The Influence of Sampling and Filtering on Measured Wind Gusts

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ABSTRACT

The theory by Rice for extreme value statistics is used to study the influence of filters in a wind measuring system on the measured gusts. An extension is made to discretely sampled data. Model results are compared with strong wind data from the Cabauw tower. On the basis of this theory a definition is proposed for the duration of gusts. Also a data reduction scheme for standard synoptic and climatological stations is proposed. Such a standardization would enhance the applicability of wind gust climatology.

1. Introduction

High-quality observations are the basis of most activities of meteorological services, ranging from daily forecasts to climatological work. The World Meteorological Organization (WMO) provides guidelines for observation systems to achieve worldwide uniform observations (cf. WMO, 1983). This is obviously crucial for basic measurements such as surface pressure and upper-air soundings. For wind measurements, however, the guidelines are very rudimentary. A number of reasons exist for this deficiency:

1) wind measurements are used for local analysis and climatology rather than for initializing models on a global scale;
2) the measuring techniques have been evolving continuously;
3) the highly stochastic nature of wind introduces the problem of how to characterize the wind signal, in particular the high-frequency part, generally called turbulence or gustiness.

More and more applications, however, demand accurate on-line wind measurements or reliable climatology. Actual wind fields and forecasts are essential for long-range transport of pollutants. Turbulence information is needed for the estimation of diffusion parameters. Climatology of wind gusts (extreme values in the wind that persist for a few seconds) is very important for wind energy feasibility studies and for risk studies for maximum load or fatigue on structures and buildings. The long-term exceedance statistics are particularly important for these applications (see Panofsky and Dutton, 1984, for a detailed discussion). Here we limit to the measuring aspects of extreme winds and consider the statistics of extremes in measuring intervals of 10 minutes in relation to filtering in the measuring chain.

Wind measurements have been made for a long time now; the instrumentation has evolved from pressure plates and pitot tubes to rotation anemometers and propeller vanes. The recording has slowly changed from manual reading and archiving, mechanical and electrical recording to data reduction and storage by microcomputer. Digital systems are very powerful now adays and can be inexpensive, provided that the meteorological community agrees on minimum specifications for sampling frequency, averaging intervals, etc. This paper tries to provide the basis and the tools necessary for such specifications. The influence of filtering and sampling on the final results (mean value, standard deviation and gusts) will be investigated.

The basic question we have to answer is: How should the wind signal be characterized to have sufficient information for most applications? Limited storage and the requirement to keep the processing as simple and economical as possible set a limit to the number of characteristic parameters to be recorded. As a compromise it is proposed to characterize the wind signal every 10 minutes by its average value, its standard deviation and its extreme value (gust). An averaging interval of 10 minutes is desirable for several reasons:

(1) it is compatible with the actual practice for synoptic stations;
(2) the time scale of 10 minutes coincides with the spectral gap separating turbulence from synoptic and diurnal changes (see Fiedler and Panofsky, 1970);
(3) standard deviations measured over 10 min intervals will only have minor perturbations by trend.

It is clear that the average wind speed fills the requirement of standard synoptic data exchange and climatology. The standard deviation is a basic parameter to characterize turbulence intensity, and Jones and Pasquill (1959) already attempted to obtain routine measurements of it for purposes of diffusion climatology. Since then, in many application areas, turbulence analysis methods were developed requiring as minimum information a standard deviation of wind over the spectral band of boundary layer turbulence, i.e., from a few seconds to 10 or 20 minutes. Such analysis are used in wind loading calculations by Greenway (1979), wind turbine design (Powell and Connell, 1980) and aeronautics (e.g., Burnham, 1970). Most usage deals with standard deviation of wind speed, but for air pollution applications the standard deviation of wind direction would be required, too.

The standard deviation of strong winds turns out to be related to the roughness of the upstream terrain (cf. Beljaars et al., 1983; Beljaars, 1987). This is clear from Monin Obukhov similarity for neutral situations with $\sigma \simeq 2.5u_*$ and $\bar{U} = (u_*/k) \ln(z/z_0)$ where σ is the standard deviation of wind speed fluctuations, u_* is friction velocity, $\bar{U}$ is average wind speed at height z, k is the von Kármán constant (0.4) and z_0 the roughness length. With σ and $\bar{U}$ available at 10 m height, u_* and z_0 can easily be estimated for strong wind conditions. This has been done by Wieringa (1976, 1986) for the Dutch wind stations on the basis of gusts instead of σ_u and it turns out to be a powerful tool to rescale wind information at one location with a certain roughness to another location with another roughness length.

