Online Determination of Noise Level in Weather Radars

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1. Introduction

All receivers detect signals that are at some level above the limit imposed by the random voltage (i.e., noise) inherent in every electronic device. Consequently, proper measurement of noise power is of paramount importance for censoring of the weather radar data, which, in turn, is essential for the correct operation of automated algorithms and accurate forecasts derived from such data. Presently, the noise in weather radars is measured in several ways. For instance, on the National Weather Surveillance Radar – 1988 Doppler (i.e., WSR-88D) the noise is measured as part of the system online calibrations performed after each volume scan. Such measurement takes place at high elevation angle and the result is adjusted for other antenna elevations. In systems that do not have capability to perform online calibrations (e.g., the National Weather Radar Testbed Phased-Array Radar) the noise can be measured offline and this hardcoded value is used in computations. Clearly the downside of such approach is that it does not capture the temporal variations of noise power. Moreover, the nature of the noise sources in radar data is such that noise can have angular dependence in both azimuth and elevation (e.g., noise from cosmic radiation and from the oxygen and water vapor molecules) (Doviak and Zrnić 1993). Consequently, the benefit of noise measurement at each antenna position becomes obvious. The only way such measurement can be performed operationally is in parallel with data collection. Thus, an efficient approach that estimates noise power from measurements that contain both signal and noise is needed.

In the past several methods have been proposed. Hildebrand and Sekhon (1974) describe a method that subjects the Fourier coefficients to a series of tests discarding coefficients until statistical conditions that suggest only noise samples remain are met. Urkowitz and Nespor (1992) used the Kolmogorov-Smirnov (K-S) test applied to the periodogram successively discarding the Fourier spectral lines until the criterion for the noise hypothesis is satisfied. Siggia and Passarelli (2004) use rank order statistics to dynamically determine the noise level. All these approaches are based on discarding excess Fourier coefficients until the remaining ones satisfy conditions for noise. Inevitably, each approach introduces bias in noise level determination. This can not be avoided and the only question is how significant the bias is. In this paper we present new algorithm for noise estimation which estimates noise power from data available at each dwell.

2. The abstract

Currently, most weather radars estimate system noise power by either offline measurements or through periodic automatic calibrations as in the U.S. network of weather surveillance radars. However, it is well-known that the system noise power on weather radars changes with time and, more importantly, with antenna position. For example, due to the presence of storms or outside interference sources, the noise power may change while scanning volumes at different azimuths. Incorrect noise power measurements may lead to reduction of coverage in cases where noise power is overestimated or to radar data images cluttered by noise speckles if the noise power is underestimated. Moreover, when an erroneous noise power is used at low signal-to-noise ratios, estimators usually produce biased meteorological variables such as in the case of reflectivity and spectrum width.

Ideally, noise power estimates should be computed for every sampling volume, for example, by using spectral noise estimation methods. However, techniques such as those proposed by Hildebrand and Sekhon (1974), and Urkowitz and Nespor (1992, 1994) introduce significant bias in noise power estimates for radar volumes with weather signals that have wide spectrum widths or if using a small number of samples. Hence, a need arises for a more precise and continuous system noise power calibration that is robust and feasible for real-time implementation on weather radars.

In this paper, we propose a novel method to estimate the system noise power dynamically from the in-phase and quadrature data for every antenna position (radial). The technique uses a novel criterion to detect radar volumes that do not contain significant weather signals and uses those to estimate the system noise power. This technique is evaluated using a time-series collected with the National Weather Radar Testbed Phased-Array Radar (NWRT) and the research WSR-88D KOUN radar, both located in Norman, OK. Results show that the proposed technique produces noise power estimates that are closely matched to the ones obtained from manually identified, signal-free radar volumes at far ranges from the radar; thus, providing empirical validation. A real-time implementation of this technique is expected to significantly improve the data quality of operational weather radars which often rely on accurate noise power estimates.

