Reducing Variation in Solar Energy Supply Through Frequency Domain Analysis

Chandrashekhar Lavania, Shrisha Rao, *Member, IEEE,* and Eswaran Subrahmanian

***Abstract*—Solar irradiation tends to vary greatly throughout the day. The difference is very large especially between the early hours of sunshine, and during the peak hours of the day. Yet, it is desirable to supply a nearly constant amount of power to loads or power grids for high reliability. Hence, we propose a technique aimed at reducing the variation in solar power generation. Solar irradiation data is considered as a time-series data and the approach involves conversion of this data to the frequency domain through Fourier analysis. A more balanced supply by a set of plants is devised by interconnecting the plants, which also requires finding the optimum number of plants to connect using the above analysis. The effectiveness of the procedure is demonstrated by applying a suitable supply prediction algorithm over the individual plants and the effective data for the plants, using real data from Nevada, Texas, and California.**

***Index Terms*—Alternative energy, frequency domain analysis, saturation, solar irradiation, solar power plants, supply prediction.**

I. Introduction

THE USE of alternative energy sources is gaining popularity worldwide, with a lot of interest in particular being shown in efficiently harnessing wind energy and solar energy. One of the biggest hurdles in using these alternative energy sources is their lack of consistency in terms of their inability to deliver a fixed power supply. Like many other alternative energy sources, solar energy is also subject to this problem. This is due to the fact that solar irradiation, only available during the daytime, is hardly constant even then due to the movement of the sun and possible cloud cover. Seasonal changes in solar irradiation also cause variability. If we can reduce the variation in the power supply from solar sources, then we come a step closer to making solar power generation viable on a massive scale.

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The motivation to reduce the variation in the solar power supply is illustrated in Figs. 1 and 2, which depict data from the Reno region in Nevada. Fig. 1 shows that a daily variation in hourly solar irradiation values of up to 600 W/m^2 is easily possible during the time period between 8 A.M. and 5 P.M., i.e., the irradiation values between the peak hour and the beginning may differ by around 600 W/m^2. It also shows that a large number of days in a year have huge daily variations in solar irradiation, thereby affecting the overall consistency of the power supply.

Similarly, Fig. 2 indicates that a difference of 200 W/m^2 is quite common between the irradiation values for consecutive hours. Here too, like Fig. 1, the data are from 8 A.M. until 5 P.M. Consider a plant that generates power by collecting solar radiation from an area of size 1000 m^2. If we consider a conversion efficiency of 20% in the solar power technology used, the difference between the power supply between consecutive hours would be around 40 kW. This is a large variation when supplying power to a load or grid at around 200 kW per hour. It is important to note that a large number of hours have a variation of only 25–50 W/m^2. This happens around the peak afternoon hours when the sun is close to its zenith. Many other alternative energy sources suffer from a similar problem—most of them, especially wind and solar energy plants, are highly dependent on the day-to-day weather at their geographical locations. The effect of variations has been studied by Elhadidy *et al.* [1], [2], while discussing the performance of hybrid solar-wind systems. Karki *et al.* [3] focused on the reliability evaluation of wind power systems and Kusiak *et al.* [4] suggested mechanisms to predict wind farm power.

Our approach aims to reduce the variation in the power supplied by solar plants. The idea is to interconnect several geographically dispersed solar plants to supply power to a single region, either together with a normal grid or as a standalone system. (This differs from the classical decentralized power systems approach [5] where each plant either feeds a single load or supplies to a grid in an individual capacity with no coordination with other plants.) These interconnected solar energy plants may be spread over a large distance (typically of the order of hundreds of kilometers). In our proposed technique, frequency domain analysis gives us the optimum number of plants to interconnect, as the reduction in variability tends to diminish as we interconnect larger numbers of plants. There is thus an optimum number of plants to connect, beyond which the added costs of interconnection would outweigh the

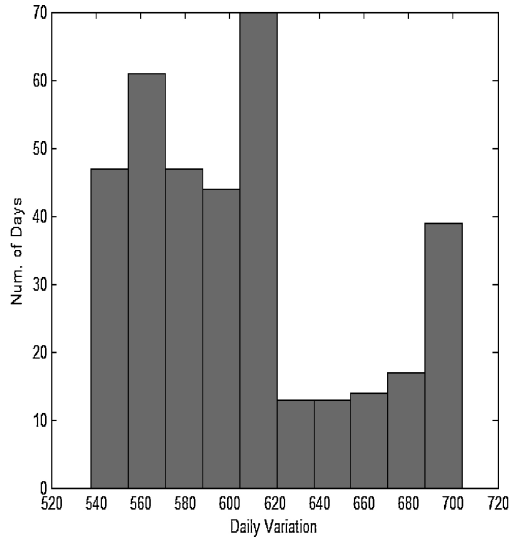

Fig. 1. Daily variations in solar irradiation (W/m^2).