Finally, it is important to have gust information for risk studies of damage of buildings and constructions. Some applications require information about extreme values of short duration, in other cases only the gusts that last for several seconds may cause damage. In most cases, the damaging gusts are assumed to be those gusts that engulf the entire structure (cf., Frost and Turner, 1982; Greenway, 1979). Therefore, long-lasting gusts are important for large structures, whereas short gusts can also damage small structures. For practical risk studies this means that we are interested in wind extremes that persist for a few seconds. Under idealized circumstances (for example, Gaussian stationary turbulence) gust statistics can be derived from the power spectrum and a measured standard deviation (cf. Greenway, 1979; Davenport, 1964). However, many extreme wind speeds are observed in thunderstorms, whose wind distribution is certainly not Gaussian. It is therefore preferable to have direct gust measurements that meet as close as possible with the requirement of the application. The Gaussian theory is used now to apply small corrections if necessary.

The arguments above show that availability of wind average, maximum gust and standard deviation seems necessary and sufficient for most practical purposes. It remains to be specified how these quantities should be measured. Up to now WMO has not prescribed satisfactorily the way gusts should be measured. The applicability of gust climatology would be enlarged if standard wind measuring systems would obey well-defined specifications. To arrive at compatibility of gust observations from various measuring systems, we have to characterize the filtering effect of the system.

The measured magnitude u' of a gust, defined as the difference between the extreme value U_{max} and the average value $\bar{U}$ in a given time interval T (in this paper always 10 minutes), strongly depends on the filtering by the measuring system. Slowly responding systems (e.g., heavy anemometer with pen recorder) smooth out the extreme values in the wind signal and measure smaller u'-values than fast-responding systems (e.g., fast anemometer with high-speed recording). It is impossible to conduct gust measurements on a routine basis to satisfy every possible application. We have to compromise here. It is proposed to measure gusts with a duration (a definition will be formulated in section 4) that is in the middle of the range of applications (a few seconds). Theory can be used to correct the data for smaller and larger gust durations. This implies that we can accept quite large uncertainties in the corrections (e.g., due to nonstationarity) because the corrections are small for most applications.

A number of studies exist in which wind gusts are analyzed and compared with Rice's theory (cf. Davenport, 1964; Greenway, 1979; Frost and Turner, 1982; Wood, 1983; Healy, 1985). Most of them do not consider sampled time series. In section 2 a short summary will be given of the extreme value theory with an extension for sampled signals (here sampling is used in the sense of taking instantaneous readings of the signal with a relatively high frequency as done by modern microcomputers, i.e., many samples are taken in one 10-minute interval). In section 3 measured gusts along the 200 m Cabauw mast will be compared with model simulations. Different spectral forms of the wind spectrum (needed as input for the model) are discussed. A definition of "gust duration" is given in section 4. This enables a very simple characterization of an arbitrary measuring chain with respect to gust measurements. Several examples are given. In the conclusions of section 5, it is suggested to standardize wind measuring systems for synoptic and climatological use.

2. Gust model for filtered and/or sampled signals

A wind measuring chain consists of different elements that influence the recorded data. The extreme values in particular will be affected by filtering in the chain. Examples of elements in a wind measuring system are the anemometer, the transmission line, an analog recorder or analog to digital conversion. Most elements (except analog to digital conversion) are approximately linear and can easily be characterized by a filter in the spectral domain.

The model for extremes by Rice (1944, 1945), applied to wind records by Davenport (1964) and Greenway (1979) relates the extreme value statistics to the spectrum of the signal. For a given spectrum of turbulent fluctuations and with knowledge about the filter characteristics of the measuring system, it is simple to determine the spectrum at the end of the chain (cf. Otnes and Enochson, 1978). In this way the effect of filtering on gusts can be evaluated quite easily. Since many stations make use of digital data logging, an extension is needed for digitized signals.

We consider a continuous stationary signal $U(t)$, with a Gaussian distribution function and power spectrum $S(n)$. The choice seems rather restrictive with respect to practical situations in which storms and convection are important contributors to extreme winds. It should be realized, however, that the model is not supposed to be used in the absolute sense. The main purpose is to rescale gusts with a particular timescale or "duration" to another gust duration (for example, as if the gust was measured with a more slowly responding system). Moreover we are dealing with the occurrence of extreme values in 10 min intervals, which is sufficiently short to avoid significant trends in most cases. In the next section an example with a convective storm will be given to illustrate the effect of nonstationarity.