3. Novel noise estimation algorithm

Apart from the previous approaches to noise estimation the algorithm presented in this paper does not produce noise estimate at each range position. Rather, it attempts to discard all samples at range locations where presence of signal is detected. The assumption is that there are enough range bins devoid of signal presence to yield noise estimate with satisfactory accuracy. This is almost always true when transmission frequencies which result in unambiguous ranges in excess of 300 km are used (i.e., long Pulse Repetition Time - PRT). On the other hand, when scanning with PRT's yielding short unambiguous ranges is used, it is possible that almost all samples contain signal due to the weather that spans the entire unambiguous range and/or the range folding. In such cases, the algorithm is unable to produce reliable noise estimate. However, the majority of such cases are dual PRT scans where the noise estimate at a given antenna position can not be estimated from a short PRT but is readily available from a long one. The novel noise estimation algorithm requires initial rough knowledge of the noise value (i.e., the default noise level) which should be in the vicinity of the true noise power (e.g., ±2 dB). It is used in the first two steps of the algorithm.

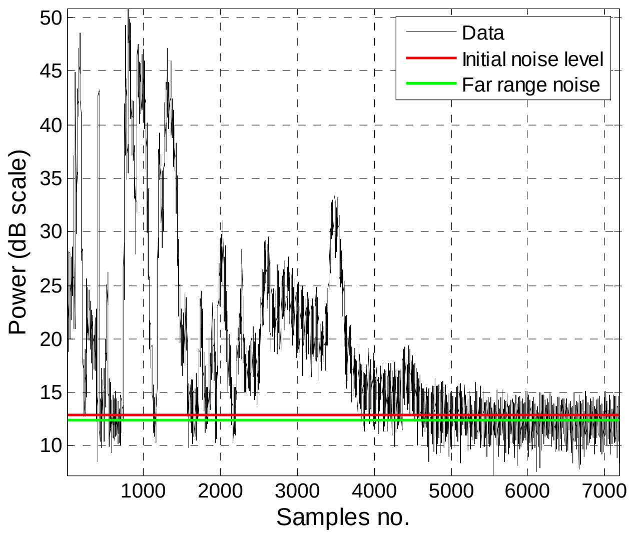

Fig. 1 Power range profile of data at the elevation angle of 0.5 deg. The number of samples at each range bin is 15 and the radar return is oversampled by 4.

Algorithm is now applied to a set of data from a dwell with unambiguous range of 465.6 km. Radar echo is oversampled by 4 ticks where each two consecutive samples are 60 m apart and the transmitted pulse is roughly 240 m long. The number of samples at each range position is 15. This data was collected using the National Weather Radar Testbed (NWRT) in Norman, OK. This radar does not perform online calibrations so the initial noise level is ascertained by offline measurement. The test power profile looks like shown in Fig. 1. By visual inspection of the Fig. 1 we see that there should be no signal beyond the 5000 samples number. By averaging all samples beyond 5000, 5500, and 6000 we get the absolute values 18.06, 17.64 and 17.6. Thus, we assume that the noise absolute power is 17.6 (12.46 dB) in this case. The default absolute noise power is 19.5 (i.e., initial noise value). First, filtering with the coherency detection (Ivić and Torres 2009) is applied. The threshold is obtained using the initial noise value. If the initial noise value were true such threshold would produce about 44 false signal detections in 10 million. Because the true noise power is lower than the initial one, the number of false signal detections is even smaller. On the other hand, if the initial noise value were lower than the true one, the number of false detections would be higher. In this case, however, we are interested in those samples that are classified as noise. Thus, it is important that the number of false detections is not too high because in that case too many noise samples may be classified as signals (hence not used for noise estimation) which can potentially bias the noise estimate significantly. Keeping the coherency based detection threshold that yields low false detection rate ensures this does not occur for a wide range of initial noise values. Then the autocorrelation coefficient (ACF) at lag 1 is calculated at each range gate and those for which it is larger than the threshold of 0.55 are deemed to contain signal and are discarded. Given the number of samples *M*, the ACF threshold is set to pass 99% of the noise samples so it does not bias the noise estimate. Because the autocorrelation coefficient is not dependent on the noise and signal powers but it measures the coherency only, this step discards samples at range positions containing highly correlated signals. After applying the first two steps we get what is shown in Fig. 2 (a). It is obvious that significant amount of signal still remains. This is reflected in the mean power of this data set which is 23.02; thus, it is still well above the far range noise level.