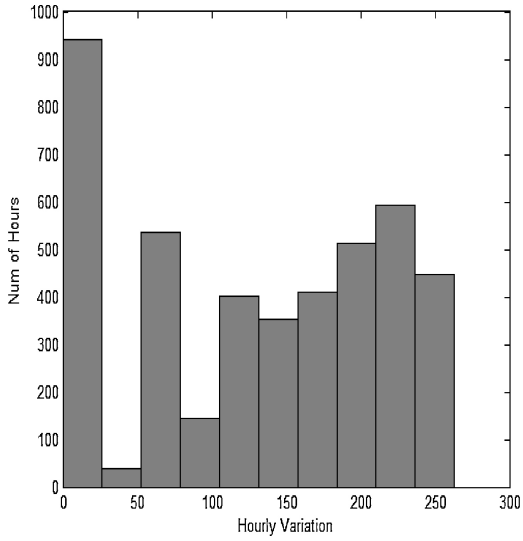

Fig. 2. Hourly variations in solar irradiation (W/m^2).

benefit of reduced variability. This optimum number is for any particular set of plants, and may change if a different set of plants is taken for consideration.

Our technique aims to reduce only the variation due to the changes in solar insolation, and we remain neutral toward the particular power generation technologies used [e.g., whether they are photovoltaic (PV) systems or solar-thermal]. It is presumed that whatever technology is used, it is able to make other routine adjustments for issues other than variation in irradiation. For instance, it may be presumed that there are suitable tracking systems of the type now found commonly, to adjust for changes in the sun's position in the sky, and that likewise, there are suitable systems in place [6] to deliver power to a grid or consumer in whatever manner may be desired.

The problems of variation in solar energy supply with space as well as with time have been well known for a long time. One early attempt at a systematic study of the problem, with some suggestions for system design, was by Hay [7]. The prospects of such renewable-energy systems in "off-grid" situations have been studied for Africa [8], India [9], [10], and other places [11].

The notion of optimizing solar power systems using concepts from neural networks and genetic algorithms has been experimented upon by Kalogirou [12], but that work aims to maximize the economic potential. Krause *et al.* [13] studied the optimization of large solar-thermal systems, while concentrating on their feasibility and energetic potential as well as the cost incurred. This also incorporates the classical optimization algorithms discussed by Press *et al.* [14]. Techniques like a knowledge-based approach [15] and linear programming [16] have been used in the past for renewable energy system design. Modern methods like fuzzy optimization [17] and artificial intelligence techniques [18] are also being used to improve renewable energy systems. Apt [19] used the concept of power spectral density to find the power required to compensate for fluctuations in the generated power while harnessing wind energy.

Variation in solar energy generation, which is the problem we address here, is a primary reason for the attempts at combining different types of alternative-energy sources (such as solar and wind) into "hybrid" generation systems [20]. The idea of weaving together alternative-energy sources into distributed generation systems is starting to gain popularity as can be seen in the reviews by Jin and Jimenez [21] and Zhou *et al.* [22]. Nema *et al.* [23] surveyed recent work that specifically combines wind and PV solar. Vallee *et al.* [24] considered the hourly wind energy production in the management of the daily thermal units. The optimization approach of Prasad and Natarajan [25] dealt with integrated wind–PV power generation systems with battery storage. The concept of interconnectivity has already been applied to supply power in various scenarios. Some of these cases involve creating a hybrid network, as opposed to a pure solar one as being proposed here. Chedid and Rahman [26] provided cores for computer-aided design tools to optimize a wind-solar power system for either grid-linked applications or autonomous use, while Bernal-Agustín and Dufo-López [27] proposed techniques for simulation of various hybrid renewable energy systems. Kane *et al.* [28] have proposed the idea of integrating two solar concentrators, two superposed organic Rankine cycles, and a bio-diesel engine, while Ashok [29] provided a general model for combining different energy components in an optimal fashion to provide energy to a rural community. In Germany, companies like Enercon GmbH, SolarWorld AG, and Schmack Biogas AG have come together with the Institute for Solar Energy Supply Technology of the University of Kassel, to come up with a combined power plant comprising of three wind parks, 20 solar power plants, four bio-gas systems, and a pump storage plant. They aim to satisfy 1/10000th of the total power demand in Germany. Protogeropoulos *et al.* [30] aimed at addressing both the sizing and techno-economical optimization of hybrid renewable energy systems while Yang *et al.* [31] proposed the hybrid solar-wind system optimization sizing approach, which optimizes the capacities of the various components of solar-wind power generation system.

Apart from the area of communications, the use of frequency analysis for performance improvement has been done in a variety of areas like sensor networks [32], where multipath propagation is reduced by creating a greater separation in frequency between paths to get an averaged fading. Likewise, in genetics [33], frequency analysis is used to compute the power spectral density for 13 microbial genomes, focusing on the low-frequency region to analyze the fractal behavior of deoxyribonucleic acid chains; in biomedical engineering [34], it is used to find the tuning curves for spatial frequency of retinal, simple, and complex cells of the cortex, especially for cats. In geology [35], it is used to account for the effects of various erosion processes on the "event-yield" frequency distribution, etc. However, to the best of our knowledge, it has not hitherto been used to balance solar power supply.

