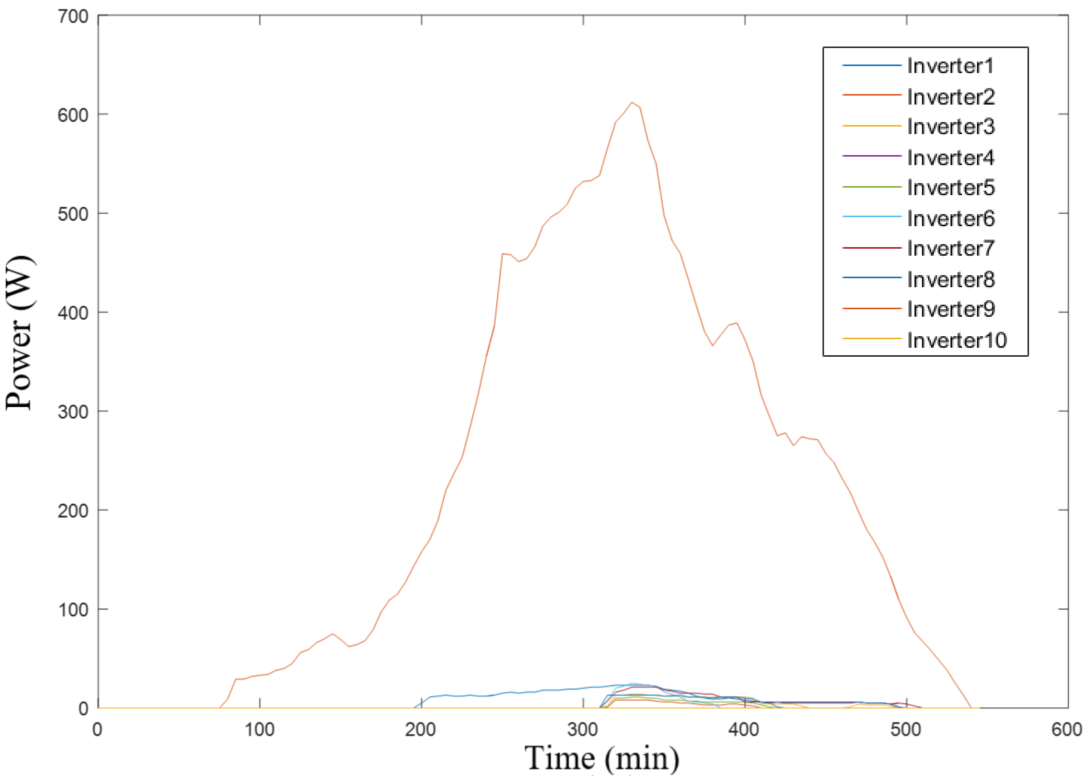


(a) – Full scale

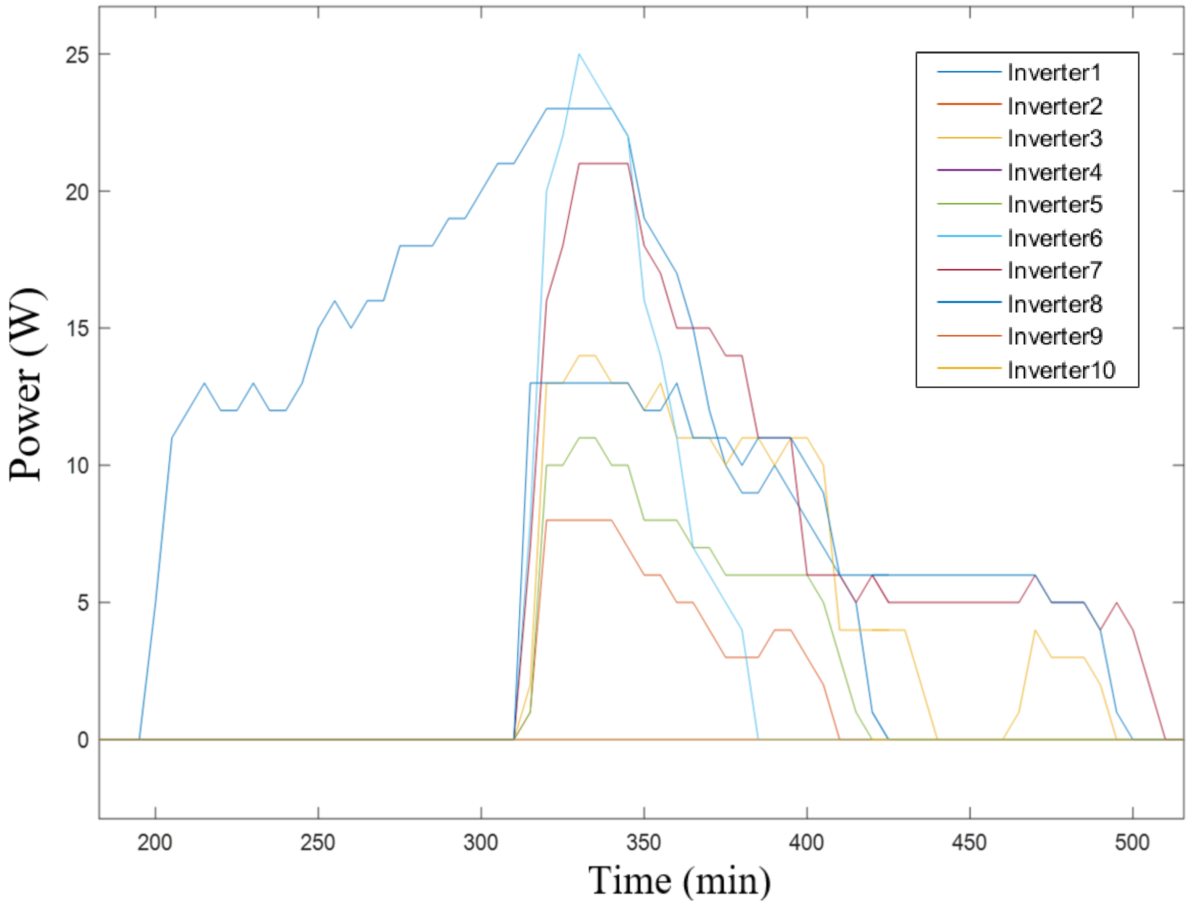


(b) – Zoomed

Figure 2.5 Generation curve data for file dated 21.06.2012



(a) – Full scale



(b) – Zoomed

Figure 2.6 Generation curve data for file dated 08.01.2013

2.5. Conclusion

In this chapter of the thesis, it was aimed to detect bad-data of PV power generation data with a method based on NRT in order to produce a solution for the problem encountered. For this purpose, the deviation from the half-wave cosine curve, which is taken as the expected and reference curve, is considered as residual. Generally, it has been seen that the suspicion threshold value as accepted as 3 by the NRT should be assigned as 5 because of the inaccuracy of the reference cosine signal.

As a result of the validation performed with the real PV generation data, it has been seen that the method can distinguish between the files of cloudy days and bad-data (corrupted files). Therefore, the method is found successful, with a zero false alarm statistic.

CHAPTER 3

STATISTICAL ANALYSIS OF SOLAR POWER DATA

In Chapter 2, a bad-data and outlier identification method is developed to use the PV power generation data of Ayasli Research Center in statistical analysis. The NRT method, which is the used bad-data identification method, is applied to the data set and the bad-data is eliminated from it. Therefore, the data set is available to use in statistical analysis in this chapter.

3.1. Introduction

The output of photovoltaic power generation mainly shows two different variation characteristics. First type of variation is regular because of seasonal changes, and day and night cycles. These variations are slow and predictable. Second type variations might be rapid and unpredictable changes in the order of minutes or even seconds due to random weather condition such as cloud passages [13]. In this chapter, the aim is obtaining information about these changes in terms of some metrics at some specific location, e.g. Ankara, and determining whether the PV system penetration is a threat in terms of voltage quality. In the literature, the photovoltaic generation curve has been investigated according to certain variables and metrics like temperature, radiation, humidity and the slope of the PV system [14]. However, these variables are not useful to investigate the real changes of the generation regime of PV system because there is an uncertainty of cloud movements, independent from these metrics. Therefore, three metrics are determined to analyze the data with this uncertainty, which are mean of total change rate in a day with respect to the expected rated generation, total variation in a day, and a total number of irregularities in a day. Therefore, three methods are used to obtain these metrics; namely relative change, total generation distortion and sign change of derivative methods are employed respectively. Moreover, with these results, monthly and seasonal histograms are drawn to further understand, clarify and evaluate the change characteristic of a PV system in Ankara.

3.2. Relative Change Method

In a data series, relative change expresses the percentage of the ratio between the absolute change of two consecutive data values, and the value of first data. The method is well known, simple and suitable to calculate the mean of total change rate in a day.

The daily power curve of a PV system varies depending on sunbathing and the shape of the curve is close to a sinusoidal. For days with a clear sky, these curves have a constant mean of total change rate; in other words, it can be used as a reference and the mean can be acceptable as a metric. Although the method does not give numeric results which can be used in a mathematical analysis, it is sufficient enough to give information about monthly and seasonal changes, and it is simple and a good start for the statistical analysis.

3.2.1. Mathematical Background of Relative Change Method

The relative change method used in power output data of PV system expressed as follows.

$$N_{RC}(n) = \frac{|P(n+1)-P(n)|}{P(n)} \times 100\% \tag{3.1}$$

$$N_{mean} = \frac{1}{N} \times \sum_{1}^{N-1} N_{RC}(n) \tag{3.2}$$

In (3.1), $N_{RC}[n]$ means relative change at n^{th} data, N_{mean} is used as the mean of total change rate in a day, and P(n) means power generation value at n^{th} data.

3.2.2. Application and Results of the Relative Change Method

As mentioned in the previous chapter, the data set includes 10 separate inverters data. Before the method is applied, this data set is gathered as a single output. For the reference, the method is applied on a clear day and the mean of total change rate is calculated as 10.49% in Matlab environment. The monthly and seasonal mean of total change rate is given in Figure 3.1 and 3.2 respectively.

