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Efficient Ray-Tracing with Real Weather Data

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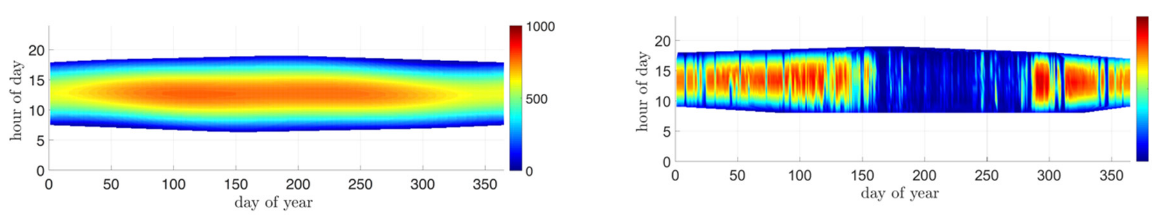
Abstract. New approaches for the computation of the sampling points for an annual simulation of a solar tower power plant are presented. The annual sun-path in azimuth and elevation and in ecliptic longitude and the hour angle are considered. Real measured weather data is considered in the computation of these sampling points.

INTRODUCTION

The simulation of solar tower power plants becomes increasingly important. It allows to assess the expected annual energy yield and to optimize the planned power plant configuration before construction. With this gain of information, the produced energy can be increased, and the costs can be reduced. For a heliostat field layout optimization, the underlying simulation model should be accurate and fast. As optical simulation model, the convolution method, as in e.g. UHC, Delsol and HFLCAL, or recently more and more the Monte-Carlo ray-tracing method, as in e.g. SolTrace, Tonatiuh and STRAL [1,2] are used. The main influences on runtime are the spatial (number of integration points or –rays, respectively) and temporal (number of time points) discretization. A higher discretization leads to a higher accuracy, but also to a higher runtime.

For the annual simulation, usually weather data from clear sky models is used, e.g. the clear atmosphere model from Hottel [3] or the meteorological radiation model (MRM) [4]. This data shows a symmetric behavior: a day is symmetric before and after noon and a year is symmetric before and after June 21st. This information is used to strongly reduce the number of temporal sample points [5].



(a) *(b)*

FIGURE 1. Plot for the DNI distribution over a whole year with the MRM model (a) and the measured weather data (b) for Mumbai from EnergyPlus.

But for industrial performance computations, real measured weather data (e.g. from a TMY file) should be used. For this case, the symmetric approach fails, compare with Fig. 1. To consider non-symmetric weather data for an annual simulation the brute-force method would be to simulate all 8760 hours of a year (weather data is usually provided in hourly data). But of course, this method is computationally too costly.

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With a smart choice of the sampling points, the number of simulations can strongly be reduced, while maintaining accuracy. In this paper, different temporal integration approaches are presented and discussed. In the following, two main concepts are presented: the temporal and the angular integration.

TEMPORAL INTEGRATION

The annual energy production E_{year} of the solar tower power plant can be computed with the sum over all days d and the integral of the daily power production,

$$E_{\text{year}} = \sum_{d=1}^{365} \underbrace{\left(\int_{\text{sunrise}}^{\text{sunset}} P(t,d)\, \mathrm{d}t \right)}_{=:\,E(\text{DNI}(d))},$$

EQUATION. 1

Where $E(\text{DNI}(d))$ describes the direct normal irradiation at day d. The computation of the annual energy production can be accelerated by dividing the underlying problem into two sub-problems:

- Reducing the number of samples per day by quadrature rules.
- Reducing the number of days by clustering.

In the following both approaches are discussed.

Quadrature Methods for Intraday Sampling

The intraday energy $E(\text{DNI}(d))$ for the above chosen days has to be computed, which is defined as the integral of the power production from sunrise to sunset, $\int_{\text{sunrise}}^{\text{sunset}} P(t,d)\, \mathrm{d}t$. Quadrature methods can be used to approximate the integral by using specific sampling points and their according temporal weight. Because hourly data is provided by the weather file, so far just quadrature methods with a constant time step of one hour are used, e.g. the summed midpoint and summed trapezoidal rule. But to reduce the number of needed sampling points per day, or to apply quadrature rules with higher order (e.g. Gauss-Legendre quadrature rule) a higher temporal resolution than just hourly constant data is helpful and would further increase the accuracy.