Assuming $U(t)$ and $\partial U/\partial t$ to be joint Gaussian, the probability Pr for the normalized extreme value for not crossing level U_s in time interval T is (cf., Davenport, 1964 or Greenway, 1979)

$$\Pr\left(\frac{U_{\max}-\bar{U}}{\sigma}<U_s, T\right)=\exp\{-E(U_s, T)\}, \quad (1)$$

$$E(U_s, T)=\nu T e^{-U_s^2/2}, \quad (2)$$

$$\nu^2=\frac{\int_0^\infty n^2 S(n)dn}{\int_0^\infty S(n)dn}, \quad (3)$$

$$\sigma^2=\int_0^\infty S(n)dn. \quad (4)$$

In these expressions, $U_{\max}$ is the maximum value of $U(t)$ in time interval T, $\bar{U}$ and σ are the mean wind speed and the standard deviation of the signal over the same time interval, $S(n)$ is the power spectrum as a function of frequency n, E is the expected number of upcrossings of level U_s, and ν is a characteristic frequency representing the width of the spectrum. Parameter ν is related to the Taylor microscale

$$\lambda_m=1/(\nu\pi\sqrt{2}).$$

Although the integral distribution function Pr of maximum values can be measured, it is more convenient to characterize the distribution by a single parameter. The median, modal or arithmetical average can be used for this. Since the distribution is quite narrow, the one parameter characterization is sufficient for most purposes (Greenway, 1979). In contrast to an earlier analysis (Beljaars and Wieringa, 1984) where the median value was chosen, we calculate the average value because it is easier to compare with data. The difference between median and average value is smaller than 5% for typical situations. The average value of normalized extreme values $[(U_{\max}-\bar{U})/\sigma]$ reads for large νT (Davenport, 1964):

$$\langle U_s\rangle=(2\ln\nu T)^{1/2}+\gamma(2\ln\nu T)^{-1/2}, \quad (5)$$

where $\gamma = 0.5772$ (Euler's constant). The angle brackets are used for ensemble averaging which will be interpreted here as averaging over different 10-minute intervals. This in contrast to the overbar that is used for averaging over 10 minutes. So far only the unfiltered wind signal has been considered. In a real measuring chain we have a number of elements that filter the signal. For linear elements this can be expressed by means of a filter function (cf. Bendat and Piersol, 1966, or Otnes and Enochson, 1978). As an example we consider a chain with three elements, namely anemometer, transmission line and recorder. The spectrum $S_3(n)$ at the end reads

$$S_3(n)=|H_1(n)|^2|H_2(n)|^2|H_3(n)|^2S(n), \quad (6)$$

where H_1, H_2 and H_3 are the filter functions of the three elements.

Common filter functions are

$$|H(n)|^2=\frac{1}{1+(2\pi n\tau)^2} \quad (7)$$

for an RC-filter with time constant τ or an anemometer with response length λ where $\tau = \lambda/\bar{U}$,

$$|H(n)|^2=\left(\frac{\sin\pi n t_0}{\pi n t_0}\right)^2 \quad (8)$$

for a filter that averages over the preceding t_0 seconds (running average filter) and

$$|H(n)|^2=\frac{1}{N^2}\left(\frac{\sin\pi n\Delta N}{\sin\pi n\Delta}\right)^2 \quad (9)$$

for a filter that averages over the N preceding samples (instantaneous readings) taken with time intervals Δ. For the extreme value analysis the filtered spectrum $S_3(n)$ has to be used instead of the original wind spectrum $S(n)$, when determining the characteristic frequency ν in Eq. (3) and the standard deviation σ in Eq. (4).

Modern dataloggers or microprocessors often use analog to digital conversion by taking samples at equidistant time intervals Δ. Sampling is used here in the sense of replacing the continuous signal by a large number of instantaneous readings of the signal. It is well known that the standard deviation of a sampled signal is unbiased when the appropriate algorithm is used (Otnes and Enochson, 1978). The situation is different for the observed extreme value. It is very unlikely that the occurrence of the extreme in the continuous record coincides with the times when a sample is taken. Therefore the observed maximum in the array of samples will generally be smaller than the maximum in the continuous record. The extreme value distribution can be evaluated by considering the expected number of upcrossings of a linearly interpolated signal between successive samples. The number of upcrossings of level U_s is (for the normalized signal)

$$E(U_s, T) = \frac{T}{\Delta} \Pr\left(\frac{U(t) - \bar{U}}{\sigma} < U_s, \frac{U(t+\Delta) - \bar{U}}{\sigma} > U_s\right), \tag{10}$$

where Pr is the probability that the normalized signal is below U_s for one sample and above U_s for the next sample. This probability can be evaluated by assuming a bivariate Gaussian distribution with covariance $R(\Delta t)$. $R(\Delta t)$ is the covariance between successive samples and can be derived from the spectrum by Fourier transformation. The result for the number of upcrossings reads (Owen, 1956 or Johnson and Kotz, 1972; cf. also Tick and Shaman, 1966)

$$E(U_s, T) = \frac{T}{\Delta}\frac{1}{\pi}\int_0^a \frac{\exp\{-\frac{1}{2}U_s^2(1+y^2)\}}{1+y^2} dy,$$

where

$$a = \left(\frac{1-\rho}{1+\rho}\right)^{1/2}, \quad \rho = \frac{R(\Delta)}{R(0)}. \tag{11}$$