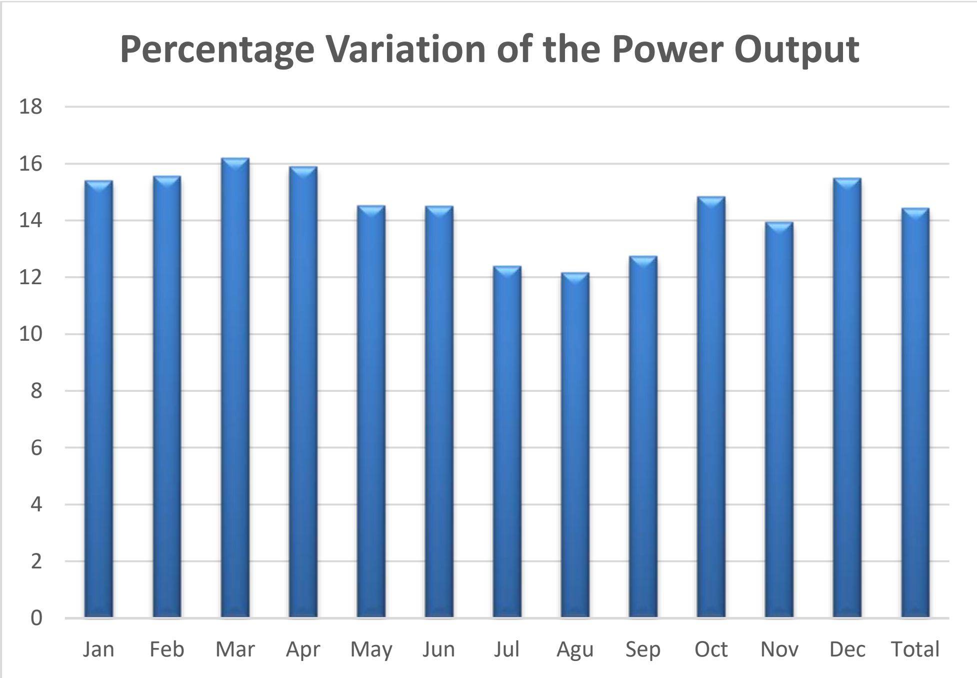


Figure 3.1 Monthly means of change rate

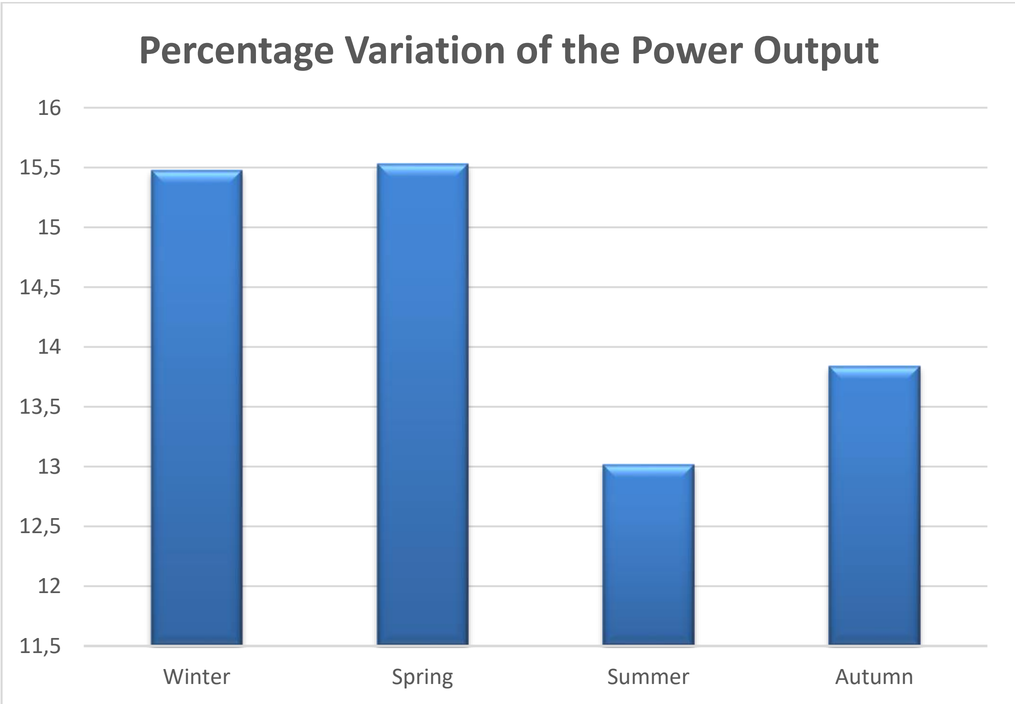


Figure 3.2 Seasonal means of change rate

Depending on the results, it can be said that power output regime of the PV system is more regular at summer days, especially in July and August. Although it is expected that regime of spring season is smoother than the regime of the winter season, their results are very close. Furthermore, the results of autumn season are well in a bit of surprise, while the spring ones are close to winter. With this metric, it can be said that the PV power generation systems have a good regime in the summer days and its effects should be more positive to the system.

The metric is a successful and quick way to get basic information about daily, monthly and seasonal regime of a PV power generation data. Although, the numerical results of the method are not proper to use in simulations or modelling, these results are a good way to interpret and compare the data set.

3.3. Total Generation Distortion Method

Total generation distortion method is a method depending on Fourier series and Fourier transforms, which represent the functions or signals as the superposition of fundamental waves. The method is generally used to analyze the current and voltage waveforms to investigate power quality of the system in power systems area. However, in this thesis, it is used to research the distortions of the power output of the PV systems. In fact, the proposed method is based on the total harmonic distortion (THD) method. The difference between them is that THD is applied to a current data and has international standards while the proposed method is applied to a power data.

As mentioned in previous sections, a daily curve of the PV systems is similar to sinusoidal sign. At the previous part, the daily curve is investigated by assuming it as a constant power supply and change rate is evaluated depending on this approach. On the other hand, in this part, the daily curve is investigated by taking daily changes of a PV supply into account. Depending on its sinusoidal characteristic, total generation distortion method is very suitable for this work.

3.3.1. Mathematical Background of Total Generation Distortion Method

In order to perform total generation distortion method with Fourier transform, the signal applied to the method should be a periodic signal. The daily curve of a PV system is similar to first half of a cosine signal, so this curve is repeated and a periodic signal is obtained. The obtained signal can be seen in Figure 3.3.

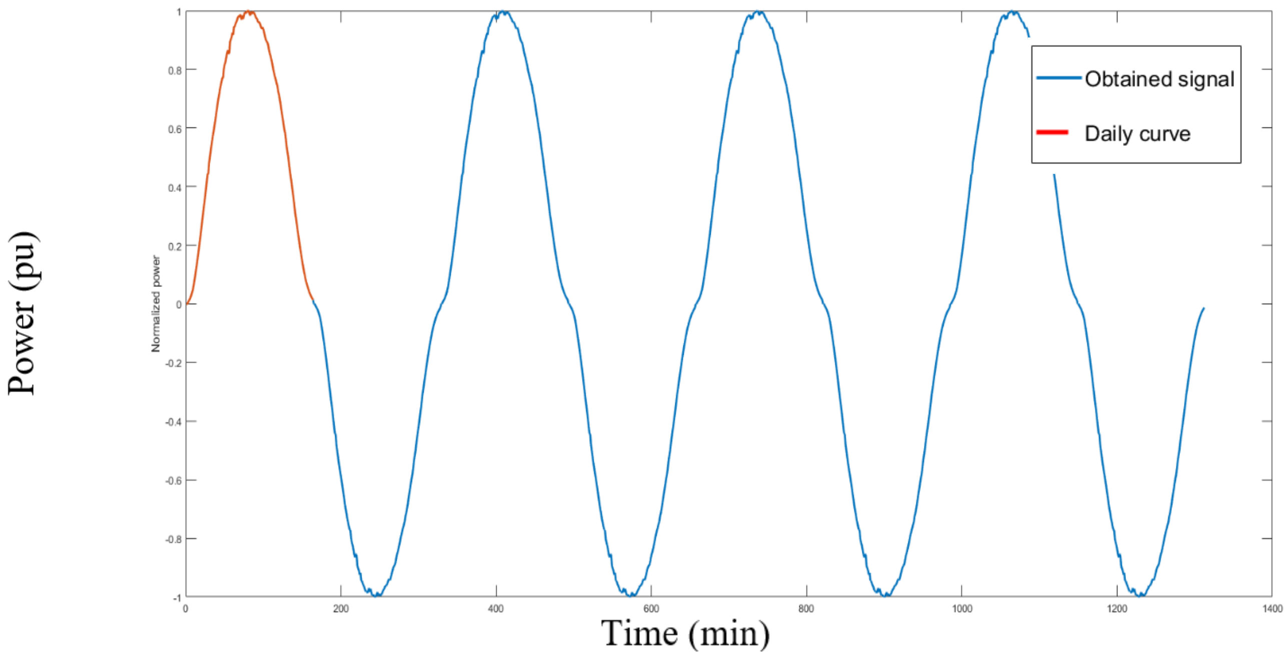


Figure 3.3 The periodic signal obtained from repetition of a daily curve

The obtained signal is now a periodic signal; it means that it is composed of many uniformly sinusoidal signals, which can be expanded as following Fourier series.

$$P(t) = P_0 + \sum_{n=1}^{N}(a_n * \cos(nwt) + b_n * \sin(nwt)) \tag{3.3}$$

In (3.3) P(t) describes power output of the daily curve, w is the angular frequency which can be calculated from $w = {}^{2\pi}/_{T}$, T is the period of the repetitive signal, P_0 is the offset and equals to 0 for the daily curve. a_n and b_n are the Fourier coefficients of harmonic orders from n=1, 2, 3, … to N and N is the highest order of harmonic signals. To simplify following calculations, T is accepted as 2π. With the simplified version of equation (3.3), Fourier series can be expressed as follows.

(3.4)

$$P(t)=\sum_{n=1}^{N}(a_n*\cos(nt)+b_n*\sin(nt))=$$

$$a_1\cos(t)+b_1\sin(t)+a_2\cos(2t)+\cdots+a_N\cos(Nt)+b_1\sin(Nt)$$

Then, $P^2(t)$ can be denoted as follows.

$$\begin{aligned}P^2(t)=(a_1\cos(t))^2+(b_1\sin(t))^2+(a_2\cos(2t))^2+(b_2\sin(2t))^2+\cdots\\+(a_N\cos(Nt))^2+(b_N\sin(Nt))^2+2(a_1b_1\cos(t)\sin(t)\\+a_1a_2\cos(t)\cos(2t)+b_1b_2\sin(t)\sin(2t)+\cdots\\+a_Nb_N\cos(Nt)\sin(Nt))\end{aligned}\tag{3.5}$$

After that, taking integral of both side one period T (0 to 2π), $P^2(t)$ will come to a state where it can be simplified.

$$\begin{aligned}\int_0^{2\pi}P^2(t)dt=\int_0^{2\pi}(a_1\cos(t))^2+(b_1\sin(t))^2+(a_2\cos(2t))^2\\+(b_2\sin(2t))^2+\cdots+(a_N\cos(Nt))^2+(b_N\sin(Nt))^2\\+2(a_1b_1\cos(t)\sin(t)+a_1a_2\cos(t)\cos(2t)\\+b_1b_2\sin(t)\sin(2t)+\cdots+a_Nb_N\cos(Nt)\sin(Nt)))dt\end{aligned}\tag{3.6}$$

Results of integral for sinusoidal functions between their own periods will be equal zero or π, depending on orthogonal properties of these functions as follows.

$\int_0^{2\pi}\sin(xt)\,dt=0$, where x is an integer and not equal to zero.

$\int_0^{2\pi}\cos(yt)dt=0$, where y is an integer and not equal to zero.

$\int_0^{2\pi}\sin(\mathrm{xt})\cos(yt)dt=0$, where x and y are integers and not equal to zero.

$\int_0^{2\pi}\sin(xt)\sin(yt)dt=0$, where x and y are integers and not equal to zero.

$\int_0^{2\pi}\cos(xt)\cos(yt)dt=0$, where x and y are integers and not equal to zero.

$\int_0^{2\pi}(\sin(xt))^2dt=\pi$, where x is an integer and not equal to zero.

$\int_0^{2\pi}(\cos(yt))^2 dt = \pi$, where y is an integer and not equal to zero.

When the elimination will be done by applying these conditions to equation (3.6), just squares of Fourier coefficients will remain.

$$\int_0^{2\pi} P^2(t)dt = \pi((a_1)^2 + (b_1)^2 + (a_2)^2 + (b_2)^2 + \cdots + (a_N)^2 + (b_N)^2) \tag{3.7}$$

Then, the root mean square (RMS) value of the P(t) can be calculated as follows.

$$P_{RMS} = \sqrt{\frac{1}{2\pi}\int_0^{2\pi} P^2(t)dt} = \sqrt{\frac{(a_1)^2 + (b_1)^2 + (a_2)^2 + (b_2)^2 + \cdots + (a_N)^2 + (b_N)^2}{2}} \tag{3.8}$$

This formula shows that RMS values do not depend on harmonic frequencies of the signal. Therefore, from the RMS values, total distortion in a daily curve can be computed as follows.

$$P_{1RMS} = \sqrt{\frac{(a_1)^2 + (b_1)^2}{2}} \tag{3.9}$$

$$P_{DRMS} = \sqrt{{P_{RMS}}^2 - {P_{1RMS}}^2} \tag{3.10}$$

In these equations (3.9) and (3.10), P_{DRMS} and P_{1RMS} correspond to RMS values of total distortion and fundamental signal.

From the daily curve, P_{RMS} can be calculated from the integral of data points. P_{1RMS} can be calculated from peak point of a daily curve for suitable days (If the peak point is seen in between the midday hours) or from the nearest successful previous day peak point by dividing it to the square root of 2.