By applying our technique, we are able to show a significant reduction in the variation in the power supply. We are further able to show its effectiveness by applying the same supply prediction algorithm using data from individual plants, and considering the effective data after optimizing and showing the gain graphically. The supply prediction which we use may not be optimal, but it is conservative in nature. The gain by using the proposed technique may change if a better algorithm is used, but by reducing the variation in the overall supply, the technique should certainly produce an improvement over the individual plant scenario.

The rest of the paper is structured as follows. Section II briefly touches upon relevant basic concepts such as frequency domain transformation, saturation, and supply prediction, which underlie the technique we propose. Section III illustrates the results observed by simulating the proposed technique using data from Nevada, Texas, and California. Section IV concludes the discussion and highlights certain possibilities for future work in this direction.

II. Concept and Theory

Analysis of the variation in the irradiation values is the basis of the overall approach. Hourly irradiation data for the U.S. at different points throughout the country are available for the years 1991–2005 [36]. A first step is to focus on localization. This is because, as we increase the distances between plants, the cost incurred to interconnect them may also increase. However, we also do not want the plants to be very close, for their solar irradiation capture patterns would then not be very different. Therefore, a tradeoff between cost and distance between plants needs to be attempted so that the costs incurred do not outweigh the gain we get by interconnecting the plants.

The approach here uses a frequency domain transformation of the given data. This transformation shows the variation in irradiation values at different frequencies. The different frequencies correspond to different values of the time period over which the variation is being calculated. The next stage in the analysis is to decide the number of plants to interconnect. This is illustrated by using a log-linear representation of the spectral distribution, which helps decide the point where adding more plants is not likely to be beneficial. This interconnection gives the effective data for each of the involved plants. These "effective" values are the average values of the system as a whole, and are identical for each identically sized plant. These are apparent values, as the actual values for the plants do not change. Due to the interconnection, any drop in the solar irradiation for a plant tends to be compensated by others in the group, thereby giving the impression that the variation in these values for the plants has reduced. The advantage of this technique over the no-interconnection scenario can be seen by using it to estimate the future supply for any plant based on its past supply characteristics.

The technique is useful for doing preprocessing before an actual plan for energy distribution is decided. For any region, this would largely just be a one-time process, and only reflects upon the sites being considered and not on others in general.

In this section, we first consider the basics of frequency domain analysis as applied to interconnected solar plants. Then we look at the issue of when "saturation" occurs, i.e., when the cost of interconnecting more plants outweighs the benefits. Finally, we consider the issue of estimating the supply that would result from a hypothetical interconnection of plants at specific locations.

A. Frequency Domain Transformation

A typical frequency domain transformation can be done as follows:

$$X_k = \sum_{n=0}^{N-1} x_n e^{\frac{-2\pi j}{N} kn}. \tag{1}$$

This is called the N-point discrete Fourier transform (DFT) [37], [38]. Here, X_k is the transform function, x_n are the solar irradiation data under consideration, and N is the number of irradiation data points. The irradiation data are treated as a time series signal, and hence the Fourier transform gives the amount of each frequency contained in this signal. In the context of irradiation data, this corresponds to the amount of daily variation, half-day variation, hourly variation, and others.

X_k is a complex function, and for our analysis we need only real values. This is done by using A_k, defined as

$$A_k = \sqrt{\Re(X_k)^2 + \Im(X_k)^2}. \tag{2}$$

This gives us the amplitude of the Fourier transform and eliminates the phase values from the function X_k. Here, $\Re(X_k)$ is the real part of X_k, and $\Im(X_k)$ is the imaginary part. The analysis is done by comparing this amplitude as we start interconnecting solar plants. These values are plotted on a semi-log graph for better illustration (as is common with data of this type). Thus the values plotted are $\log_{10} A_k$ instead of plain A_k.

As we increase the number of interconnected plants, the improvement tends to saturate, i.e., further increases in connectivity do not result in corresponding decreases in variation. This saturation point gives us the optimal number of plants P that should be connected.

Fig. 3 shows the frequency domain representation, on a semi-log graph, of the effective irradiation values obtained by interconnecting three sites, viz., Sakagway, Yakutat, and Petersburg, AK. The x-axis represents A_k, i.e., the spectral

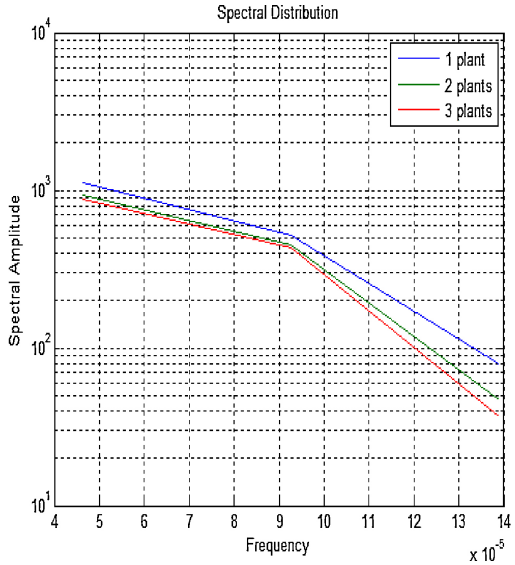

Fig. 3. Frequency domain representation of irradiation values from Sakagway, Yakutat, and Petersburg in Alaska.