The next step is to apply the profile filter. It finds 10 or more consecutive power values that are larger than the median power and discards them along with 10 samples on the edges. The rationale for choosing 10 consecutive samples is following. The probability that one power sample is larger than the median is 0.5; thus, the probability for 10 randomly chosen independent samples to be all larger than the median is $0.5^{10} = 9.76\times10^{-4}$. Consequently, this filter should take advantage of larger sample powers in the areas of range profile where signal is present. Consequently, these samples are discarded while leaving those in predominantly in noise areas. This is important so as not to underestimate the noise. After applying this filter we obtain Fig. 2 (b). The mean power is 19.69 (or 12.94 dB). The matrix of samples is now reshaped into vector where the samples from 1 to M belong to the first column of the samples matrix. The samples from M+1 to 2*M belong to the second column of the samples matrix and so on. Then a running average of 750 samples is performed to get Fig. 3 (a). The formula for running average is

$$RAVG(m) = \frac{1}{K}\sum_{k=0}^{K-1}\left|V(m-k)\right|^2 \text{ , and } m \geq K. \tag{1}$$

where K is 750 and $V(k)$ are the elements of the samples vector. Because $m \geq K$ the first K elements are always discarded. We notice that this makes the part of the range profile where signal is still present more visible. In noise only case the probability that one averaged point is larger than the mean N times D is (Ivić and Zrnić 2009)

$$\frac{M}{N\cdot(M-1)!}\int_{D\cdot N}^{\infty}\left(\frac{M}{N}p\right)^{M-1} e^{-p\frac{M}{N}}dp = \Gamma_{inc}\left(D\cdot M, M\right). \tag{2}$$

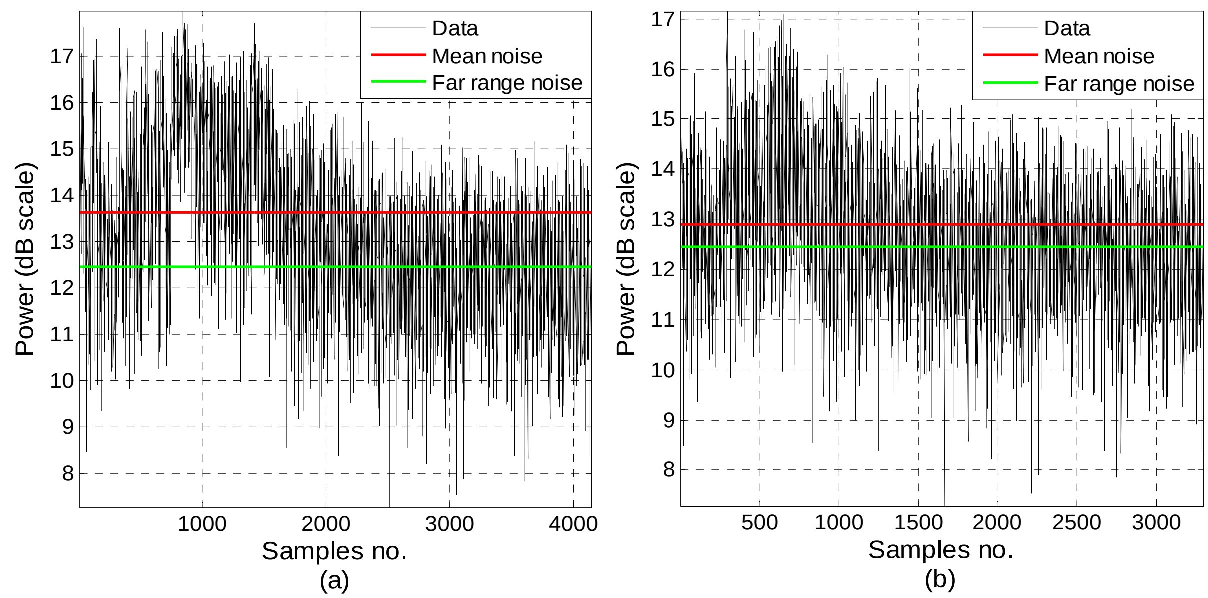

Fig. 2 (a) Power range profile after the first two steps of the algorithm.(b) Range power profile obtained after the step that applies the profile filter which discards 10 or more consecutive powers larger than the median.