3.3.2. Application and Results of Total Generation Distortion Method

The method is applied to same data set in the previous step. The application is realized in Matlab environment. For better understanding, fundamental signal values normalized to 1. To calculate P_{RMS} value, "rms" function of Matlab is applied to the daily curves. Results of monthly and seasonal averages can be seen in Figure 3.4 and Figure 3.5.

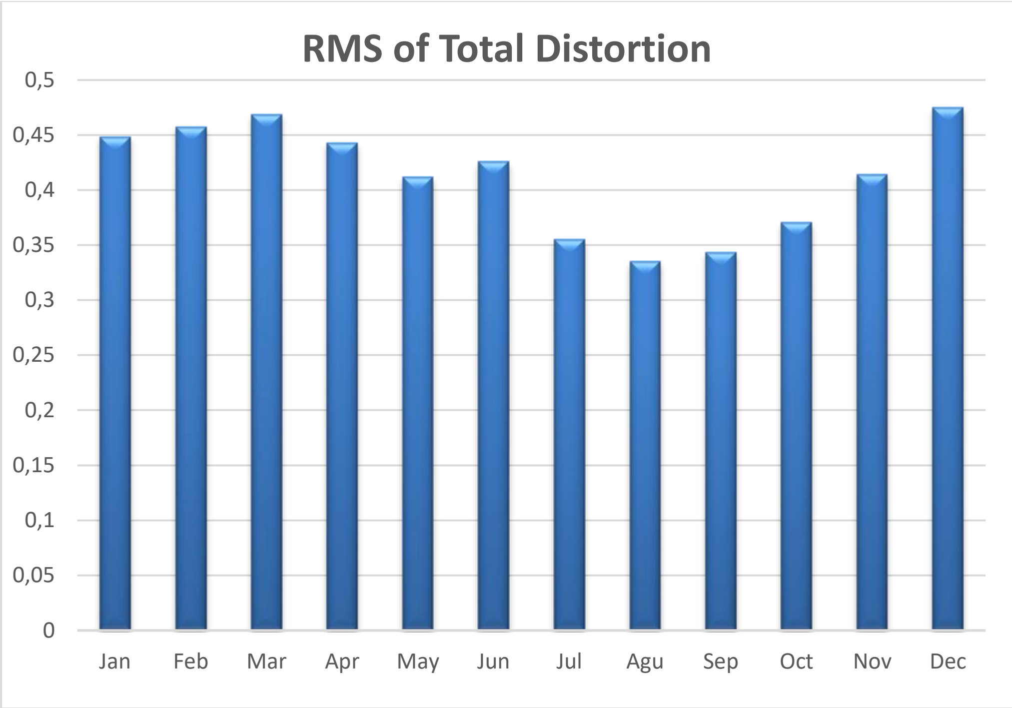


Figure 3.4 Monthly averages of RMS values of total distortions

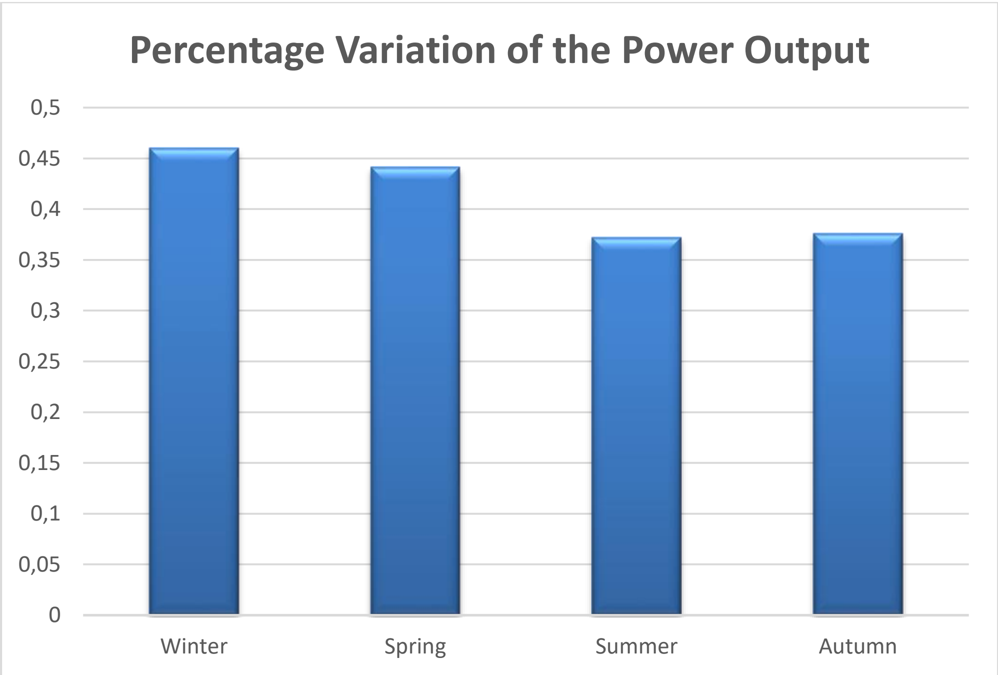


Figure 3.5 Seasonal averages of RMS values of total distortions

The monthly and seasonal results are approximately same as the results of relative change method and that supports the reliability. It can be said that the power generation of the PV system showed the less distortion in the summer and autumn days. Especially in August and September months, the values of the distortion reach the lowest values.

The numerical results of the previous method are just giving an idea about sun bathing variation regime of Ankara and cannot be used in a simulation as an input. On the other hand, the numerical results in this part are more reliable and meaningful. Therefore, they can be used for obtaining the variation of PV system generation to determine the feasibility of the system in terms of voltage quality.

3.4. Sign Change of Derivative Method

During the daily variation of the PV system generation, on a smooth, cloudless day, the sign of derivative is positive until midday, after midday it comes to negative. When there is a cloud or any weather condition to affect the PV system like power generation irregularities, there is a sign change of derivative. These variations in supplied power can be easily tracked by checking the sign of derivative of a daily curve. Therefore, in this part of the thesis, the method is used to find how frequent these events occur, and also it gives locations of these events in time. Overall, the magnitude of the variations can be obtained along with its frequency using this method.

3.4.1. Mathematical Background of Sign Change of Derivative Method

The derivative of a function P(t), which can be denoted as P'(t), is the slope of the tangent line of the function at point t. The first derivative gives information about the function whether it is increasing and decreasing, and how much it increases and decreases. In terms of derivatives, this relationship can be written as follows.

$$P'(x) = \frac{dP}{dt}(x) > 0 \rightarrow \; P(t) \; is \; increasing \; at \; t = x.$$

$$P'(x) = \frac{dP}{dt}(x) < 0 \rightarrow \; P(t) \; is \; decreasing \; at \; t = x.$$

$$P'(x) = \frac{dP}{dt}(x) = 0 \rightarrow \; t = x \; point \; is \; called \; as \; the \; \; critical \; point.$$

An example of the daily curve of PV system generation is given in Figure 3.6 with its derivative. This curve belongs to a cloudless smooth day and the derivative function is multiplied by ten to easier understand. As it is seen, the derivative is changing sign at midday times and its magnitudes are small. On the other hand, Figure 3.7 is from some cloudy day. The sign of derivative is changing with the power generation irregularities, and also its magnitude can be noticed.

To analyze the characteristic of the power generation curve of a PV system, these sign changes can be recorded daily together with the number and magnitude and investigated monthly and seasonally. For the data points before the midday, the derivative value should be recorded at the point where the derivative value passes from positive to negative, this value gives the magnitude of the power generation irregularity. On the other hand, for the data points after the midday, the derivative value of previous point is recorded when the derivative value passes from negative to positive because the derivative values are negative after the midday, so when the derivative changes the sign, it has already passed the point where the power generation irregularity happened. The logic is given as follows. In this equations, t/2 refers to the time of midday point.

$$For\ x < \frac{t}{2}\ , if\ P'(x) < 0\ and\ P'(x-1) > 0, record\ P'(x).$$

$$For\ x > \frac{t}{2}\ , if\ P'(x) > 0\ and\ P'(x-1) < 0, record\ P'(x-1).$$

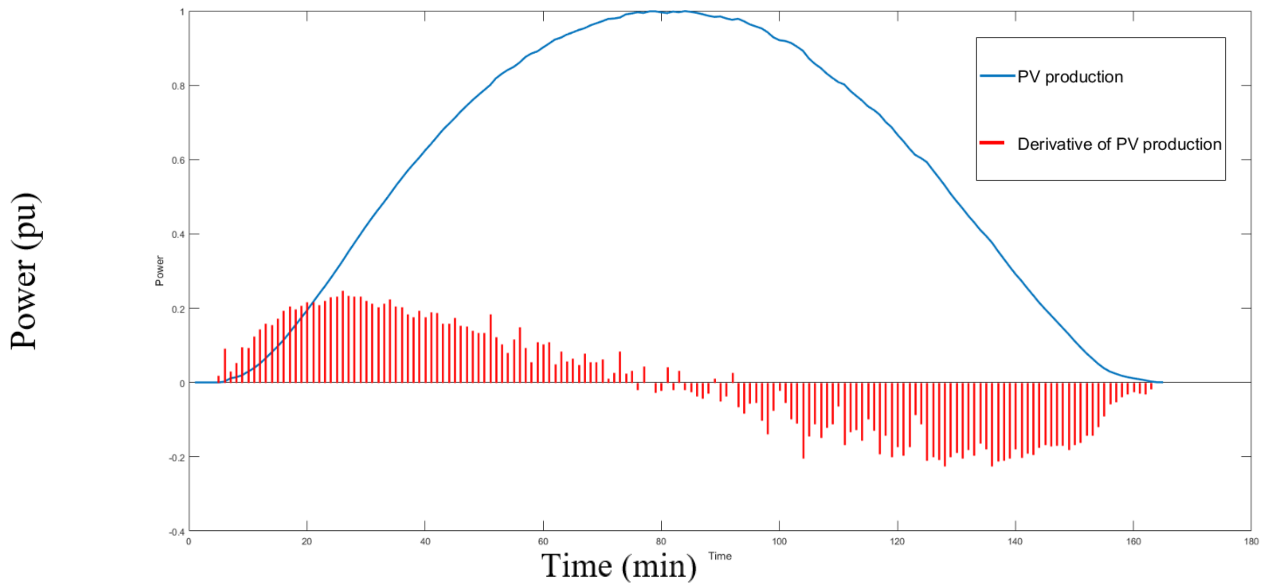


Figure 3.6 A daily curve and its derivation from cloudless and smooth day

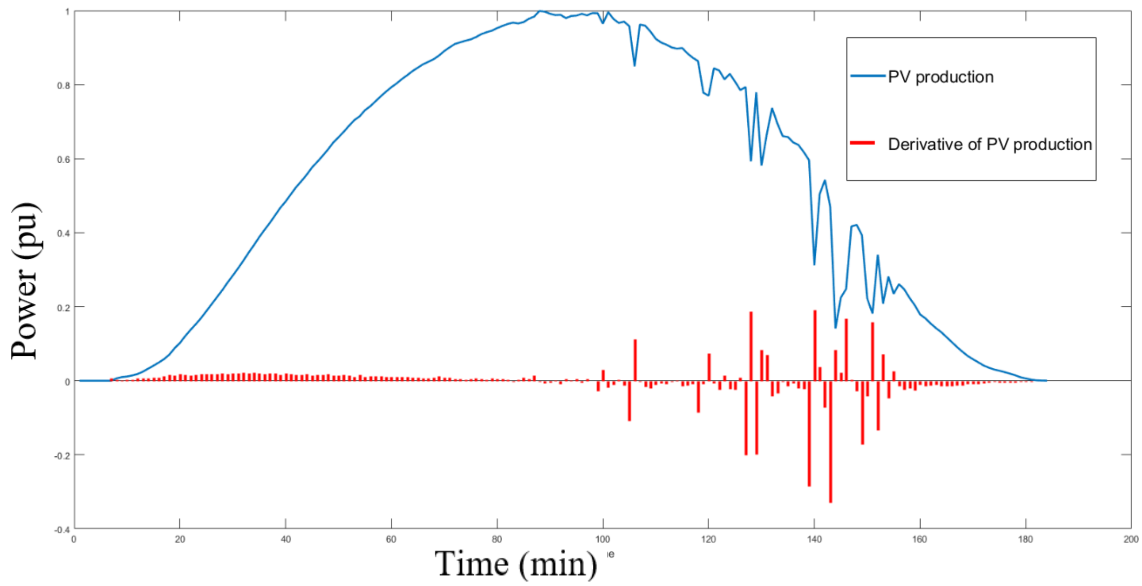


Figure 3.7 A daily curve and its derivation from some cloudy day

3.4.2. Application and Results of Sign Change of Derivative Method

The sign change of derivative method is applied to the same data set passed from bad-data identification. The application is performed in Matlab environment by recording numbers and magnitudes of the events daily. The magnitudes of the power generation irregularities are classified at certain intervals such as 0.5 and 1-kilowatt intervals up to the maximum.