amplitude values, and the y-axis corresponds to the frequency values. It can be clearly seen in Fig. 3 that the variation in irradiation values comes down as the frequency is increased. Therefore, the reduction in variations for higher time periods (lower frequencies) is much less as compared to the reduction at smaller time periods (high frequencies). It should also be noted that the maximum reduction is observed in the hourly variation, which is good as we are also concerned mostly with the hourly variation, which causes the power supply to fluctuate relatively rapidly.

The interconnection of multiple plants gives an effective distribution of solar irradiation for each of these plants. Let solar irradiation values obtained by interconnecting L plants and averaging it for one plant be defined as

$$x_{n,L} = \frac{1}{L}\sum_{l=1}^{L} x_{n,l}. \tag{3}$$

Here, $x_{n,l}$ is the irradiation value for a specific plant l. The frequency components for this irradiation distribution are to be compared with the components obtained by combining a different number of plants ($L \in \mathbb{N}$, where $\mathbb{N}$ is the set of natural numbers). Let $X_{k,L}$ be the frequency domain representation of $x_{n,L}$. It is to be noted that the values corresponding to time-series irradiation values and the DFT are $x_{n,L}$ and $X_{k,L}$, respectively, when L plants are interconnected. This can also be indicated as follows:

$$x_n \longrightarrow x_{n,L} \tag{4}$$

$$X_k \longrightarrow X_{k,L}. \tag{5}$$

Plugging $X_{k,L}$ and $x_{n,L}$ into the definition of the basic DFT (1) gives

$$X_{k,L} = \sum_{n=0}^{N-1} x_{n,L} e^{\frac{-2\pi j}{N}kn} \tag{6}$$

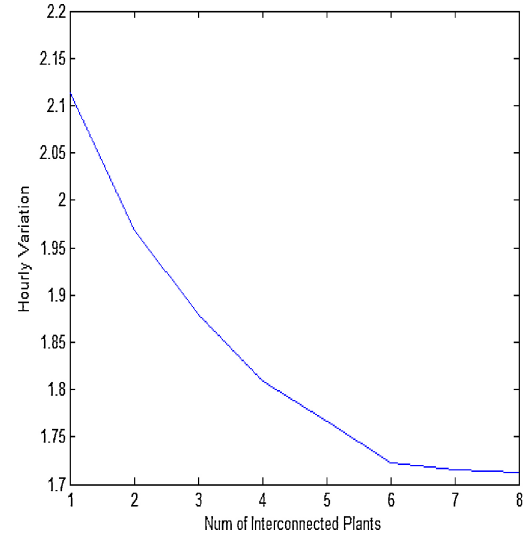

Fig. 4. Change in irradiation (W/m^2) values per hour for different numbers of interconnected plants.

$$= \frac{1}{L}\sum_{n=0}^{N-1}\sum_{l=1}^{L} x_{n,l} e^{\frac{-2\pi j}{N}kn}. \tag{7}$$

$X_{k,L}$ helps us analyze the change in variation by progressive interconnection of plants. The actual values used for the plots are $A_{k,L}$, where A_k is the set of values for L equal to 1. It can be seen that using (4) and (5) in (7) with the value of $L = 1$ gives us (1) which was the basic DFT definition, and which also corresponds to the scenario when no interconnections of plants exists.

B. Saturation

The best number of plants to interconnect is determined using the concept of saturation.

Saturation can be described as the point when the reduction in variation becomes inconsequential as we increase the number of interconnected plants. This saturation point gives us the optimum number of plants, as we no longer gain much by adding more plants and may expect to see disadvantages due to the transmission and other costs incurred in connecting a larger number of plants. Fig. 4 clearly depicts this. The reduction in the variation of the irradiation by adding beyond six plants and averaging for one plant is very small, not enough to be considered beneficial. (It may be recalled that logarithmic values of the spectral amplitude have been plotted in Fig. 4, and not absolute values.)

Saturation can be formally defined in the following manner.

Definition 1: ϵ-Saturation: The ϵ-saturation point for any given region is P iff $\exists k$ such that

$$\log_{10}\frac{X_{k,P+1}}{X_{k,P}} \leq \epsilon. \tag{8}$$

Here, the saturation point is P, if on a logarithmic scale and at the kth frequency the difference between spectral amplitude for $P + 1$ plants and P plants is bounded above by the value ϵ. The value of ϵ may be chosen given the distribution model or technology to be applied, and is as such a design parameter. The value $\epsilon = 0.01$ has been used in our simulations

to find the saturation point, but our results and conclusions are not significantly altered if other small values are chosen instead.