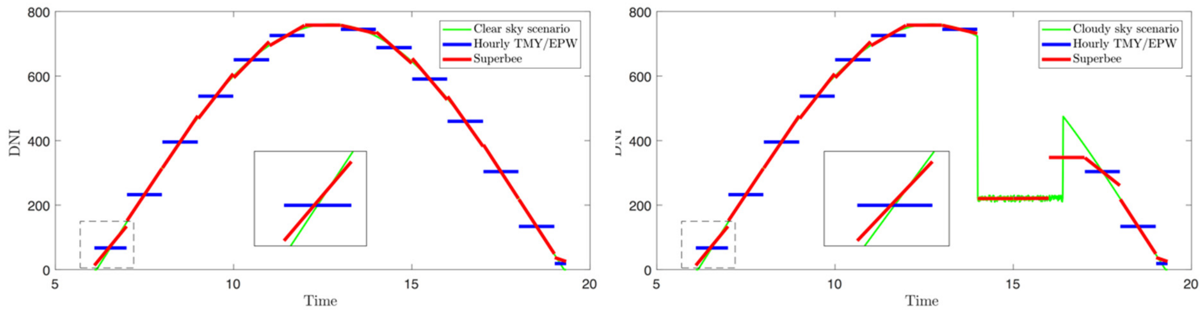
It is possible to achieve a higher resolution from the hourly averaged measured data by using data reconstruction. The main idea of reconstruction is to replace the hourly constant DNI values by a linear curve, see Fig. 2. Thus, every instant of time will be reconstructed by replacing the piecewise constant values by piecewise linear curves through the midpoint of each interval. The DNI value at day d around the time t_i changes as follows:

$$\text{DNI}(t,d) = \text{DNI}(t_i,d) + \sigma(t_i) \cdot (t - t_i), \qquad t \in \left[t_i - \tfrac{\Delta t}{2},\, t_i + \tfrac{\Delta t}{2}\right],$$

EQUATION. 2

With instant of time t_i, its originally measured value $\text{DNI}(t_i,d)$, and reconstructed slope $\sigma(t_i)$. For each curve, it must hold that it is conservative, which means, that its integral is equal to the integral of the constant curve. Furthermore, the linear curves should not deliver overshoots, such that unphysical values are reached. Therefore, we just use limiters with the TVD (total variation diminishing) property [6].

For the different reconstruction approaches the error is computed. A clear sky scenario, as used in the MRM model, as well as a cloudy sky scenario was investigated. The validation shows that the superbee limiter can reduce the error from the hourly averaged values by 85% for a clear sky scenario and by 31% for the cloudy sky scenario, see Fig. 2.



(a) *(b)*

FIGURE 2. Reconstruction with the superbee limiter (red) of the hourly averaged measurements (blue) for a clear sky scenario (a) and a cloudy sky scenario (b).

With this data reconstruction, the following quadrature methods can be applied to approximate the power production from sunrise to sunset, $\int_{\text{sunrise}}^{\text{sunset}} P(t,d)\,\mathrm{d}t$:

1. Midpoint rule,
2. Trapezoidal rule,
3. Gauss-Legendre quadrature rule,
4. Constant azimuthal quadrature rule.

The last method was proposed by Noone et al. [7] who recommend using equidistant azimuthal steps (which does not behave linearly with the time).

Clustering of Days

The clustering of days is used to reduce the number of computations. While the *Selection* method simply selects a subset of days, the *Aggregation* method considers all days. A reduction of the number of days is simply achieved by aggregating several days into one representative day. In the following, both methods are presented.

1. The *Selection* method choses a subset of $m \ll 365$ days of the whole year, with $1 = d_1 < \cdots < d_k < \cdots < d_m = 365$. Each selected day is representing the whole period between two selected days, see Fig. 3. The summed trapezoidal rule is used to approximate the annual energy production,

$$E_{\text{year}} = \sum_{d=1}^{365} E(\text{DNI}(d)) \approx \sum_{k=1}^{m-1} \frac{d_{k+1} - d_k}{2} \left(E(\text{DNI}(d_{k+1})) + E(\text{DNI}(d_k))\right).$$

EQUATION. 3

Thus, with this method, the non-selected days are just ignored.