There are 38288 power generation irregularities, which can be found by the method. 18962 of these sags are between 0 and 500 W, and when considering that the rated power of the installed PV capacity is 50 kW, this power interval is less than 1%, so these sags can be ignored. Figure 3.8 shows that the percentage of the number of events in terms of magnitudes of the variation. In other words, it gives the frequency and magnitude results of the power generation irregularities of the PV system. Moreover, to simplify the investigation, the months, which have same change characteristics from the previous methods, are grouped according to similarity of their results from the previous methods. Depending on Figure 3.1 and 3.4, 5 different month groups are created. Group-1 includes July, August and September, Group-2 includes January, February, March, April and December, Group-3 includes May and June, Group-4 includes October and lastly Group-5 includes November. Their results can be also seen in Figure 3.9 to Figure 3.13.

Depending on the results, almost 50% of the events are between 500-2000 W interval. It can be said that the probability of occurrence of large power generation irregularities is very small based on the large PV data set sampled in every 5 minutes, spanning 4 years. However, these large power generation irregularities have most crucial effects on reliability of the system. In the light of this information, these power variations will be used as input of PV system in power system simulation for reliability assessment.

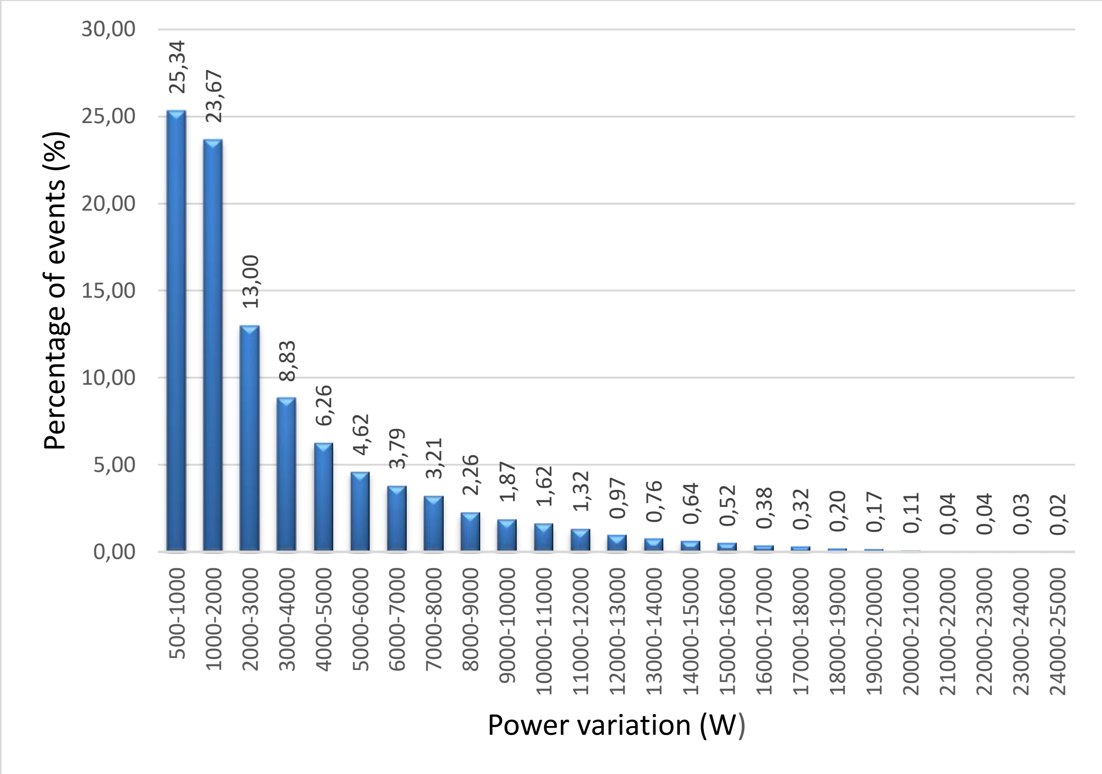


Figure 3.8 Percentage of events in terms of power variation

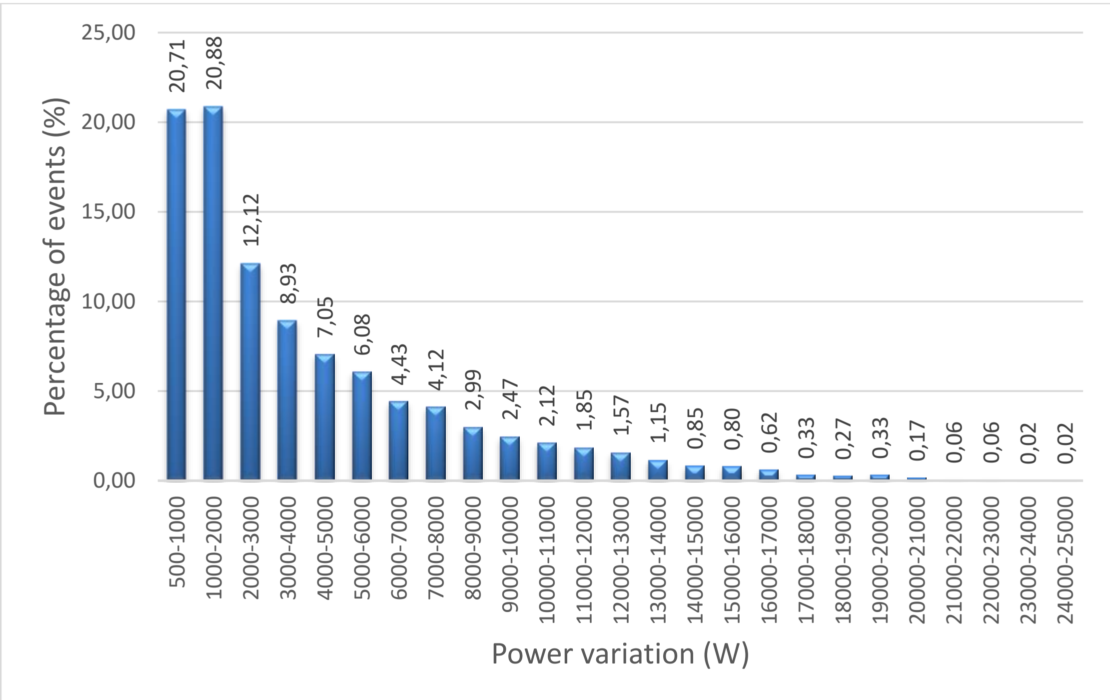


Figure 3.9 Percentage of events in terms of power variation for Group-1

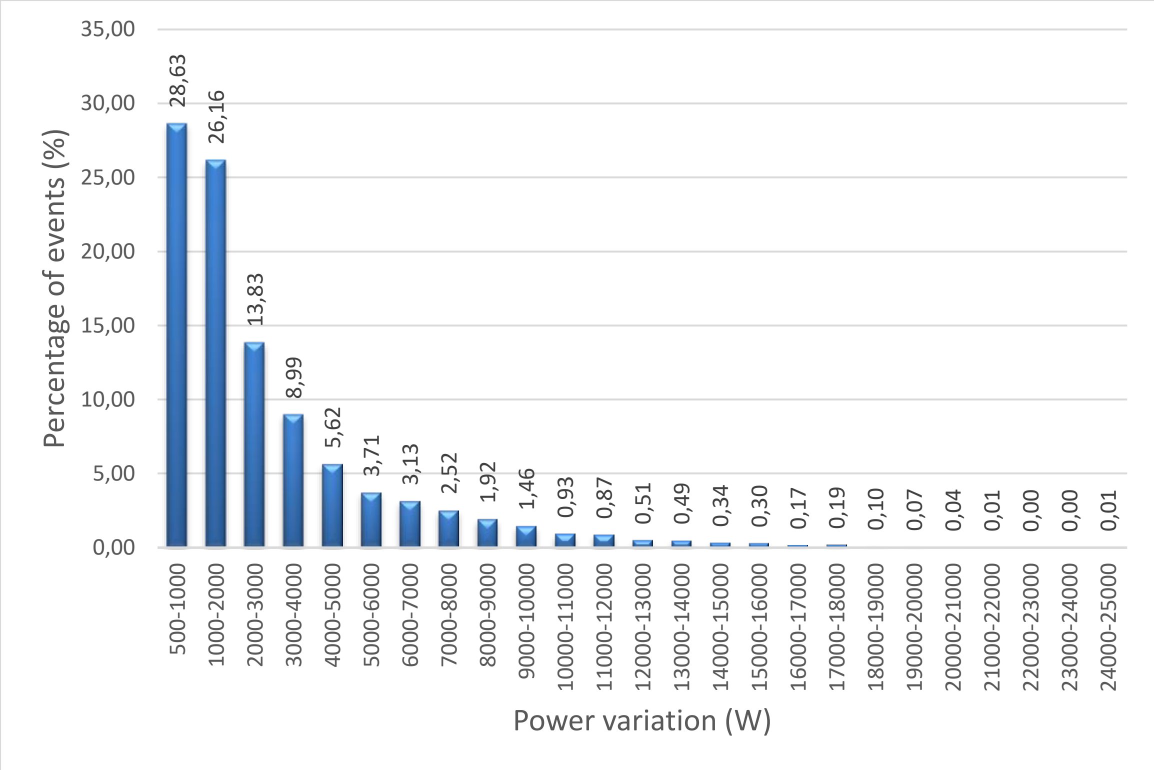


Figure 3.10 Percentage of events in terms of power variation for Group-2

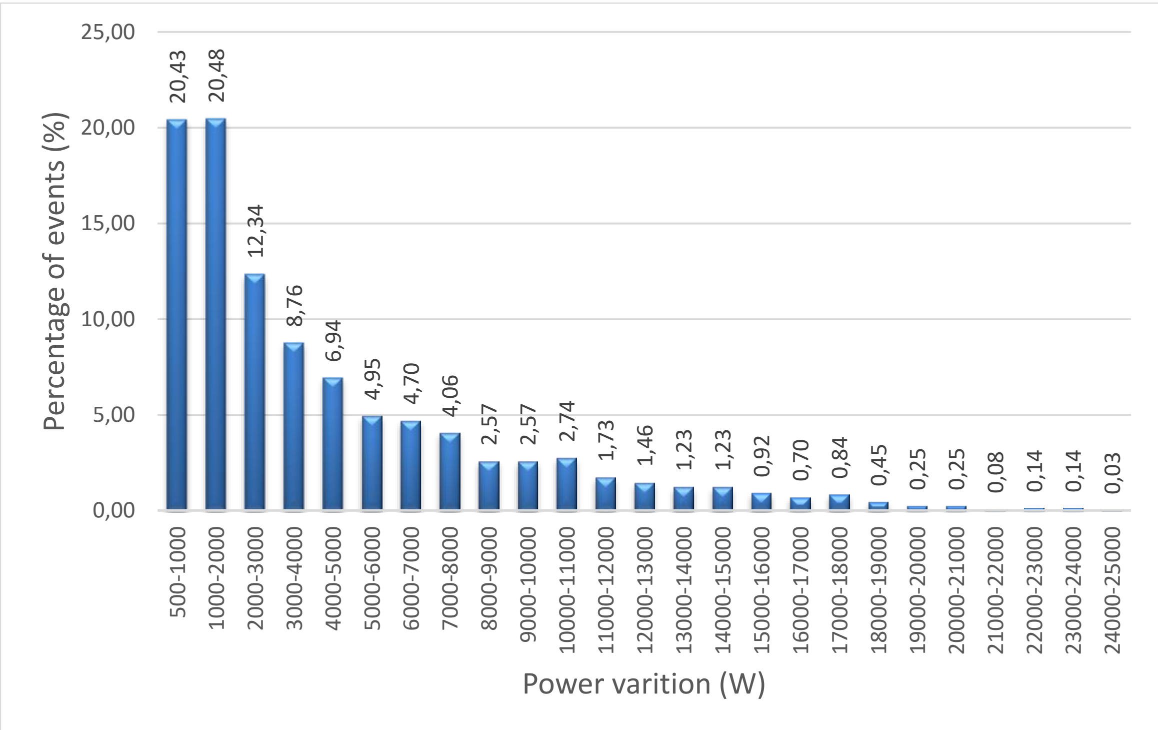


Figure 3.11 Percentage of events in terms of power variation for Group-3

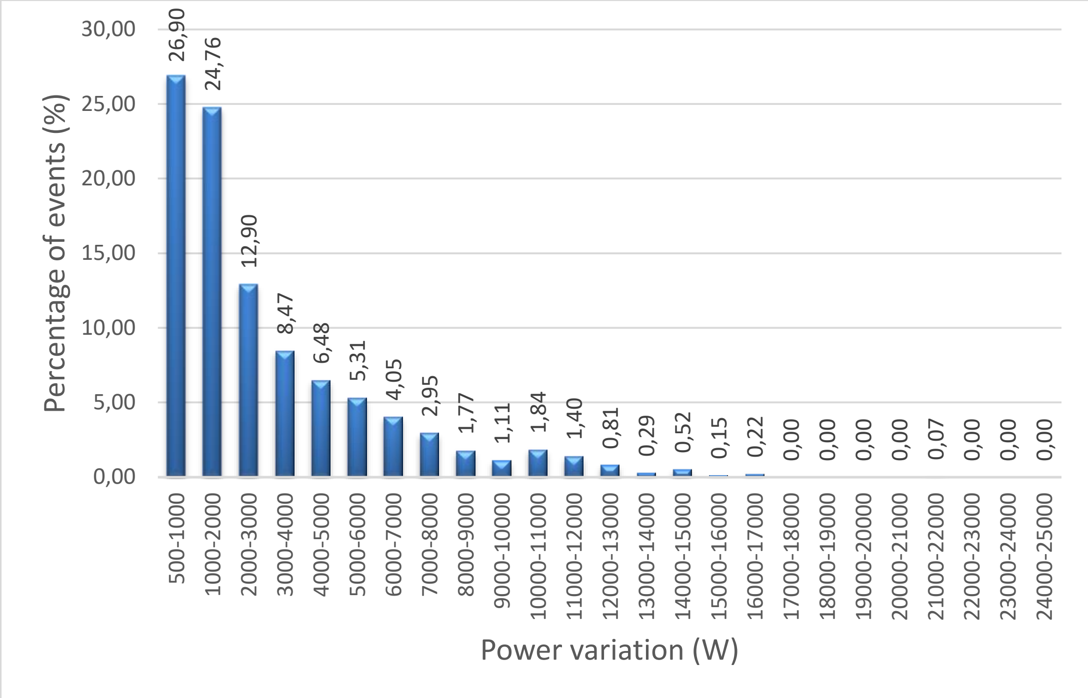


Figure 3.12 Percentage of events in terms of power variation for Group-4

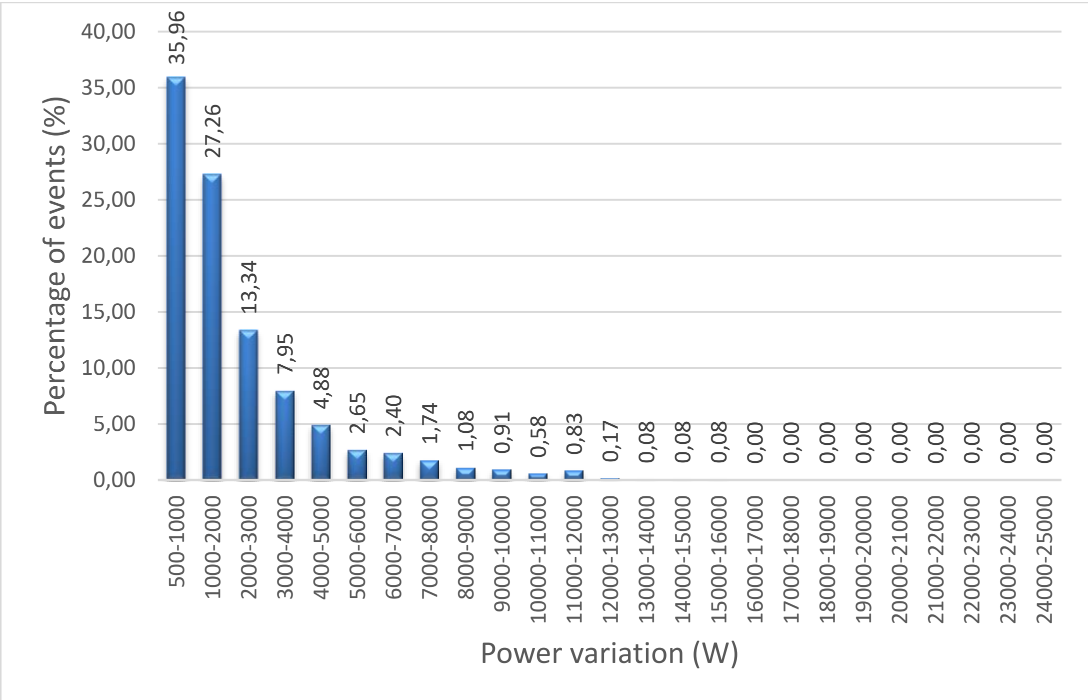


Figure 3.13 Percentage of events in terms of power variation for Group-5

3.5. Discussion

In this chapter, it is aimed that the solar power data is investigated statistically. In the literature, except of forecasting of solar power generation, there are no statistical analyzes to investigate formally the system operation and feasibility of PV systems, hence three methods were developed. With these three methods, this chapter especially focused on the characteristic of the change in the solar power data. The first method concentrated to make comment about the change rate of a solar power generation, as if it is a constant power generator, in a fast and convenient way. The second method is like an improved version of the first method. It was investigated the changes in the solar power data as half-wave cosine sign as it is approximately same as the curve of PV power generation in a smooth and cloudless day. This method inspired from the THD method, which is well-known and mostly used in power quality investigations of the power systems. With this method, it is found how much the daily power curve of a PV deviates from the reference curve, half-wave cosine sign. Moreover, its numerical results are more reliable than of the first method. The third and last method is based on sinusoidal characteristic of the daily curve. The sign of derivative for a half-wave cosine sign is positive up to the peak point and negative after that. The frequency and magnitude of changes in the daily curve were found by this method according to sign change of derivative. Furthermore, the months are grouped according to similarity of the results of the first and second method because of simplifying comparison of the results for the reliability assessment. Therefore, with the results of this method, the randomness of weather conditions, especially cloudiness, can be implemented to power system simulations. Moreover, these results prove that these methods can be used to find that the PV is feasible, or not for new regions where new PV systems will be constructed.