The value of ϵ is to be chosen based upon past heuristics and transmission costs. According to Acciona solar power [39], the cost of transmission lines is around \$1.5 million per mile. Therefore, ϵ values should be taken such that the gain by interconnecting plants is not dwarfed by the additional costs like those due to transmission lines. Major cost increases can occur when creating a subnet of plants which are not connected to one another by an existing external grid. This would be especially prominent in remote areas like the Sahara Desert, which receive ample solar irradiation and are thus suitable for solar power plants, but are poorly connected to existing major power grids.

Another approach can be when the supply through power grids is taken into account. Even though the notion of global grids with transmission distances of upto 4300 miles is becoming popular, there are many grid elements that supply power more locally, transporting power for a distance of around 350 miles to 1500 miles [40]. Due to the local nature of such grids, there may be a need to create additional transmission lines so that all plants to be connected can come under one network. This again can cause an increase in the transmission costs. As compared to the additional cost of forming a separate subnet, the expenses incurred to connect plants to an existing grid may be small. Hence, it is important to determine a suitable ϵ value during the preprocessing, keeping all such factors in proper perspective.

C. Supply Prediction

The effectiveness of the whole process can be demonstrated using a supply prediction method over the individual plant data, and comparing with the results obtained by using the proposed optimization. The prediction method helps in the estimation of the supply from a plant by itself, and as part of a specific connected network.

The prediction used here relies upon assigning weights to the different plants for each hour, based on the power supplied by them in the past. The concept of weights is very popular in predictive data mining. The use of weights for prediction has been suggested by Enumula and Rao [41] for demand prediction and analysis in a Potluck Problem scenario of variations in both supply and demand. Maity and Rao [42] have used the concept of weights in the domain of solar energy to analyze a solar-powered electrical microgrid.

In our case, the weight of each plant denotes its ability to supply power to a load or grid, as compared to other plants in the system. These weights help in predicting the percentage of the total demand that the corresponding plants may satisfy. A plant with higher weight has more ability and as such supplies more power to the load as compared to others. The weights are variable, and can change every time a prediction is made, as they depend upon the past performances of the plant. This is similar to the weighted majority algorithm of Littlestone and Warmuth [43], where the weights change for each iteration depending on whether the predictor came close to the observed values or not.

TABLE I
SUPPLY PREDICTION

Plant ID i	Past Value $s'_{i,h}$ (kW)	Weight $w_{i,h}$ (kW)	Current Value $S_{i,h}$ (kW)
1	110	0.3056	106.96
2	150	0.4167	145.845
3	100	0.2778	97.23

The prediction for any plant is also dependent upon past supply values for that plant. These past values show the general supply capability of that plant at any given hour, and give a picture of the supply possible from the plant. By using the weights and the past supply values for a given plant, one can thus estimate the supply from that plant likely in the near future. The current prediction is the estimate of the supply for the immediate future. This whole process can be further elaborated in many ways, depending upon the prediction mechanism used. One such mechanism can be the following.

Let $w_{i,h}$ be the weight for the ith plant for the hth hour. A load R_h is there for the hour h. Also $s'_{i,h}$ is the supply at the ith plant for the hth hour in past estimations, with $S_{i,h}$ being the current supply. The estimate for a plant i based solely on the weights for hour h is given by $E_{i,h}$. Then the supply prediction follows from (9) and (10) as

$$w_{i,h} = \frac{s'_{i,h}}{\sum_j s'_{j,h}}. \tag{9}$$

Therefore, if we consider the duration between 8 A.M. and 5 P.M. for our analysis, $s'_{2,3}$ refers to the past predicted value of power supply for plant 2 based on solar irradiation values between 10 A.M. and 11 A.M., i.e., the third hour (the starting time being 8 A.M.). Hence, the weight of a plant is the past predicted power supply of this plant as compared to the past predicted values of all the plants supplying power. This is considered heuristically by taking an average of the past values. Furthermore

$$E_{i,h} = w_{i,h} \times R_h \tag{10}$$

$$S_{i,h} = \min(s'_{i,h}, E_{i,h}). \tag{11}$$

The weights are designed such that a plant with higher capacity provides a higher share of the supply to the load or grid, as compared to a plant with a lower capacity. The weight is proportional to a plant's share in the total supply based on its past predicted supplies. The actual supply takes into consideration these weights as each plant tries to supply a fraction of the total load demand, i.e., $w_{i,h}R_h$, based on that plant's weight. There is of course the case that a plant cannot supply more than its capacity and therefore will merely choose to supply its whole capacity if $w_{i,h}R_h$ is more than what it can produce for that hour. Consider the following scenario, where three plants are supplying power to a load. Let the load require 350 kW of power between 9 A.M. and 10 A.M. The load in consideration comes under the customer class "large power" and is in use for general service. Table I shows how the prediction works. The method described here is a conservative approach as it uses the minimum value given by (11) when it

TABLE II
HISTOGRAM COMPARISON

No. of Plants	Max Value (h)	Min Value (h)	Std. Dev. (h)
One plant (original)	942	40	246.5081
Six plants	878	236	183.3121
Nine plants	875	251	180.2843

predicts the current supply. In the scenario where the actual available power is more than the prediction using the weights, especially in a grid-like system, it may be useful to modify the prediction to suit the needs of the grid.