2. The *Aggregation* method picks up the drawback of the *Selection* method, by considering each day of the year. Thus, once again a subset of $m \ll 365$ days with $1 = d_1 < \cdots < d_k < \cdots < d_m = 365$ is chosen. But instead of using the original DNI of the day d_k, now the averaged DNI of the neighboring days is used. Thus, the aggregated DNI is given by

$$\widetilde{\mathrm{DNI}}(d_k) \;=\; \sum_{i\,=\,\frac{d_{k-1}+d_k}{2}}^{\frac{d_k+d_{k+1}}{2}} \frac{2}{d_{k+1}-d_{k-1}}\,\mathrm{DNI}(d_i),$$

EQUATION. 4

see Fig. 4. Finally, the annual energy production is given by the summed trapezoidal rule,

$$E_{\text{year}} = \sum_{d=1}^{365} E(\mathrm{DNI}(d)) \approx \sum_{k=1}^{m-1} \frac{d_{k+1}-d_k}{2}\left(E\big(\widetilde{\mathrm{DNI}}(d_{k+1})\big) + E\big(\widetilde{\mathrm{DNI}}(d_k)\big)\right).$$

EQUATION. 5

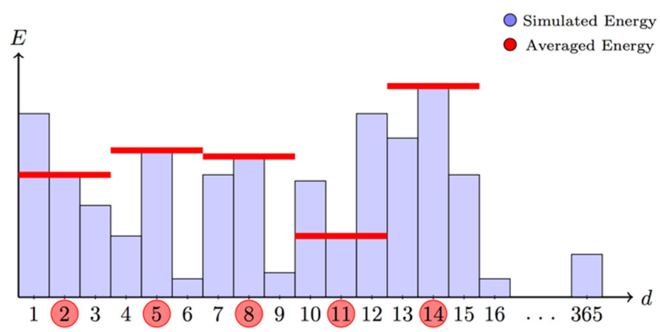


FIGURE 3. Clustering of days using the *Selection* method. Every third day is chosen as representative day.

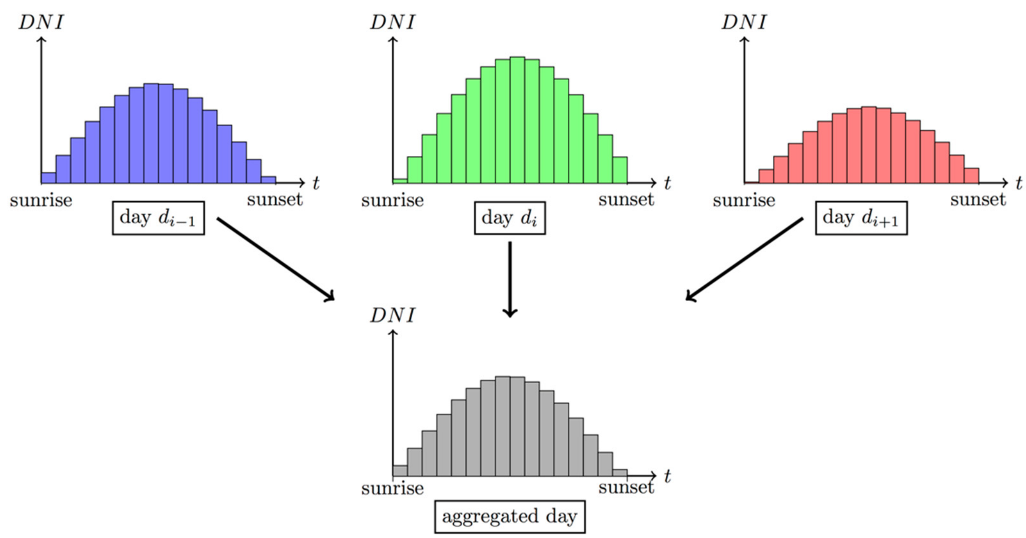


FIGURE 4. Clustering of days using the *Aggregation* method. Here, the three days d_{i-1}, d_i, and d_{i+1} are aggregated to one day.