CHAPTER 4

NUMERICAL ANALYSIS

In the previous chapters, the PV generation data obtained from the Ayasli Research Center is investigated. The investigation started with a bad-data identification because the recording device at the research center was corrupted. After elimination of the bad-data in the data set, the data was analyzed statistically to get the change regime of a solar power generator in Ankara and to use for the evaluation of reliable system operation. For this purpose, 3 different methods were applied to the data set, and a conclusion was made about the change characteristic of the solar power generation with monthly and seasonal histograms by these methods. In this chapter, a PV system will be investigated in a sample power system, which includes two residential loads and two industrial loads connected radially to observe the effects of PV systems on the voltage quality of the system.

4.1. Introduction

The increasing population of PV systems brought many concerns. One of the main concerns is the effects of PV systems on reliability and power quality of the system. As it is said in the Chapter 1, the power quality can be accepted as equivalent to the voltage quality. In the literature, many researchers focus on the adverse effects of PV systems. On the other hand, in this thesis, it is concentrated on the reliability of the power systems by evaluating the effects of PV systems on the voltage quality with the weather condition variations assuming as there are no power storage units connected to the PV system.

To conduct the study, a sample power system is modeled with a PV system, two residential loads and two industrial loads connected radially. The model consists of two different load types because residential and industrial loads have different characteristics with respect to weekdays and weekends. The difference is used to create different load scenarios.

The effects of PV systems on the reliability are analyzed with the variation of PV generation obtained from the third chapter, based on the voltage variation and flicker.

In this chapter, firstly, the system model, which contains the PV system and its control, the residential and industrial loads, the transformers and the lines is given in detail with its single line diagram. These sub-systems are based on real-data obtained from relevant institutions and organizations. Secondly, the effects of PV generation variation on the considered power system are analyzed in computer environment, using Matlab/Simulink. The resulting data from this simulations is investigated in Matlab environment. Lastly, the overall results are analyzed in terms of the effects of PV systems on the voltage quality in the conclusion part.

4.2. System Model

The system is modeled considering that a distributed PV system is connected to a load bus, which can be a residential or an industrial load, to evaluate the effects of a PV system on the voltage quality for different circumstances. For this purpose, the change characteristic data of PV system obtained from the previous chapter is used. The whole system that consists of the source, the HV/MV transformer, and the MV transmission lines are modeled depending on the real data from the system operator, Turkish Electricity Transmission Company (TEIAS). The whole system is described in detail as follows.

The system consists of a high voltage (HV) substation, high voltage to medium voltage (HV/MV) transformers, medium voltage to low voltage transformers (MV/LV), medium voltage (MV) transmission lines, a PV system and loads. Three phase diagram of the system is given in Figure 4.1. To evaluate the effects of a PV system on voltage quality, the PV system is modeled based on real data from the MILGES project [2]; HV substation, transmission lines, and transformers are also modeled based on real data of Turkish Electricity Transmission Company (TEIAS), which is the system operator in Turkey. Except the PV system, the data belongs to the records of Turkish Electricity System.