The integral (11) can be written as a series expansion that converges rapidly for small values of a (Owen, 1956). Combined with (1) this leads to the following distribution function for the maximum sample in time interval T:

$$\Pr\left(\frac{U_{\max} - \bar{U}}{\sigma} < U_s, T\right) = \exp\left[-\frac{T}{\Delta}\frac{a}{\pi} e^{-1/2U_s^2}\left\{1 - \frac{1}{3}\left(1 + \frac{U_s^2}{2}\right)a^2 + O(a^4)\right\}\right]. \tag{12}$$

Expression (12) reduces to (1) for small time interval Δ between successive samples. Davenport (1964) calculates the average extreme value $\langle U_s \rangle$ by means of (in an approximation for large νT)

$$\langle U_s \rangle = \int_0^\infty U_s \frac{\partial \Pr}{\partial U_s} dU_s = \int_0^\infty U_s \exp(-\xi) d\xi, \tag{13}$$

where Pr is the cumulative distribution function (1) and $\xi = \nu T \exp(-\frac{1}{2}U_s^2)$ for the continuous case. A series expansion that expresses U_s in ξ for large νT leads to solution (5). For the discretely sampled signal we use

$$\xi = \frac{T}{\Delta}\frac{a}{\pi} e^{-1/2U_s^2}\left\{1 - \frac{1}{3}\left(1 + \frac{U_s^2}{2}\right)a^2 + \cdots\right\}, \tag{14}$$

and write U_s as a function of ξ in a series expansion for small a and small $\delta = 1/\ln(aT/\Delta\pi)$, retaining only terms of the order a^2 and δ:

$$\langle U_s \rangle = \left(2 \ln \frac{Ta}{\Delta\pi}\right)^{1/2}(1 - \tfrac{1}{6}a^2) + \gamma\left(2 \ln \frac{Ta}{\Delta\pi}\right)^{-1/2}. \tag{15}$$

3. Comparison of the gust model with data

Extreme values are affected by filtering in two ways: (i) the standard deviation at the end of the chain will be modified (reduced in most cases) and (ii) the filtering changes the second moment ν^2 of the spectrum. Both parameters, as well as $R(\Delta)$ in the case of sampled data, are derived from the spectrum or the filtered spectrum by means of numerical integration. This enables us to deal with arbitrary spectral forms and filter functions.

Before model calculations can be done, the wind power spectrum has to be known. The spectrum of longitudinal wind fluctuations has been subject to many studies and a number of empirical forms has been proposed (cf. Busch, 1973). Earlier studies (Kaimal et al., 1972) had described spectra in the framework of Monin Obukhov similarity. It was realized, however, that the low-frequency part of the spectrum was influenced by large eddies with dimensions much larger than the observation height (Panofsky et al., 1977). This implies that the boundary layer thickness has to be included in the scaling laws (cf. Kaimal, 1978; Højstrup, 1982; Panofsky et al., 1977). Two empirical forms are considered here: the spectrum proposed by Højstrup (1982) for the unstable and neutral boundary layer

$$\frac{nS(n)}{u_*^2} = \frac{0.5f_i}{1 + 2.2f_i^{5/3}}\left(\frac{z_i}{-L}\right)^{2/3} + \frac{105f_{ru}}{(1+33f_{ru})^{5/3}}\frac{(1-z/z_i)^2}{(1+15z/z_i)^{2/3}}, \tag{16}$$

where

$$f_i = nz_i/\bar{U},$$
$$f_{ru} = f/(1 + 15z/z_i),$$
$$f = nz/\bar{U},$$

and the expression proposed by Kaimal (1978):

$$\frac{nS(n)}{u_*^2} = \left\{1 + 0.75\left|\frac{z}{L}\right|^{2/3}\right\}0.3f^{-2/3} \quad \text{for} \quad n > \bar{U}/2z$$
$$= \left\{1 + 0.75\left|\frac{z}{L}\right|^{2/3}\right\}0.48(2f)^{-p} \quad \text{for} \quad \bar{U}/2z \geq n \geq \bar{U}/0.67z_i$$
$$= \left\{12 + 0.5\left|\frac{z_i}{L}\right|\right\}^{2/3}\frac{f_i}{1 + 3.1f_i^{5/3}} \quad \text{for} \quad n < \bar{U}/0.67z_i \tag{17}$$

with

$$p = \ln\left\{0.44 \frac{(12 + 0.5|z_i/L|)^{2/3}}{1 + 0.75|z/L|^{2/3}}\right\} \Big/ \ln(0.33 z_i/z).$$

In these expressions n is the frequency, S the spectral density, u_* the friction velocity, L the Obukhov length, z_i the boundary layer height and $\bar{U}$ the mean wind speed at measuring height z.