ANGULAR INTEGRATION

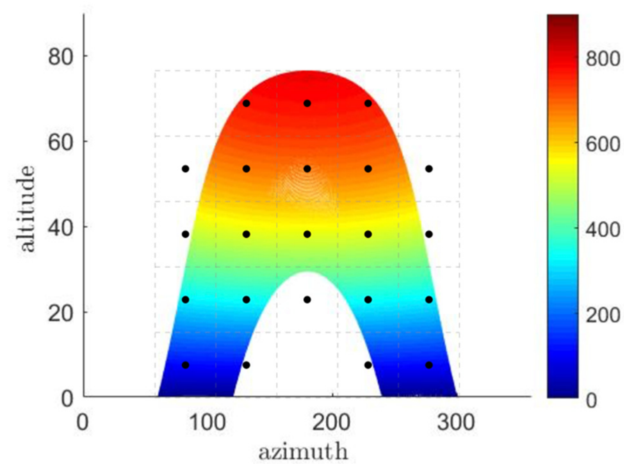
A second, completely different approach for computing the annular energy production E_{year} considers the sun path in the domain of the solar angles instead of the time domain. Therefore, the DNI needs to be transformed from the time domain into the angular domain. Then, two-dimensional quadrature rules can be used to compute the annual energy, e.g.

1. Midpoint rule,
2. Trapezoidal rule,
3. Gauss-Legendre quadrature rule.

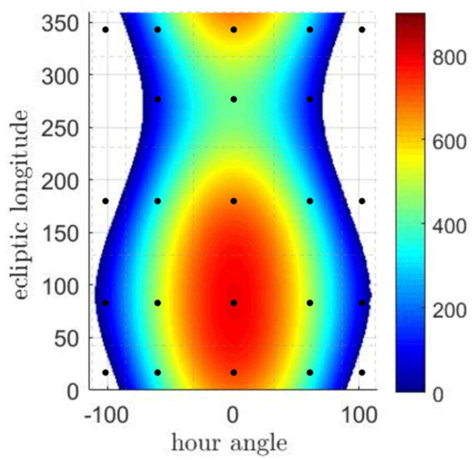
The underlying quadrature method defines a region in the angular-solar domain. All DNI values of this region are aggregated to one average DNI value, while the number of data points resemble the temporal weight of this region. For the solar domain, the following two coordinate systems are proposed:

1. Azimuth and elevation,
2. Hour angle and ecliptic longitude.

While Schöttl et al. [8] use the azimuth and elevation domain, Grigoriev et al. [9] propose the transformation to the hour angle and the ecliptic longitude which gives further enhancements, such as the almost rectangular shape of the integration domain, see Fig. 5.



(a)



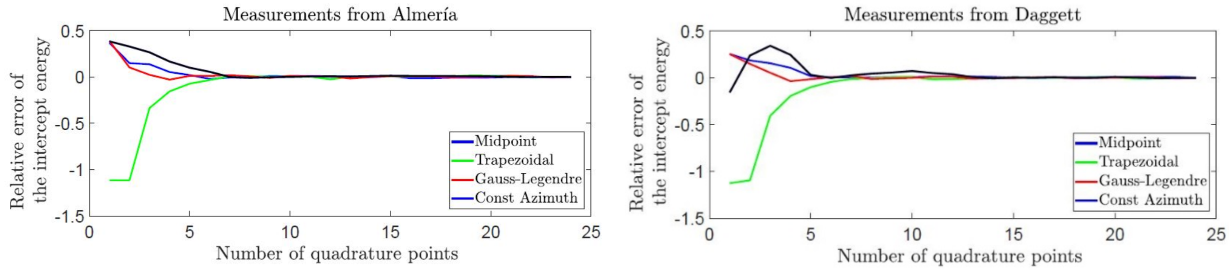
(b)

FIGURE 5. Integration domain for the transformation to azimuth and altitude with a midpoint grid (a) and to ecliptic longitude hour angle with a Gauss-Legendre grid (b).

RESULTS

Altogether, we have two (day clustering) times four (intraday sampling) different methods for the temporal integration and two (solar domain) times three (quadrature rules) different methods for the angular integration. Thus, we have 14 different methods which need to be compared. In the following all the different methods will be compared and the most suitable method will be investigated.