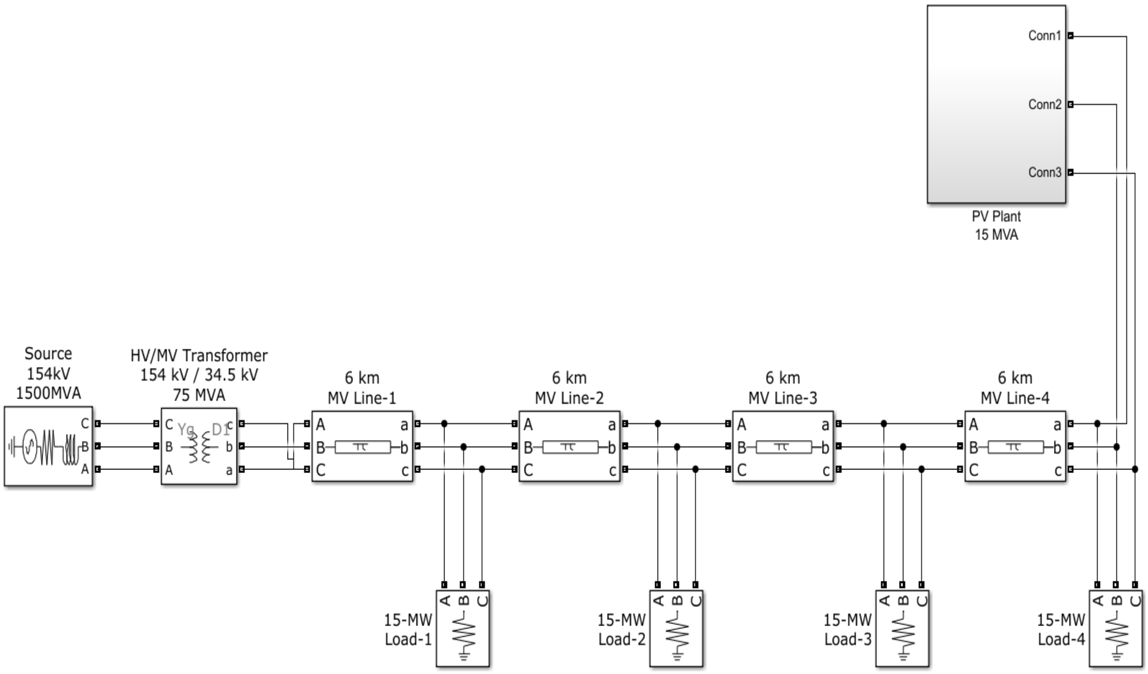


Figure 4.1 Three phase diagram of the system

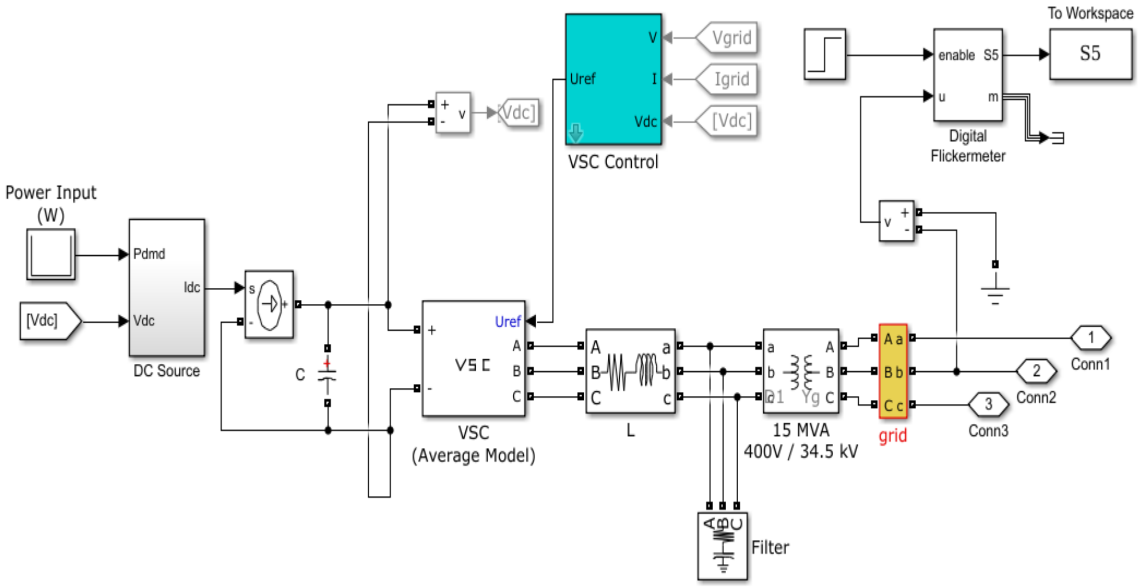


Figure 4.2 Diagram of the PV system

The substation data is given in Table 4.1, which is typical data from Turkish Electrical System. The HV/MV transformer's rating is shown in Table 4.2 also.

Table 4.1. The typical HV substation data from Turkish Electrical System

Voltage (kV)	SCMVA (MVA)
154	1500

Table 4.2. The typical HV/MV transformer substation data from Turkish Electrical System

Voltage (kV)	S (MVA)	R (pu)	X (pu)
154/33.6	75	0.0147	0.1200

The PV system rating is selected based on the Turkish Electricity standard, which restricts the renewable energy generation in a MV power system as 20% of the rating of the HV/MV transformer to which the PV system is connected [15]. Hence, the PV system rating is decided as 15 MVA. As the assessment includes voltage variation and flicker, the PV system is modeled with an average model of voltage source control (VSC) and it was considered as qualified.

The transmission line between the PV system and the substation is specified based on Table 4.3, which is the typical data from Turkish Electrical System.

Table 4.3. The typical transmission line data from Turkish Electrical System

Line Type	R (Ohm/km)	L (mH/km)	Capacity (A)
Hawk	0.14	0.983	460

There are 4 load substations with intervals of 6 km MV lines. The loads are considered as two residential and two industrial loads and each of them has a rating of 15 MW. For the reliability assessment, three different load scenarios are generated. The first scenario is generated as considering that all loads are at their peak points (15 MW) in a weekday. For the second and the third scenarios, they are accepted as light load conditions in an example of a weekend. According to [16] and [17], residential load and industrial load demands are accepted as 10 MW and 5 MW respectively in a weekend. For the second scenario, Load-1 and Load-2 are accepted as industrial loads. For the third scenario, Load-1 and Load-2 are accepted as residential loads. All load scenarios are given in Table 4.4.

Table 4.4. The load scenarios

Scenario	Load-1 (MW)	Load-2 (MW)	Load-3 (MW)	Load-4 (MW)
1	15	15	15	15
2	5	5	10	10
3	10	10	5	5

4.3. Voltage Quality Assessment

Power system reliability can be defined as a measure of the ability of a system, generally given as numerical indices, to deliver power to all points of utilization within acceptable standards and in amounts desired. Although the reliability term is generally accepted as power outage of the system, in the thesis, it is proposed that the reliability term should involve voltage sags and swells because they can cause outages of some electronic based systems. Therefore, the reliability is investigated in terms of the flicker and the voltage variation according to the variation of the PV system generation from the previous chapter.

4.3.1. Flicker

Flicker is the variation in the light output of various lightning source because of the voltage fluctuations described as systematic variations of voltage waveform envelope, or a series of random voltage changes. Although the voltage fluctuations can cause harmful technical effects, the flicker has negative effects on human health from negative psychological effects to epileptic attacks for photosensitive people. The variations and their effects on the light level are illustrated in Figure 4.3 and Figure 4.4. With the increasing use of the florescent lambs, flicker is being neglected in power quality studies. It has still kept its place in voltage quality standards, although it has lost its importance.

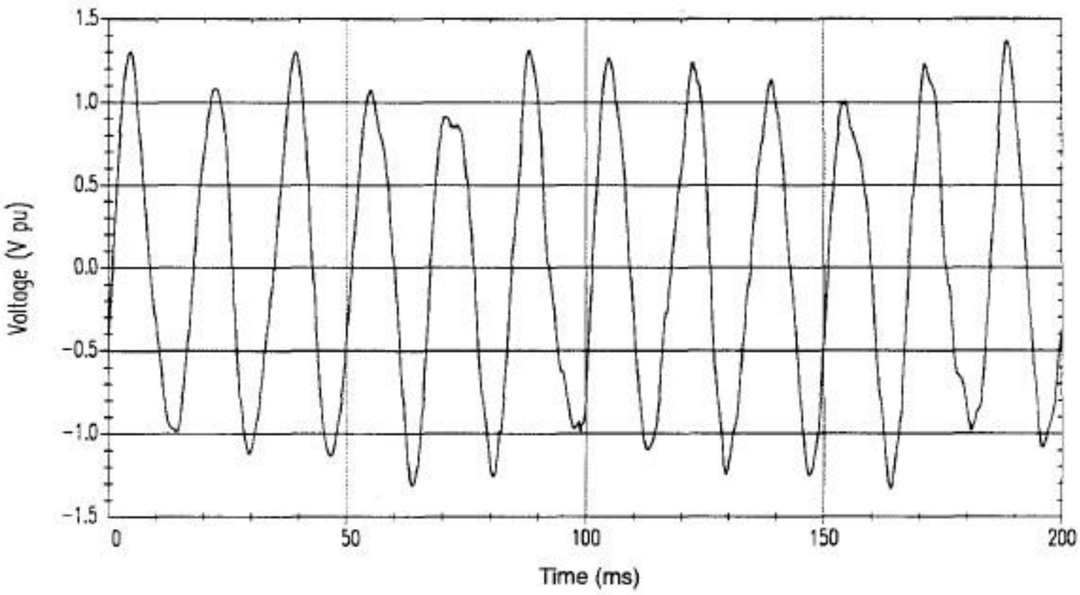


Figure 4.3 An example of voltage versus time graph for flicker [18]

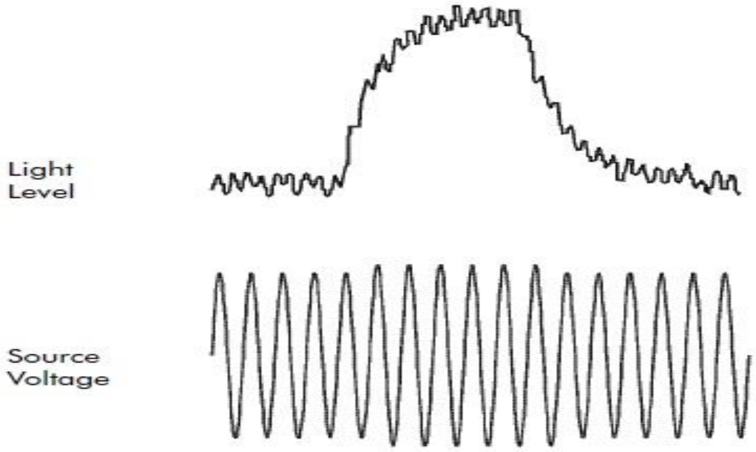


Figure 4.4 Illustration of voltage and light level of a flicker event [18]

In the next parts, the standards about the flicker are given and a flicker measurement method is explained. After that, the method is applied to the sample system with the variation of the PV system generation and the effect of it on flicker is observed.

4.3.1.1. Flicker Measurement and Standards

The standard IEC 61000-4-15 [19] defines the flicker measurement requirements and intensity of flicker by two indices, which are short-term and long-term flicker intensities. The short-term flicker intensity is denoted as P_{st} and the long-term one is denoted as P_{lt}. P_{st} is calculated by probability distribution function over a predefined observation interval. P_{lt} is calculated from P_{st} values by taking cubic averages of them. In the standard IEC 61000-3-3 [20], the observation time intervals and limiting values are specified. The short-term flicker P_{st} should be calculated for instantaneous, or intervals of 1-minutes and 10-minutes. On the other hand, the long-term flicker P_{lt} should be calculated for intervals of 2-hours.