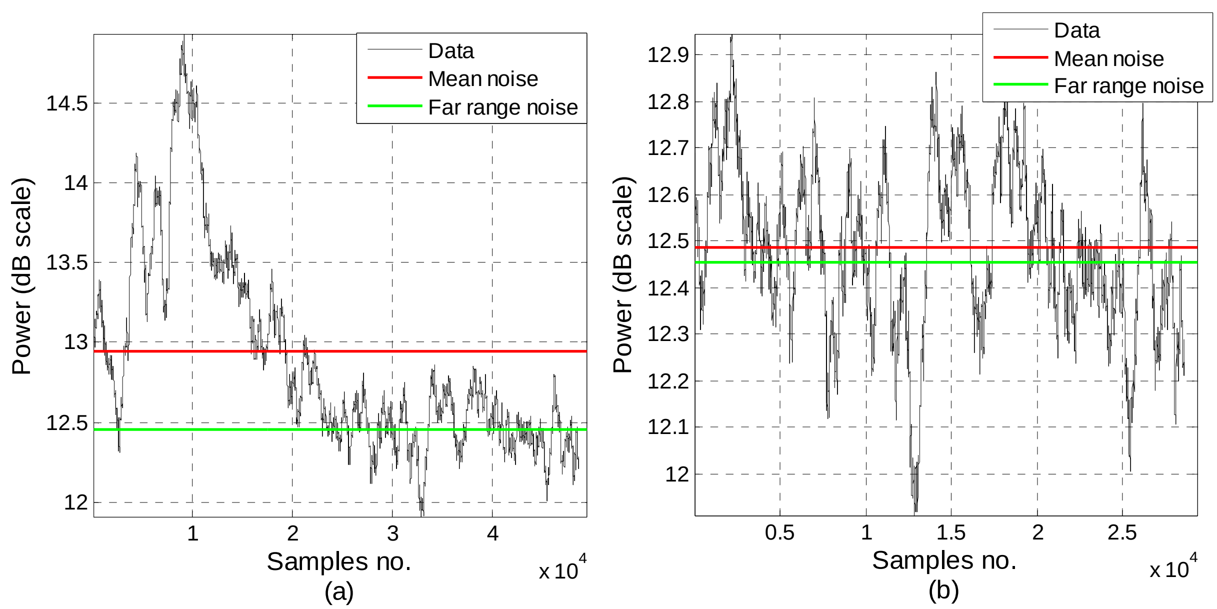

Fig. 3 (a) Range power profile obtained after applying the profile filter, and performing the running average of 750 points. (b) Range power profile obtained after applying twice the running average filter.

When D is 1.1 (or 110% of the mean noise power) and M is 750 this probability is 0.38%. The mean is found from the data last filtered by the profile filter. Averaged points that are larger by 1.1 of the so found mean are detected and all points used to obtain those particular averaged points are discarded. This is repeated while the number of discarded samples is larger than the 0.0038 times the total number of samples or up to five times at most. In this particular case the range filtering is performed twice. After this we get Fig. 3 (b). The mean power of this data is 17.728. Finally, instead just using plain average the mean power can be obtained using the rank order statistics as shown in Appendix A. In this particular case this yields the noise power estimate of 17.672.