For the temporal integration, the resulting plots of the intraday sampling show in Fig. 6 that with the Gauss-Legendre quadrature the least number of samples per day are needed. As number of samples about four or five per day seem to be sufficient, obviously independent from the degree of symmetry of the DNI distribution.

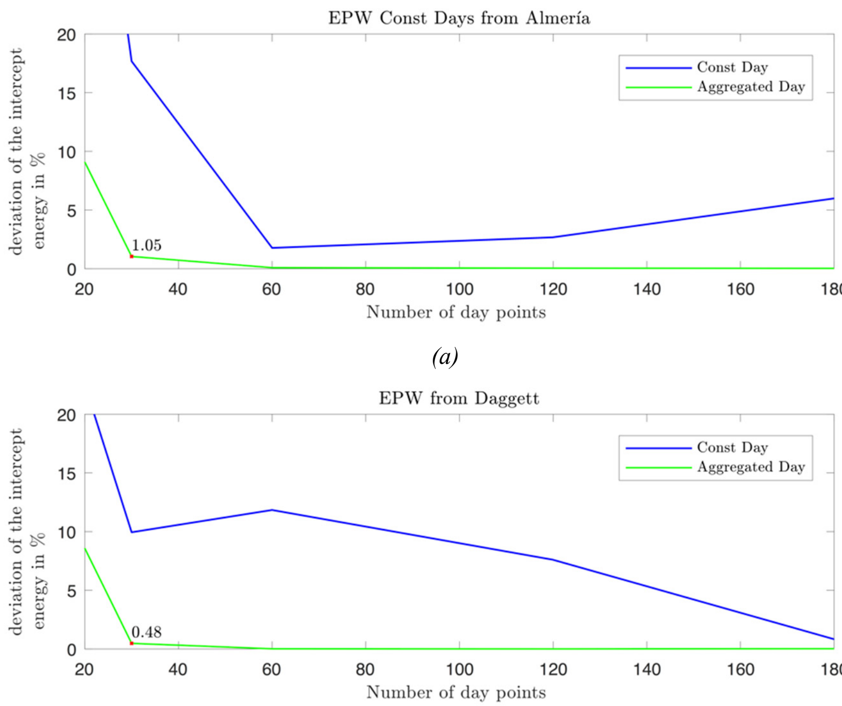


(a) *(b)*

FIGURE 6. Computation with four different quadrature methods for the intraday sampling on the 21st of June in the time domain with measured weather data from Almería (a) and Daggett (b). As reference solution, the midpoint rule with 1000 sample points was used.

Using these 5 sample points per day the annual energy using the *Selection* method and the *Aggregated* method was computed for the DNI data from the measurements.

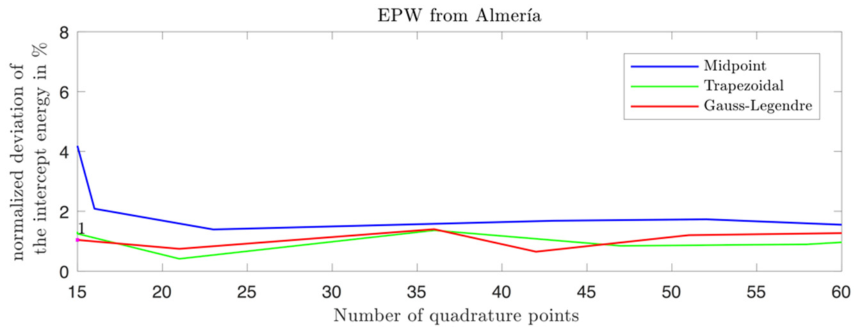
Fig. 7 shows clearly that with the Aggregated method significantly less points are needed for an accurate value of the annual energy.