In the sample power system used in the thesis, the data of power samples of the PV system has 5-minutes interval, so the short-term flicker P_{st} is used to measure the flicker in this study. The calculation of P_{st} is almost impossible, however, based on the formulas in the standard IEC 61000-3-3 [20], P_{st} values can be estimated as feasible and realistic as much as possible. The formulas are given as follows.

$$P_{st} = \left(\frac{2.3 * n}{T_p}\right)^{\left(\frac{1}{3.2}\right)} * F * \Delta d$$

$$d = \frac{dv}{V_{net}} * 100 \tag{4.1}$$

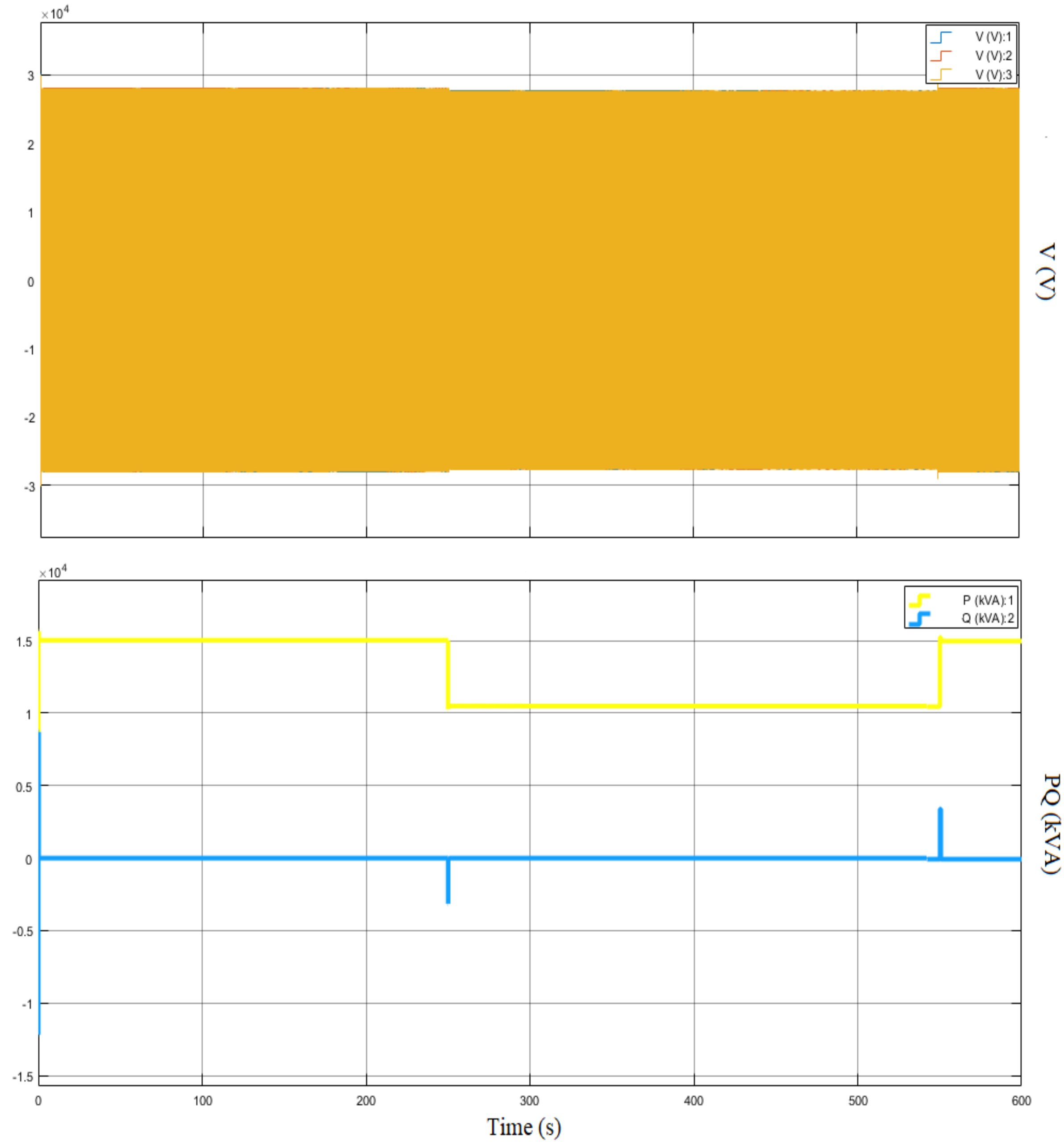
In the equation (4.1), n represents the number of load changes in the observation interval, T_p represents the duration of the observation interval in seconds. F is the shape factor and can be accepted as 1 for step-wise voltage changes. Moreover, in the standard [20], there are different shape factors for different curve forms.

For the flicker measurement, Matlab Simulink flickermeter block is used, as seen in Figure 4.2. The digital flickermeter block produces instantaneous flicker probability signals and recording. The recorded data is used by “power_flicker” function block of Matlab environment. This block is based on the formulas in the standard IEC 61000-3-3 [20].

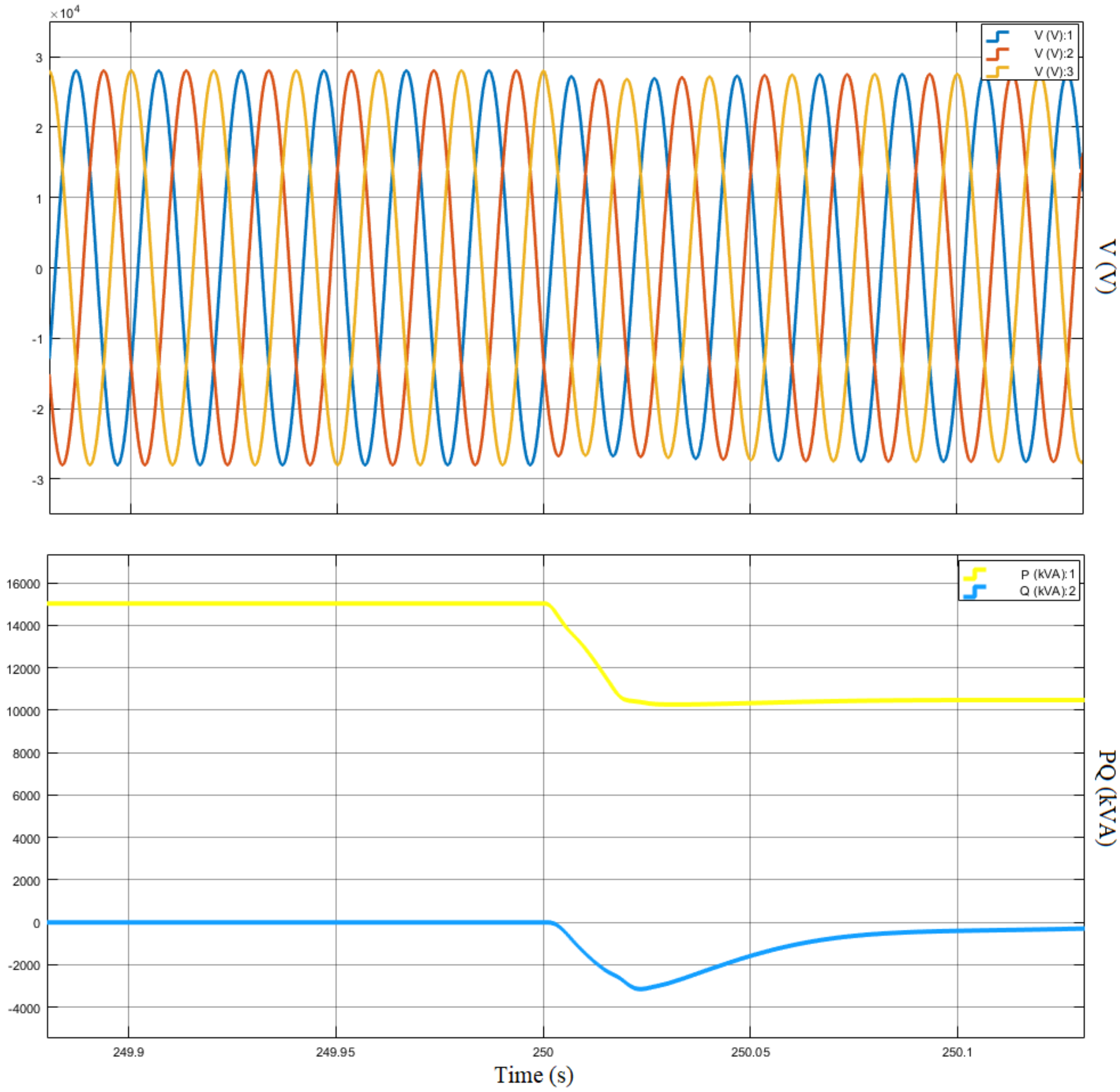
The standard EN50160 [21] stands on voltage characteristics of supplied electricity and indicates that the P_{st} value for a MV power system should be smaller than 1. This limit is used to investigate the reliability of the PV systems according to stay within the limit with the variations of the PV system generation obtained from the previous chapter.

4.3.1.2. Flickermeter Results

For the flicker measurement, the modeled system is used. In the simulation program Matlab Simulink, the modeled system is examined applying the variation of the PV system generation in an increasing manner and finding the critical point, where the P_{st} value exceeds 1. Because the PV system generation data has a 5-minutes intervals data set, the simulations' time set to 10 minutes and each of them includes 1 power variation. This process is applied for three different load scenarios explained in the system modeling part to observe the effects of the variation of the PV system generation for different circumstances. In Figure 4.5, an example of the PV power generation and the voltage at the MV side versus time graphs with a power variation of the PV system can be seen. Moreover, the digital flickermeter screen in Matlab Simulink can be seen in Figure 4.6.



a- Full view



b- Zoomed view

Figure 4.5 An example of PV power generation and voltage at the MV side versus time graph

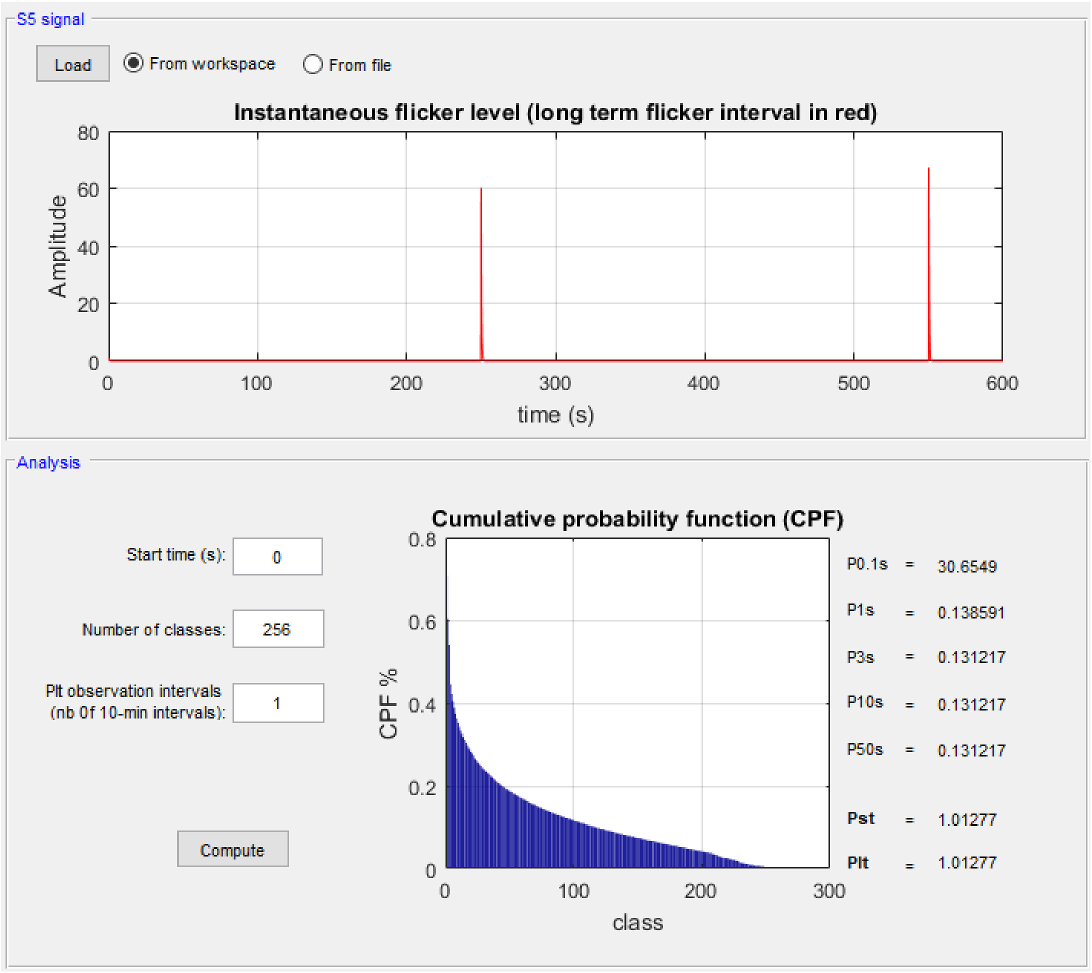


Figure 4.6 Digital flickermeter screen in Matlab Simulink

The flickermeter results are tabulated in Table 4.5. In the table, the minimum power variation in percentage, P_{min}, that causes P_{st} value exceeds 1, and the corresponding P_{st} value at this point is shown.

Table 4.5. Flickermeter results

Scenario	**P_{min}**	**P_{st}**
1	34%	1.0422
2	34%	1.0603
3	32%	1.0128

The flicker results seen in the table show that a small part of the variation of the PV system generation does not conform the EN 50160 [21], which says P_{st} value should not exceed to 1 for a MV power system.