Olesen et al. (1984), in a review of different spectral forms, state that both spectra (16) and (17) fit the available data reasonably well. It should be noted, however, that the two spectra have fundamental differences, which are particularly important for the analysis of strong wind cases. For small z/z_i and small z_i/L Eq. (16) reduces to the Monin Obukhov form proposed by Kaimal et al. (1972): $105f/(1 + 33f)^{5/3}$. The frequency scales with z and wind speed $\bar{U}$, which means that the spectrum shifts towards lower frequencies with increasing height. The spectral form proposed by Kaimal (1978), (17), behaves differently for $z/z_i \rightarrow 0$ and $z_i/L \rightarrow 0$. Only the high-frequency part scales with height z; the major part of the spectrum is independent of z and scales with z_i.

For practical purposes it is very inconvenient to have a number of unknown parameters in Eqs. (16) and (17). Usually we deal with observations at 10 m height without knowledge about z_i and L. Since gust analysis is often limited to strong wind cases it can be assumed that the Obukhov length L is large (of the order of 1000 m). Although z_i/L is therefore of the order one, it turns out to be a good approximation to assume the neutral limit $z_i/L = 0$ in the analysis of the normalized gust $(U_{\max 1} - \bar{U})/\sigma$. The parameter σ is the unfiltered standard deviation and $U_{\max 1}$ is the extreme value after one filtering element. The reason for the weak dependence on z_i/L is that z_i/L influences the magnitude of σ rather than the second moment of the spectrum. The normalized gust $(U_{\max 1} - \bar{U})/\sigma$ measured with a running average filter (t_0 ranges from 2 to 40 s) varies only about 2% when L is changed from $-\infty$ to -100 m in spectrum (17) with $z_i = 1000$ m.

To investigate the effect of different spectral forms a recent dataset obtained at the Cabauw 200 m tower (cf. Driedonks et al., 1978, for technical details) has been analyzed. Wind speed was measured at 10, 20, 40, 80, 140 and 200 m height by means of propeller vanes (type Gill 8002D, $\lambda = 2.2$ m, see Monna and Driedonks, 1979 for details). The velocity signals were sampled with a frequency of 2 Hz and recorded on tape. Since all samples were stored, it was possible to analyze the same record with different digital filters. The filtering was done by taking a running average over a number of samples varying from 2 to 40 samples. The corresponding measuring chain is illustrated in Fig. 1. The parameters σ and $U_{\max}$ have a subscript 1, 2 or 3 depending on the position in the chain where they are measured or computed. The unfiltered standard deviation can obviously not be measured; when needed, σ_1 is used. It is not very different from σ because of the short response length of the anemometer. The standard deviation σ_1 has been computed from the basic 2 Hz samples without averaging.

Measuring Run 86013 will be used for basic analysis. Other runs will be used afterwards to see if the results are valid for different circumstances. Run 86013 is 15 h long and starts at 1400 UTC 13 January 1986. The boundary layer is near neutral with small heat flux towards the surface (of the order of 50 W m^{-2}). Monin Obukhov length is larger than 500 m, mainly because of the strong wind. Although we are dealing with a slightly stable boundary layer here, its neutral aspects turn out to be dominant. The spectral models (16) and (17) are therefore still applicable. The wind signal is filtered by arithmetical averaging over 2, 6, 10, 20 or 40 samples (cf. Fig. 1). The maximum wind, the average and the standard deviation are determined over each 10 min interval. This leads to a series of 90 values for $U_{\max 3}$, σ_3 and $\bar{U}_3$ $(=\bar{U})$ (see Table 1 for profiles of $\bar{U}$ and σ). To arrive at statistically stable values, the normalized gust $(U_{\max 3} - \bar{U})/\sigma_1$ and the ratio σ_3/σ_1 are averaged over all 90 10-minute values, an operation that is indicated by $\langle\ \rangle$.

The performance of the model is investigated by comparing with the experimental results for Run 86013. The Højstrup spectrum (16) as well as the Kaimal spectrum (17) are used as input for the model. The spectrum is multiplied by the filters that correspond to the measuring chain of Fig. 1. The zero and second moment of the spectrum as well as parameter $R(\Delta)$ are evaluated by numerical integration.

First, the effect of filtering on the standard deviation is investigated. The measured reduction of the standard deviation is given in Table 2 for different heights as a function of the number of samples over which the signal has been averaged. The same results are depicted in Fig. 2 for three heights in comparison with model calculations with both the Højstrup and Kaimal spectrum as input. The height z and the wind speed $\bar{U}$ are taken as measured, L is taken very large (neutral limit) and for the inversion height z_i two values are tried out namely 1000 and 2500 m. The most striking result is

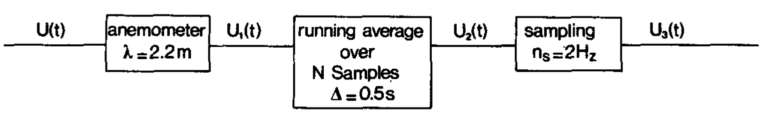

FIG. 1. Measuring chain with anemometer, digital filter and sampling.