Enumula and Rao [41] show the benefits of using weights on predictors based on the performance of these predictors. We use a similar notion to apply weights using the past predicted values for the power supply of each plant under consideration to estimate the current supply. They also use the concept of variable weights for each of their predictive iterations, which further strengthens the use of variable weights in our supply prediction.

The results obtained after application of the supply prediction algorithm are compared with the power demand of the load [44] and the difference is plotted as a difference spectrum graph. An interconnection of three plants collecting irradiation in areas of $1000\,\mathrm{m}^2$ each is used for the simulation.

The difference spectrum graphs plotted later, Figs. 6, 8, and 10, show the variation in the difference of the total supply to the load and the actual load demand on an hourly basis, on a semi-log graph. The apparent supply from each plant after the application of the proposed optimization technique is identical, as this is the supply achieved by interconnecting the optimum number of plants for the particular region under consideration.

III. RESULTS

The technique is demonstrated using real-life data [36] from Nevada, Texas, and California. A point to note is that for each of these three examples, the pattern in which the variation changes (as the number of interconnected plants increases) is different. In Nevada, the reduction in the variation by adding subsequent plants is high until the saturation point, unlike Texas. In Texas, this gain is small even though the overall gain by interconnecting the optimum number of plants is large as compared to the scenario when there was no interconnection. Also, for California, saturation occurs with a smaller number of interconnected plants.

A. Nevada

Fig. 5 shows the distribution for Nevada. As can be clearly seen, there is a significant drop in the spectral amplitude as we go higher along the spectrum, i.e., from daily variation toward hourly variation. We can see that saturation occurs at around six plants with $\epsilon = 0.01$. Therefore, the optimum number of plants P which can be interconnected in this case is 6. The data in consideration are from 8 A.M. to 5 P.M.

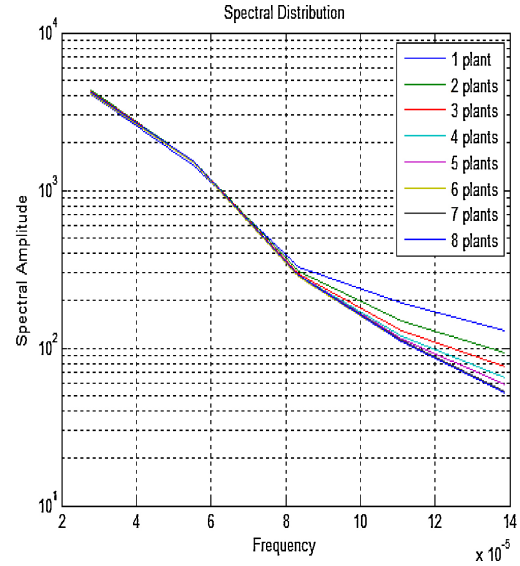

Fig. 5. Frequency domain representation of irradiation values from Nevada.

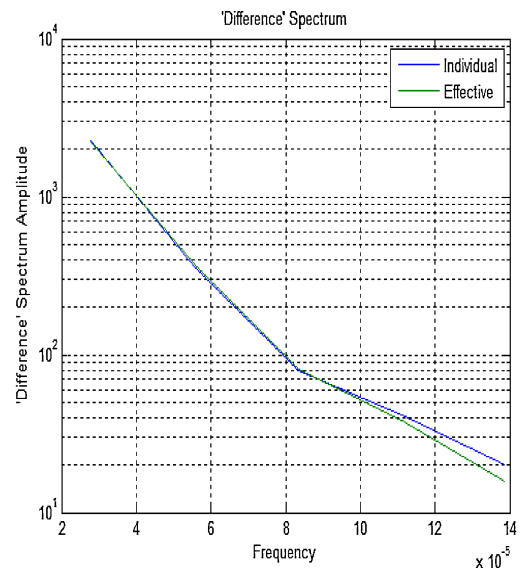

Fig. 6. Frequency domain representation of difference values from Nevada.

The data considered covers almost the whole of Nevada. This gives an example of a scenario where the region under consideration has almost similar geographical characteristics. Another point to note is that this scenario uses three types of data nodes, viz., Class 1, Class 2, and Class 3. According to the National Renewable Energy Laboratory [36], Class 1 nodes have the most accurate and reliable data for the past 15 years, Class 2 nodes have readings which are not as accurate as Class 1 but the data available is continuous, i.e., there is no gap in the hourly readings, and Class 3 nodes are not very reliable and there are also gaps in the readings.

Fig. 6 shows the difference spectrum for the state of Nevada. Among the two plots on the semi-log graph, one shows the distribution when each plant is considered individually, and the second shows when the proposed optimization procedure is used to find the effective output for each plant given the interconnection.