The steps of the algorithm are summarized below:

1) *Censor using coherency based censoring (Ivić and Torres 2009) with default noise level.*
2) *Censor using the autocorrelation coefficient (ACF) with threshold set to pass 99% of noise samples based on the number of pulses (i.e., M).*
3) *Censor with profile filter that discards 10 or more consecutive samples with power larger than the median (including 10 surrounding samples).*
4) *Reshape all samples into a one dimensional array.*
5) *Set counter to zero.*
6) *Obtain mean power.*
7) *Perform running average of 750 points.*
8) *Discard samples used to obtain each averaged point larger than 1.1 of the mean power.*
9) *If the number of discarded samples is larger than the 0.0038 times the total number of samples go back to step 6. Increase counter by one and if it's less than 5 go back to step 6. Otherwise, proceed to step 10.*
10) *Estimate the mean power using rank ordered statistics as described in Appendix A.*

4. Real-time examples

In this section examples of the algorithm implementation on time-series are presented. The first set of data is collected with the National Weather Radar Testbed Phased-Array Radar (NWRT). This radar does not perform online calibrations thus if noise is not estimated from data the default value of 19.5 (obtained by offline measurements) is used for product generation. The presented data is from a split cut with long PRT of 3.104 ms and the short PRT of 0.896 ms, at elevation of 0.51 deg. Fig. 4 (a) shows the averaged noise estimates from the long and the short PRT. The estimator is set so that if less than 1000 samples remain in step 9 the estimator defaults to zero and reports it is unable to produce an estimate. By imposing the requirement that the estimates are made from at least 1000 samples prevents the algorithm from producing result when majority of samples contain signal. Also if exactly 1000 samples are used for estimation, the estimate is within ±10% of the true mean with 0.998 probability. In this particular case the algorithm fails to produce results rather often in the short PRT; thus, if the short PRT estimate is not available only the one from the long PRT is used. Moreover, even in the cases when the algorithm produces results in the short PRT the data is so heavily inundated with signal that the noise is overestimated in many instances. Consequently, the short PRT estimate is compared to the long PRT one and the two results are combined only if two are within the 10% of each other. Otherwise, only the long PRT estimate is used.

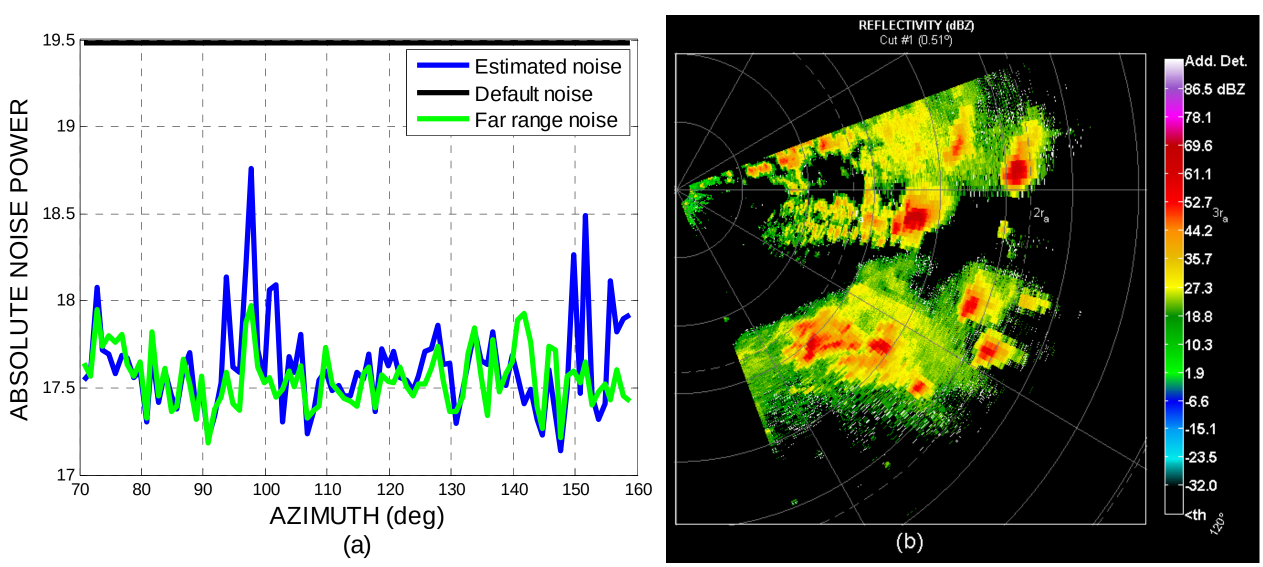

Fig. 4 (a) Noise estimates compared to the default and the far range noise, and (b) reflectivity field with additional detections obtained using estimated noise highlighted in white.