TABLE 1. Profiles of wind speed and standard deviation for Run 86013. $\langle \bar{U} \rangle$ and $\langle \sigma_1 \rangle$ are the wind speed and standard deviation averaged over all 10 minute intervals. $\bar{U}$ and σ_1 are the 10 min values after the anemometer.

z	$\langle \bar{U} \rangle$	$\langle \sigma_1 \rangle$
200	18.0	1.29
140	16.6	1.36
80	14.6	1.44
40	12.8	1.51
20	12.0	1.63
10	10.8	1.65
m	m s^{-1}	m s^{-1}

that the reduction of the standard deviation is almost independent of height for the entire range of filtering times. This suggests that the height dependence of the spectrum must be weak. It is clear from Fig. 2 that the Kaimal spectrum leads to better results at low heights. The reason for the unrealistic behavior of the Højstrup spectrum is the shift of the low-frequency part towards higher frequencies when z decreases. The influence of z_i is relatively small, especially at low heights.

The same picture emerges when the extreme values are considered. The normalized maximum wind in a 10-minute interval averaged over all 10-minute intervals is given in Table 3 and Fig. 3. The height dependence is again weak and the Kaimal spectrum leads to better predictions than the Højstrup spectrum, especially at the 10 m level. The z_i dependence is also relatively weak for both spectra.

The preliminary conclusion we draw here is that the Kaimal spectrum yields the best predictions for gusts and that a rough estimate of z_i will be sufficient. For further analysis, spectrum (17) will be used with z_i = 1000 m.

To gain insight in the performance of the model in different situations, some other runs are analyzed. In all cases the model computations are carried out for the measuring chain that was used during the experiment including sampling. The only common feature of the different runs is the strong wind; the other conditions are quite different. A short summary of the different runs is given:

1) Run 85091 at Cabauw with the same instrumentation as in Fig. 1. Gust data and model results are compared in Fig. 4. The main feature of this run is its nonstationarity. As illustrated in Fig. 5 extreme wind speeds occur in a short period due to convective shower activity. The averaged normalized gust $\langle (U_{max3} - \bar{U})/\sigma_1 \rangle$ is predicted very well. The standard error of $(U_{max3} - \bar{U})/\sigma_1$ has become much larger than in Fig. 3.

2) Run 81161 at Cabauw with a sonic anemometer at 3.5 m height and a trivane at 22 m height. This is a 3-hour early afternoon run, reasonably stationary, sampled with a frequency of 10 Hz. (This run was also used by Beljaars et al., 1983). The Obukhov length was between −100 and −200 m. Gust data are compared with model calculations in Fig. 6, with a neutral Kaimal spectrum as input.

3) Flevo data above open water. Details about these measurements are given by Wieringa (1973). Gust data and model results are compared in Fig. 7. It shows that the model predicts gusts above water with equal accuracy as gusts above land. This suggests that the normalized gust $(U_{max} - \bar{U})/\sigma$ is independent of the turbulence level σ and therefore also independent of the roughness length.

4) Run 81161 at Cabauw was analyzed in a different way to test the sampling part of the gust model separately. The basic samples digitized every 0.1 second were low pass filtered by taking a running average over 30 samples. This new series was sampled again by using one sample every $1/n_s$ seconds resulting in a sample frequency n_s (by dropping the samples in between). In this way the effect of discrete sampling could be isolated using the same record. The results are shown in Fig. 8 in comparison with model calculations. The agreement between model and data is reasonable; the tendency as a function of sample frequency is well predicted by the model.

The general conclusion to be drawn is that the gust model gives reasonably accurate results for the normalized gust in arbitrary situations with strong winds. The tendency as a function of averaging time is especially well predicted. This is very useful since it can be used to convert an extreme wind speed measured with a given system and given response characteristics to another desired gust duration. Gusts measured with a system that averages over 3 seconds can for instance be converted to corresponding hypothetical gusts measured with a 10-second averaging filter (this might be necessary for load calculations on very large structures). It has been shown above that such a correction works well in the statistical sense. We will now illustrate this with the individual gusts of 10-minute intervals for the very nonstationary Run 85091. In Fig. 9 the filtered time evolution of the 10 m wind is shown during the occurrence of a strong-wind event shortly after 2100 hours (cf. also Fig. 5). In the same figure the ratio $(U_{max3} - \bar{U})_N/(U_{max3} - \bar{U})_6$ is indicated for all 10-minute in-

TABLE 2. The reduction of the standard deviation $\langle \sigma_3/\sigma_1 \rangle$ due to filtering (cf. Fig. 1) for Run 86013.