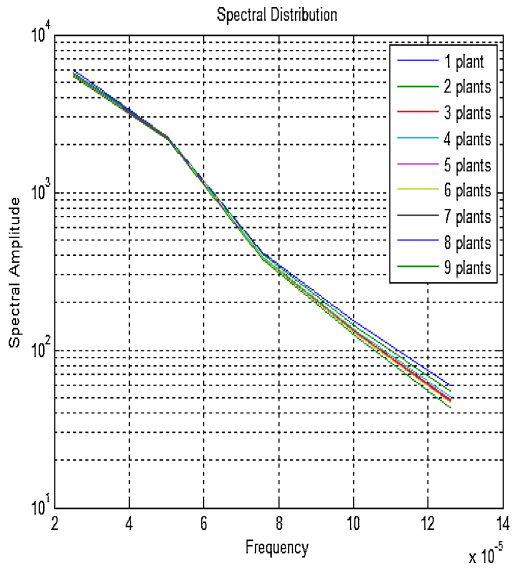

Fig. 7. Frequency domain representation of irradiation values from Texas.

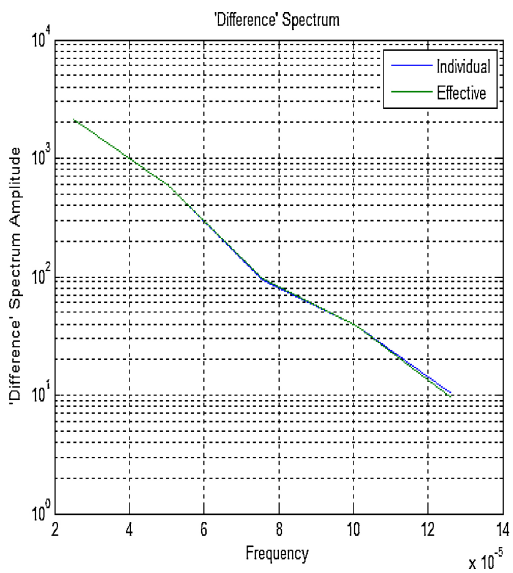

Fig. 8. Frequency domain representation of difference values from Texas.

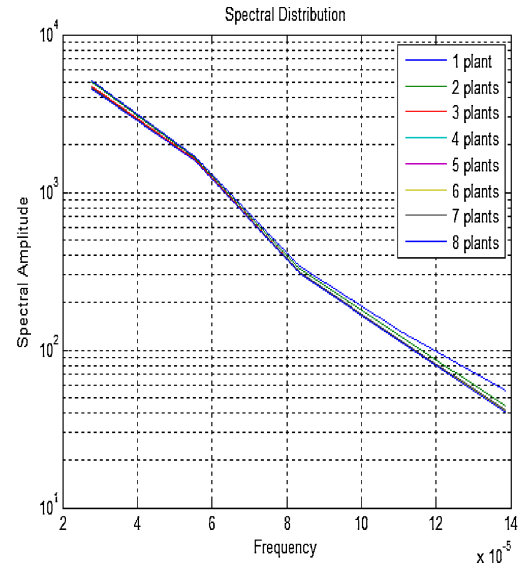

Fig. 9. Frequency domain representation of irradiation values from California.

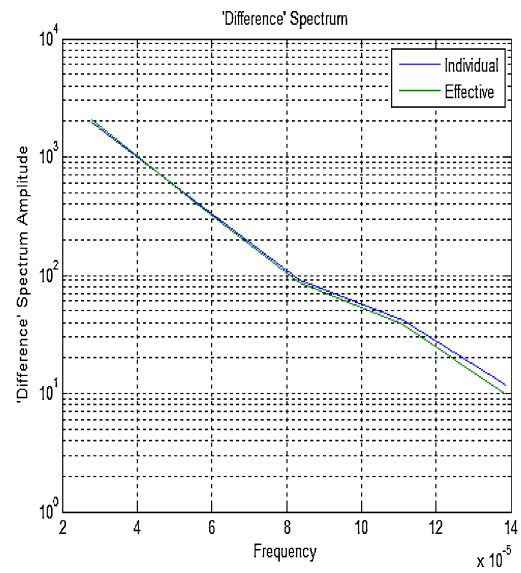

Fig. 10. Frequency domain representation of difference values from California.

B. Texas

Next in focus is Texas. The data are taken from sites in a radius of around 300 miles. Fig. 7 shows that the saturation point for Texas comes near seven plants with $\epsilon = 0.01$. Another thing to note is that though the saturation occurs at seven plants, unlike Nevada the spectral distributions for successive additions of plants are quite close. This indicates that the saturation is affected by the actual sites we take and not just the distance between them. Also, Texas being a huge state, a similar analysis done in a different region of Texas can give different spectral distributions, and perhaps slightly different saturation points. Thus, the technique proposed is to be used for preprocessing in the region of interest, rather than to make more general assumptions. It may be noted that only Class 1 nodes were considered for this state.

Fig. 8 shows the difference spectrum for the state of Texas. The gain for the effective distribution over the individual is not as much as that found for Nevada. This is because of the relatively small gain achieved by adding subsequent plants to the whole system as compared with Nevada.