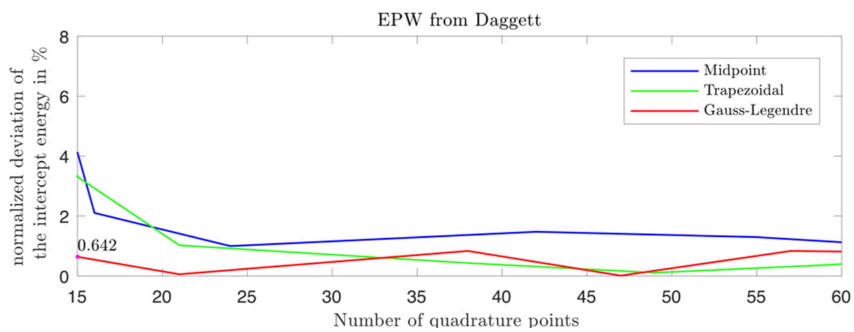
(b)

FIGURE 7. Computation of the annual energy with the constant *Selection* method and the *Aggregated* method for the DNI data from the measurements for Almería (a) and Daggett (b). As reference solution, 365 days are considered.

For the integration in the solar domain spanned by the azimuth and elevation angle the number of sample points can be reduced further, see Fig. 8. For both location, Almería and Daggett the Gauss-Legendre and the Trapezoidal rule result in similar normalized deviation values.

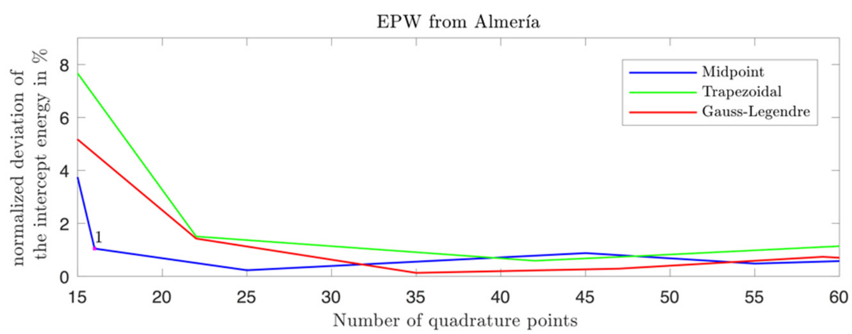


(a)

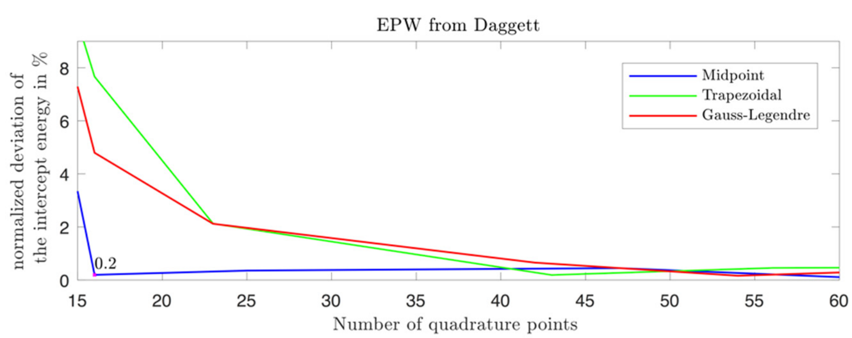


(b)

FIGURE 8. Computation of the annual energy with the *Azimuth-Elevation* method for the DNI data from the measurements for Almería (a) and Daggett (b) with the three different quadrature methods.



(a)



(b)

FIGURE 9. Computation of the annual energy with the *Ecliptic Longitude – Hour Angle* method for the DNI data from the measurements for Almería (a) and Daggett (b) with the three different quadrature methods.

As expected the deviation of the computation of the annual energy with the *Ecliptic Longitude – Hour Angle* method is the smallest, see Fig 9. This is due to the almost rectangular shape of the integration domain. Here the midpoint quadrature rule performs the best.

Comparing all the different methods and summarizing the individual results for the temporal integration the total number of simulation points for the computation of the annual energy depends on many factors. For using measured DNI data in the simulation, different methods than the *Selection* method have to be chosen to get a reasonable result of the annual intercept energy with the smallest number of sample points. The new integration methods allow to reduce this high number of simulated days.

CONCLUSION

For industrial performance computations, real measured weather data should be used. For that case, smarter integration methods can be used, such that the simulation time is strongly reduced. With smart choices of the sample points the number of total simulation points for the computation of the annual energy can be reduced.

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