z (m)	N = 2	6	10	20	40
200	0.99	0.94	0.91	0.84	0.74
140	0.99	0.94	0.91	0.84	0.75
80	0.99	0.94	0.91	0.84	0.74
40	0.99	0.94	0.90	0.83	0.73
20	0.98	0.93	0.89	0.82	0.73
10	0.98	0.92	0.88	0.81	0.71

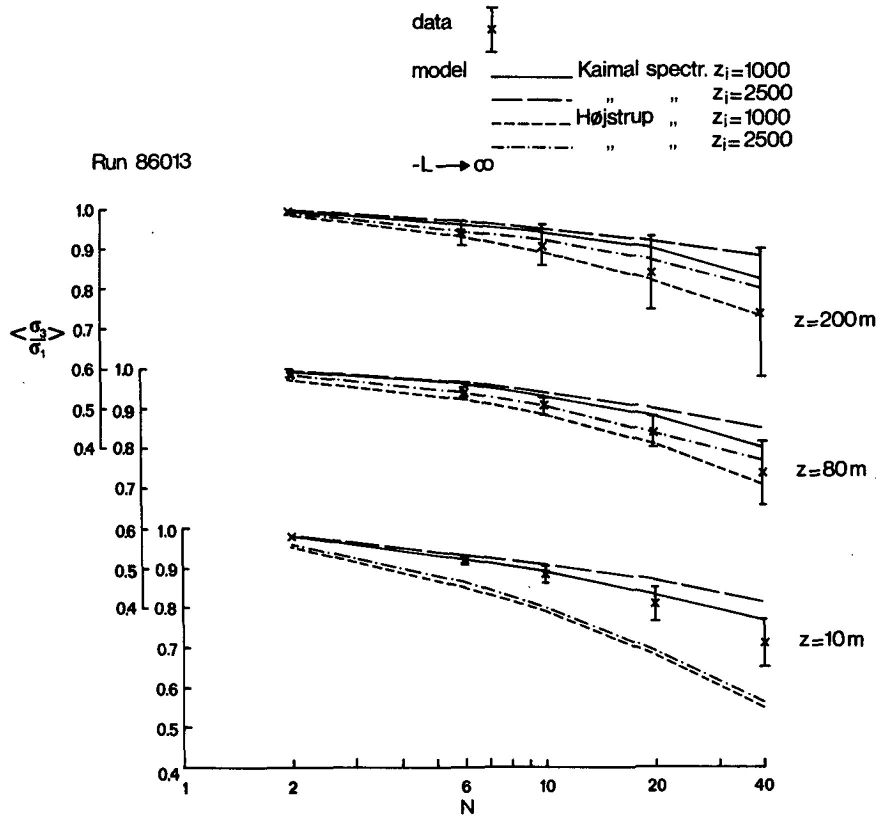

FIG. 2. Reduction of the standard deviation for the measuring chain in Fig. 1. Experimental results for Run 86013 (×) are compared with model simulations. The error bars indicate ±std. dev. (σ_3/σ_1).

tervals, where N and 6 indicate that N and 6 samples have been averaged respectively. An interesting feature in Fig. 9 is that this ratio shows little of the nonstationarity of the $U(t)$ time history. An explanation might be that the signal is much more stationary on the time scale of 10 minutes than on the time scale of several hours (compare also Fig. 5 and Fig. 9).

4. Definition of gust duration

In the previous section it has been shown that Rice's theory is reasonably accurate in predicting the dependence of the magnitude of gusts on the response time of filters in the measuring chain. Since all elements in the chain contribute to the filtering, it is very difficult to characterize a measuring system with a single parameter. Still it is important for the application (for instance a risk study) to know how gust measurements were obtained. When the measuring system has a small time response, the climatology of recorded gusts has to be interpreted differently from that of a slowly responding system. The most obvious way of characterizing measured gusts is to specify a gust duration which is related to the width of the spike that causes the wind extreme in a 10-minute interval. However, the "width" of a spike is a very subjective specification. We propose to define gust duration with the help of a single simple filter, namely a running average filter.

TABLE 3. The normalized gusts $\langle(U_{max3} - \bar{U})/\sigma_1\rangle$ for Run 86013 as measured with the chain in Fig. 1.

z (m)	N = 2	6	10	20	40
200	2.72	2.41	2.24	1.95	1.60
140	2.78	2.50	2.32	2.02	1.68
80	2.78	2.50	2.34	2.08	1.73
40	2.88	2.60	2.41	2.09	1.74
20	2.83	2.52	2.34	2.07	1.72
10	2.88	2.53	2.35	2.07	1.70

Definition:

> An arbitrary measuring chain produces gusts with duration t_G if the same normalized gust magnitude is obtained (according to the model) with a running average filter with $t_0 = t_G$.