C. California

California differs from the previous two states considered in the fact that, unlike them, its length from north to south is much larger in comparison with its width from east to west. Therefore, for all the sites in consideration, the latitudinal difference is higher as compared to the longitudinal difference. Fig. 9 depicts the spectral distributions for California, and it can be seen that unlike Nevada and Texas, saturation occurs after interconnecting just four plants in consideration with $\epsilon = 0.01$. This may be because of the same factor.

Fig. 10 shows the difference spectrum for California. The saturation point P for California is just 4, thereby making

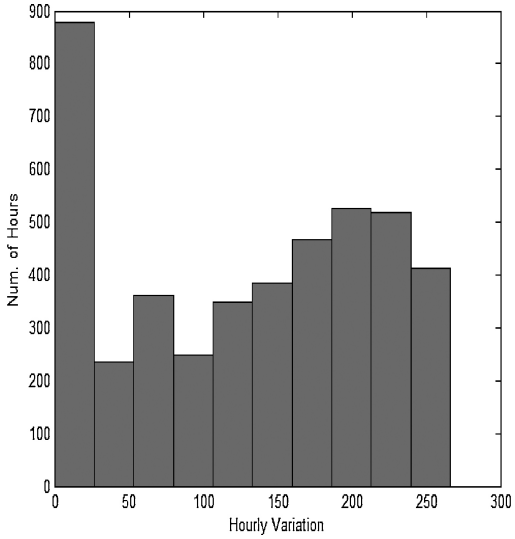

Fig. 11. Hourly variation in apparent solar irradiation (W/m^2) after application of proposed technique.

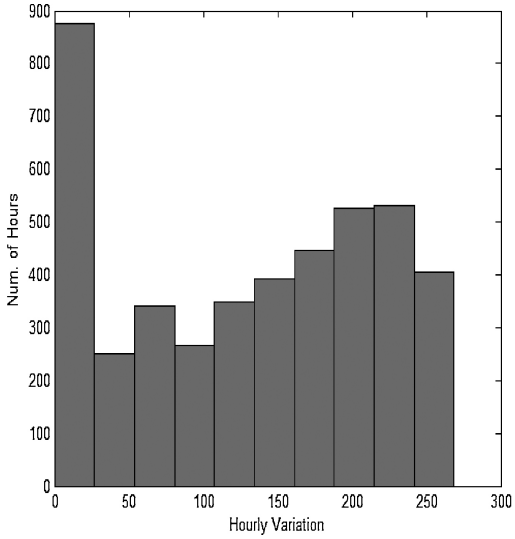

Fig. 12. Hourly variation in the apparent solar irradiation (W/m^2) after application of the proposed technique and using more than the optimized number of plants.

the gain of the difference spectrum for effective supply over individual supply relatively small.

IV. Conclusion

The analytical approach we have outlined gives a scheme for connecting plants in a way that causes a significant drop in the variation of the solar energy supply to a load or grid, especially in case of hourly variation. Fig. 11 emphasized this fact as it shows that the number of hours with high variations in supply have come down. Table II further suggested the strength of the technique by showing that the standard deviation for the optimized histogram (Fig. 11) was much less as compared with that of Fig. 2. Table II also showed that the gain by adding additional plants (Fig. 12) and bringing the number of plants to nine ($\epsilon = 0.005$) beyond the saturation point ($\epsilon = 0.01$) is 6, which is very small. This also shows the importance of choosing a suitable value for ϵ as the gain by selecting a very small value may be offset by the total cost of the system incurred by connecting additional plants. The use of this optimizing technique with a suitable supply predictor gives a gain over the case when each plant is considered a separate entity and no interconnection is done.

Future Work: For the future, we suggest that the next step is to find the effect of the sequence in which the plants are interconnected (or the effect of disconnecting specific plants for maintenance or other reasons). The actual spectral distributions may differ depending upon the sequence in which the sites were interconnected, but the overall trend should remain the same for a given region and set of plants. It is also important to find the effect of distance and size when interconnecting plants, e.g., to see if it would be beneficial to interconnect with two smaller plants which are near or a big plant which is far away. From the perspective of suppliers who wish to apply our technique, it is important to figure out if by looking at the variation patterns for a few plants one can hypothesize the saturation point without too many detailed calculations.

The subsequent stage can be to apply the proposed technique on hybrid systems providing supply of renewable energy to any given load. A solar-wind hybrid system can be the new focus for our technique. Here, apart from the issue of the number of plants to interconnect, a question can be if the focus should be more on solar plants or wind plants. Our procedure would need to be modified slightly to optimize the number of solar plants and wind plants in the interconnected system as two separate entities, apart from optimizing the total number of plants to be used in the interconnection. This can be further extended to solar and any other set of renewable energy sources with the same concerns as above. Another angle to look at can be to combine solar with traditional and conventional sources in a grid, and to apply the proposed technique on them to analyze any obtainable gain.

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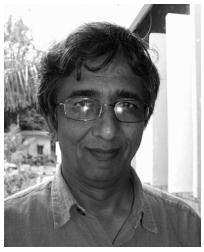

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