For the first load scenario, which can be called as full load scenario, 0.93% of the PV system generation variations cause flicker problem according to the standard. Contrary to expectations, based on the variation information in the previous chapter, most of these variations have happened at summer months and months close to them (Group-1 and Group-3, July-August-September and May-June). In the months when the PV system was not expected to work more regularly, the generation variations happen more often, but their magnitudes are smaller. Hence, their effect on the reliability of the PV system is much smaller. In fact, in October (Group-4) and November (Group-5), there is almost no generation variation that does not conform the standard.

For the second load scenario, which can be called light load scenario, the result of flicker assessment is same as the first one in terms of reliability. In addition to first load scenario, depending on flicker results, it can be said that the effect of PV system generation on flicker increases when the total load of the system decreases.

For the third load scenario, which can be called light load worst-case scenario, percentage of the variation of the PV system generation, which causes flicker problem, increases up to 1.31%. For this scenario, it can be said that the comments of previous scenarios are acceptable. Moreover, depending on the difference between the second and the third scenario, when the loads move away from the PV system, its effect on the flicker increases. Furthermore, it can be seen from Figure 3.8 to 3.13, when the percentage of variation decreases, the number of events, which the generation variations happen, increases approximately exponentially. With decreasing the total load, the flicker problems can be done in far more numbers, even in October and November, which are the least problematic months.

4.3.2. Voltage Variation

For the voltage quality of electrical power, voltage variation is one of the most important parameters. In the literature, it is accepted that PV systems has a negative effect on the voltage quality. In this thesis, the PV system is accepted as not connected to an energy storage system and the effects have been investigated for 10-seconds because it takes 1-2 seconds to the voltage waveform reach steady state condition again, after a variation of the PV system generation. According to EN50160 standards [21], the voltage variations in a MV power system does not exceed 4% of nominal voltage. Infrequently, the voltage variations can happen up to 6% of nominal voltage several times a day. This standard will be taken into account as the variations exceeding 6% of nominal voltage are not acceptable when the results are interpreted.

In this part, the proposed method to analyze the voltage variation is explained. After that, the results of the method are given and the effect of the PV system on the voltage variation and the reliability of the system is expressed.

4.3.2.1. Measurement of Voltage Variation

The measurement of the voltage variation is made over Matlab Simulink graphs. For this purpose, the load voltage, where the PV system is connected, is observed when the variation of the PV system generation happened and the PV system generation returned to normal state. The simulations have performed for 3 different load scenarios with increasing the variation of the PV system generation up to the point where the voltage variation exceeds 6% of nominal voltage. These 3 different load scenarios explained in previous parts. After the limit points are indicated from the simulations, they are used to investigate the reliability of the PV system according to the change characteristic data obtained from Chapter 3.

4.3.2.2. Voltage Variation Results

As it is said in the previous part, the load voltages are generated in Matlab Simulink environment for the 3 different load scenarios. The voltage variation is calculated from the difference between the voltage values before and after the variation of PV power generation happened. With increasing the percentage of variation of the PV system generation, this process has repeated until 6% voltage variation is reached. The limiting points exceeding 6% voltage variation are calculated for all 3 load scenarios. The voltage variation results can be seen in Table 4.6. The table consists of the voltage variation and corresponding the variation of PV system generation.

Table 4.6. Voltage variation results

Scenario	**Smallest variation of PV system generation**	**Voltage variation (%)**
1	44%	6.076
2	42%	6.177
3	42%	6.213

As seen in Table 4.5, the effect of the variation of the PV system generation on the voltage variation is less than the effect on the flicker according to the EN50160 standard [21]. In other words, the voltage variation standard was less restrictive according to the variation of the PV system generation in terms of reliability.

For the first load scenario, 0.09% of the variations of the PV system generation cause violation of the EN50160 standard [21] about the short term voltage variation. Most of these variations happen in May and June months (Group-3). Especially, except May-June and July-August-September months (Group-3 and Group-1), it can be said that these variations of the PV system generation do not have an effect on the voltage variation in terms of the reliability according to the standard.

For the second and the third load scenarios, 0.13% of the variations of the PV system generation is violating the standard. With the decrease in the smallest variation of the PV system generation, the violating variations are beginning to be seen in December-January-February-March-April and October months (Group-2 and Group-4). For the light load scenarios, both the time interval that the voltage variation violations can occur, and the probability of occurrence increases.

4.4. Discussion

In this chapter, the voltage quality, which is one of the main concerns about the increasing population of PV systems, is investigated on a modeled power system which includes 2 residential and 2 industrial loads with the 3 different load scenarios. The modeled system is based on real-data obtained from relevant institutions and organizations. The residential load, the source, and the transmission lines are obtained from TEIAS. The assessment is conducted with this model in terms of flicker and voltage variation.

For the flicker investigation, the model is simulated in Matlab Simulink environment and the 10-minute voltage data set of the load bus where the PV system is connected is recorded. This simulation has been made with 3 different load scenarios, which are full load, light load and light load worst case scenarios. According to the results of Chapter 3, to analyze the effects of the power change characteristic on flicker, the model have been simulated with increasing the change of the PV system generation. A flickermeter simulation in Matlab environment is applied to these voltage data sets and P_{st}, which is perceptibility of flicker severity, results are calculated based on this simulation. This process has been applied up to reach the P_{st} value, which violates the EN50160 standard with the smallest change in the PV system generation. According to the results, variations of the PV system generation with 34%, 34% and 32% are respectively the violating smallest variation percentages of the 3 load scenarios. Depending on the worst-case scenario, 1.31% of the variations are not acceptable for the flicker standard.

The voltage variation was also investigated with the same system model except for the changed simulation time to 10 seconds because this time enough to observe the steady state condition of the system after the variation of the PV system generation. Same procedure with the flicker part is applied for the voltage variation investigation. For the 3 load scenarios, with increasing the variation of the PV system generation, the critical points where the voltage variation exceeds 6% of the nominal voltage are calculated. 44%, 42%, and 42% are the smallest variation percentages of the 3 load scenarios respectively. Depending on the worst-case scenario, 0.13% of the variations are not acceptable for the voltage variation standard.

There are 206787 recorded PV generation data with 5-minute intervals in the data set in Chapter 3 and the 18962 data points were investigated when these variations in PV generation percentages were obtained. For the reliability assessment, these percentages are multiplied by the ratio of the number of PV generation's variations to the total number of all generation data (18962/206787). Therefore, the assessment can be concluded by calculating the probability of flicker problem occurrence and voltage variation problem occurrence per 5-minutes. According to the worst-case results of the flicker and voltage variation, they are approximately 12×10^{-5} and 1.19×10^{-5}. In the light of this information, it can be said that the probability of flicker problem occurrence is much more than the probability of voltage variation problem occurrence. Moreover, depending on the grouped histograms in Chapter 3, the flicker problem can be shown in every month of a year, although the voltage variation problem occurs in just May-June and July-August-September months (Group-3 and Group-1) for these load scenarios.

Furthermore, except the probability of violating conditions, the different load scenarios show that the load characteristics have an importance for the voltage quality of the PV connected systems. Primarily, light load conditions are more affected by PV system generation in terms of flicker and voltage variation. Moreover, when the loads are more distant from the PV system, its effects are increasing on them. The difference between weekdays and weekends for load characteristic comes into question at this point. Most of the workshops in the industrial area do not work on weekends. Industrial load power decreases approximately one-third of weekdays' power in weekends at peak time. On the other hand, there is less variation between weekdays and weekends of residential loads' power at peak times. Therefore, to achieve a more reliable PV system, it can be connected from the nearest bus where a large residential load is connected.

In conclusion of this chapter, the numerical assessment has been made in terms of flicker and voltage variation. The reliability of PV systems is investigated by implementing the variation of PV system generation obtained from the previous chapter. The results show that the flicker is a more decisive factor than the voltage variation depending on the standards, and also the reliability of PV systems can be improved by selecting connection point depending on load characteristic at the point.

CHAPTER 5

CONCLUSION AND FUTURE WORK

The environmental concerns, decreasing installation cost with developing photovoltaic technology and governmental incentives supporting the renewable energies lead to a rapidly increasing population of PV systems all over the world. In Turkey, there is a rise above the average in an increase of PV systems because the solar potential of Turkey is high and the government is supporting PV systems by giving incentives. As a consequence of this increasing population, effects of the PV systems on system reliability and power quality have begun to gain importance. This thesis has investigated the effects of PV systems on system reliability and voltage quality using PV data and statistical analysis of it. Three metrics are developed and utilized in the assessment process. Although the main focus of the thesis is the evaluation of the effects of PV systems on system voltage quality, a method for bad-data identification for solar power generation data is also developed based on the normalized residuals.

In this thesis, a set of methods is developed to evaluate photovoltaic systems in terms of voltage quality. It has started with the investigation of 4 years of PV system generation. To verify the generation data given that it can be big data, a bad-data identification method is proposed. NRT method is modified for this purpose. 3-sigma rule for outliner detection is changed to 5-sigma because a half wave cosine curve is selected as the reference curve and it does not exactly meet a reference for smooth daily generation curve, it is approximate. The suspicious threshold value is chosen as 5 and the all data set, which includes 1652 days' PV generation curves, is investigated by this method. 158 days are marked as bad-data, and the method is verified as one by one. Hence, it is stated that this modified NRT method can be used as a bad-data identification method for PV system generation data.

Sinusoidal characteristic of PV system generation is helpful to develop methods to classify and evaluate it. The PV system generation curves are classified by thinking as a deterministic power generator curve (Constant power output) and sinusoidal curve. For this purpose relative change and total generation distortion methods are used. The PV generation curves are investigated by these methods and grouped according to their results as monthly. The quality assessment of PV systems requires the change characteristic of them as frequencies and magnitudes of the changes. The sign change derivative method is proposed for this purpose. The method has found 18962 variations of PV system generation, which exceeds 1% of PV system power rating in 206787 generation points. Moreover, the method has classified these variations as their magnitudes to use them in the reliability assessment. These methods are successful to meet the requirements to obtain necessary PV system generation change characteristic parameters.

The quality assessment is made by simulating a sample power system with the variations of PV system generation obtained from the sign change derivative method. Flicker and voltage variation standards in a MV power system from EN 50160 is used as a reference to decide the system is working under suitable conditions, or not. These standards state that P_{st} (Short-term flicker probability) value and voltage variation should not exceed 1 and 6% of nominal voltage respectively. The simulations are made in Matlab Simulink environment and average model of VSC is used in modeling of PV system because it is adequate for flicker and voltage variation simulations. The simulations have been repeated with increasing the percentage of PV system generation variation until the point where the standards are violated. The results are that the probability of a flicker occurrence, which is violating the standard, is 12×10^{-5} per 5 minutes, and the probability of a voltage variation which is violating the standard occurrence is 1.19×10^{-5}. They are showed that flicker is a more significant factor for the reliability assessment of PV systems depending on the standards.

Although it is not the main aim of this thesis, the effect of load type and loading on the reliability assessment is also observed with different load scenarios in terms of flicker and voltage variation. There are 3 load scenarios, heavy load, light load and light load worst case. The heavy load and the light load scenarios showed that less loaded systems are more affected by variation of PV systems' generation. On the other hand, the light load and the light load worst case scenarios stated that load types have also an effect on the reliability, for example, industrial loads' loading is much more decreasing than residential loads' one in weekends, so PV systems connected to industrial loads are less reliable in weekends.

In conclusion, it can be said that the set of methods proposed in this thesis is succeeded to evaluate the reliability of PV systems with verified historical data. The numerical results can be used to determine the PV system is feasible, or not for a specific area whose historical PV system generation data exists.

For the future works, reliable system operation assessment can be expanded by investigating other topics included in EN 50160 standard, for instance, voltage unbalance and harmonics. Furthermore, the investigation can be made for large PV systems, as the 1-GW power plant to be constructed in Konya, Turkey.

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