In Fig. 4 (a) the estimated noise is also plotted against the one obtained from the distant ranges free of visible signals. It shows that the estimated noise follows rather well the power obtained from the far ranges. This implies that the noise estimation algorithm indeed produces value close to the true noise power. Fig. 4 (b) shows the reflectivity field obtained using the estimated power and the coherency based censoring for detection (Ivić and Torres 2009). The additional detections obtained using the estimated noise as opposed to the default one are highlighted in white.

Another example shows the surveillance scan data collected by the dual polarized KOUN WSR-88D research radar in Norman, OK. The PRT used for this scan was 3.1 ms with 17 pulses (i.e., $M = 17$). The comparison between the far range and the estimated noise is given in Fig. 5 (a). As in the previous case, it is apparent that the estimated and the far range noises agree very well. Moreover, the noise estimation procedure filters out the jumps in the far range noise (most likely caused by the point target interferences). Fig. 5 (b) shows the reflectivity field with additional detections obtained using the noise estimation algorithm highlighted in white. In this particular case, the noise obtained by the online calibration is about 1 dB larger than the one produced by the dynamic estimation.

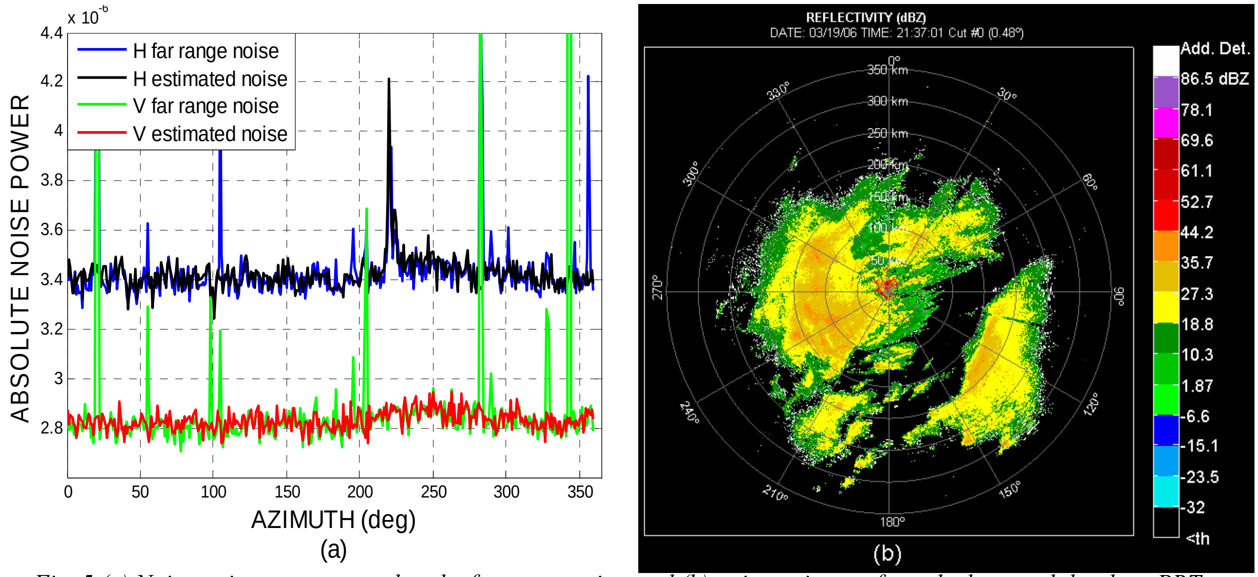

Fig. 5 (a) Noise estimates compared to the far range noise, and (b) noise estimates from the long and the short PRT.

