Solar energy production: Short-term forecasting and risk management
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Abstract: Electricity production via solar energy is tackled via short-term forecasts and risk management. Our main tool is a new setting on time series. It allows the definition of “confidence bands” where the Gaussian assumption, which is not satisfied by our concrete data, may be abandoned. Those bands are quite convenient and easily implementable. Numerous computer simulations are presented.

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1. INTRODUCTION

1.1 Generalities

The following lines by Reikard (2009) provide an excellent introduction to our subject: The increasing use of solar power as a source of electricity has led to increased interest in forecasting radiation over short time horizons. Short-term forecasts are needed for operational planning, switching sources, programming backup, and short-term power purchases, as well as for planning for reserve usage, and peak load matching. There are many approaches as summarized by Trapero, Kourentes & Martin (2015): The diversity of solar radiation forecasting methodologies can be classified according to the input data and the objective forecasting horizon. For instance, NWP (Numerical Weather Prediction) models, which are based on physical laws of motion and conservation of energy that govern the atmospheric air flow, are operationally used to forecast the evolution of the atmosphere from about 6 h onward. Although NWP models are powerful tools to forecast solar radiation at places where ground data are not available, many near-surface physical processes occur within a single grid box and are too complex to be represented and solved by equations. Thus, NWP models cannot successfully resolve local processes smaller than the model resolution. Satellite-derived solar radiation images are a useful tool for quantifying solar irradiation at ground surface for large areas, but they need to set an accurate radiance value under clear sky conditions and under dense cloudiness from every pixel and every image. . . . These limitations have placed time series analysis as the dominant methodology for short-term forecasting horizons from 5 min up to 6 h. See Kleissl (2013) for a slightly different standpoint.

Diverse viewpoints on time series have of course been employed. See, e.g., Bacher, Madsen & Nielsen (2009); Diagne, David, Lauret, Boland & Schmutz (2013); Duchon & Hale (2012); Lauret, Voyant, Soubdharis, Paoli, Navarro, Marchante & Cony (2010); Reikard (2009); Trapero, Kourentes & Martin (2015); Voyant, Muselli & Nivet (2011); Voyant, Paoli, Muselli & Nivet (2013); Voyant, Soubdharis, Lauret, David & Muselli (2015); Yang, Sharma, Ye, Lim, Zhao & Arypeput (2015), and the references therein. We follow here another model-free setting1 (Fliss & Join (2009, 2015a,b); Fliss, Join & Butt (2011a,b)). With respect to solar energy production they have already been compared to techniques stemming especially from persistence and from artificial neural nets by Join, Voyant, Fliss, Nivet,

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1 See Fliss & Join (2013) for the importance of the model-free viewpoint in control. It might worthwhile in our context to stress that this approach has also been successful for the renewable energy production (Jama, Noura, Wahyudie & Assi (2015); Join, Robert & Fliss (2010)).
According to a theorem due to Cartier & Perrin (1995) the following additive decomposition holds for any time series $X$ under quite weak assumptions:

$$X(t) = E(X)(t) + X_{\text{fluctuation}}(t)$$  \hfill (1)

where

- the mean, or average, or trend, $E(X)(t)$ is quite smooth,
- $X_{\text{fluctuation}}(t)$ is quickly fluctuating.

The decomposition (1) is unique up to a “small” additive quantity. Our short-term forecast techniques are based on a local mathematical analysis of $E(X)(t)$ (Fliess & Join (2009); Fliess, Join & Hatt (2011b)), which is inspired by recent advances in the field of estimation. They yield good results and are quite easy to implement. Their simplicity’s sake, set the following elementary persistence scheme for volatility

$$\text{Vol}_{\text{pred60}}(t) = \text{Vol}(t)$$

where $\text{Vol}_{\text{pred60}}(t)$ is the forecast 1 h ahead of $\text{Vol}(t)$.

Let us associate to Equation (2) the Equation

$$\text{Diff}(t) = X(t) - X_{\text{pred60}}(t - 60)$$

Three classic normality tests (see, e.g., Bourbonnais & Terraza (2010); Cryer & Chan (2008); Jarque & Bera (1988); Judge, Griffiths, Hill, Lütkepohl & Lee (1988); Thode (2002)), namely

- Jarque-Bera,
- Kolmogorov-Smirnov,
- Lilliefors,

reject the Gaussian property of the signal Diff(t) for the twelve months of 2013. This is illustrated by Figures 1-(a) and 1-(b).

2.4 Towards confidence bands

Define a first confidence band $\text{CB}_{1, \text{pred60}}(t)$ by its frontiers

$$X_{\text{pred60}}(t) \pm \text{Vol}_{\text{pred60}}(t)$$

See Figures 4 and 8.

In order to improve $\text{CB}_{1, \text{pred60}}(t)$, define $\text{CB}_{2, \text{pred60}}(t)$ by new frontiers

$$X_{\text{pred60}}(t) \pm \alpha \text{Vol}_{\text{pred60}}(t)$$

where the parameter $\alpha$ is determined here by asking that during the three last days 68% of the measured data were in $\text{CB}_{2, \text{pred60}}(t)$. See Figures 5 and 9.

3 Here again, we do not reproduce the calculations.

4 The quantity 68% is obviously inspired by the confidence intervals.
Fig. 1. Signal distribution (blue) and the Gaussian distribution (red)

Fig. 2. February: irradiance (blue) and its prediction (red)
3. CONCLUSION

Improving short-term forecasting and the corresponding confidence bands will be tackled in future publications. Seasonalities (see, e.g., Fliess & Join (2015b)) will of course play some rôle.

This communication shows that a “good” forecast (see, e.g., Murphy (1993)) should incorporate a measure of risk. Since, according to Section 2.3, classic statistical confidence intervals are meaningless, we have introduced confidence bands, which do not necessitate any a priori probabilistic knowledge. Those bands will of course be further developed and applied to other domains.

The fact that no probabilistic description is needed has been already addressed in Fliess (2006); Fliess & Join (2009); Fliess, Join & Hatt (2011b). It is quite new in applied academic sciences, where a probabilistic description plays too often a key rôle. This fundamental epistemological issue ought to be further developed (see also Ayache (2010)).

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Fig. 6. June : irradiance (blue) and its prediction (red)

(a) Monthly view
(b) Zoom of 6-(a)
(c) Zoom of 6-(a)

Fig. 7. June : volatility (blue) and its trend prediction (red)

(a) Monthly view
(b) Zoom of 7-(a)
(c) Zoom of 7-(a)

Fig. 8. June: irradiance (blue), its prediction (red), confidence band (black - -) (case: CB1)

(a) Monthly view
(b) Zoom of 8-(a)
(c) Zoom of 8-(a)

REFERENCES


Fig. 9. June: irradiance (blue), its prediction (red), confidence band (black - -) (case: CB2)