5. Summary

Method to estimate noise power dynamically from data is presented. Through the set of consecutive steps the algorithm classifies all samples as those that contain signal and those that do not. The approach requires the initial rough guess on the noise power. In systems that use online calibrations such value is already available. Other possibility is to have it measured offline. First, the coherency based detection using the initial noise guess is applied to the data. Then, the range positions which exhibit strong correlations along sample-time are discarded using the measured autocorrelation coefficient. Range positions with powers that are consecutively higher than the median one are disposed of next. At this point all the remaining samples are rearranged into a long vector and the running average is performed to make the remaining weak signal areas more visible. To dispense with the remaining signal all samples associated with the averaged points larger than the 110% of the mean power are discarded. The last step is repeated until the ratio of the number of discarded samples and the total ones falls under the probability that the averaged point exceeds 1.1 times the mean power value (i.e., 0.0038). The noise estimate is produced from the remaining samples using the rank ordered statistics. In the implementation presented in the paper the minimum number of the remaining samples required to produce reliable estimate is set to be 1000. The algorithm accuracy was verified by comparing its results to the powers obtained from the data at the far range positions devoid of visible signals. Such comparison shows the technique to produce noise powers with improved accuracy as opposed to the online calibrations with minimal biases.

Acknowledgment

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Appendix A

When we have n samples that are exponentially distributed with mean power N and these samples are arranged in ascending order this results in the distribution function that can be associated with each Y_i (i is the position in the ascending vector) viewed as random variable.

$$\begin{aligned} f_{Y_i}(y) &= \frac{n!}{(i-1)!(n-i)!}\left[1-e^{-y/N}\right]^{i-1} e^{-y/N(n-i)} \frac{1}{N} e^{-y/N} \\ &= \frac{1}{N}\frac{n!}{(i-1)!(n-i)!}\sum_{j=0}^{i-1}\frac{(i-1)!}{j!(i-1-j)!}(-1)^{(i-1-j)} e^{-y/N(i-1-j)} e^{-y/N(n-i+1)} \\ &= \frac{n(n-1)\cdots(n-i+1)}{N}\sum_{j=0}^{i-1}\frac{(-1)^{(i-1-j)}}{j!(i-1-j)!} e^{-y/N(n-j)} \end{aligned} \quad (A.1)$$

Then we can obtain the most likelihood value at each position in the ascending array as:

$$\begin{aligned} \frac{df_{Y_i}(y)}{dy} &= \frac{1}{N}\frac{n!}{(i-1)!(n-i)!}\left(\frac{(i-1)}{N}\left[1-e^{-y/N}\right]^{i-2} e^{-y/N(n-i+2)} - \frac{n-i+1}{N}\left[1-e^{-y/N}\right]^{i-1} e^{-y/N(n-i+1)}\right) \\ &= \frac{1}{N^2}\frac{n!}{(i-1)!(n-i)!}\left[1-e^{-y/N}\right]^{i-2} e^{-y/N(n-i+1)}\left((n-i+1)+ne^{-y/N}\right) \end{aligned} \quad (A.2)$$

So,

$$\frac{df_{Y_i}(y)}{dy} = 0 \Rightarrow y = N\ln\left(\frac{n}{n-i+1}\right) \quad (A.3)$$

Having an array of ascending powers values the mean power can be found as one that minimizes the mean square error between the measured powers and the most likelihood values.

$$\begin{aligned} R^2 &= \sum_{i=0}^{n-1}\left(y_i - N\ln\left(\frac{n}{n-i+1}\right)\right)^2 \\ \frac{\partial R^2}{\partial N} &= -2\sum_{i=0}^{n-1}\left(y_i - N\ln\left(\frac{n}{n-i+1}\right)\right)\ln\left(\frac{n}{n-i+1}\right) \\ &= -2\sum_{i=0}^{n-1} y_i\ln\left(\frac{n}{n-i+1}\right) + 2\sum_{i=0}^{n-1} N\ln^2\left(\frac{n}{n-i+1}\right) \\ &= 0 \end{aligned} \quad (A.4)$$

So,

$$\hat{N} = \frac{\sum_{i=0}^{n-1} y_i \ln\left(\frac{n}{n-i+1}\right)}{\sum_{i=0}^{n-1}\ln^2\left(\frac{n}{n-i+1}\right)} \quad (A.5)$$