This definition implies, that $t_G = t_0$ for a measuring chain that consists of a running average filter only. For

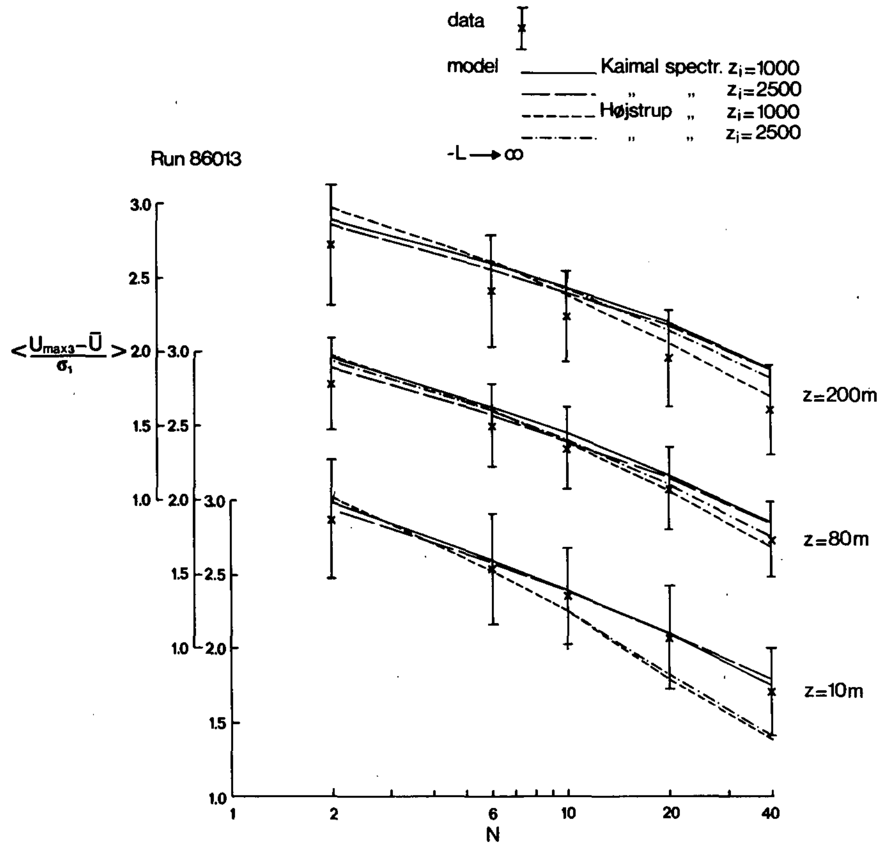

FIG. 3. As in Fig. 2 but for the normalized gust.

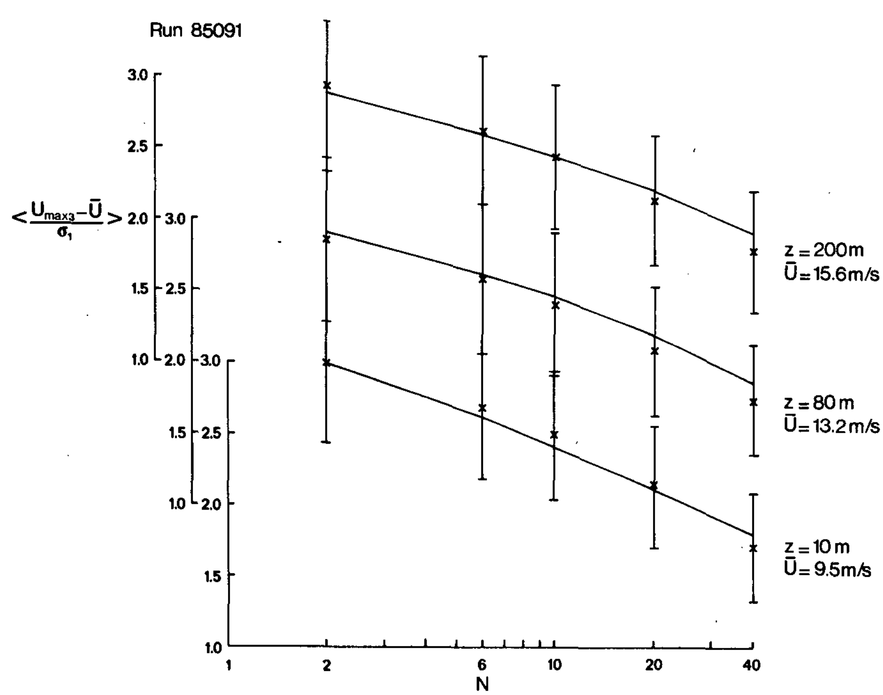

FIG. 4. Normalized gusts measured with the system of Fig. 1 (×) for Run 85091 in comparison with model calculations (solid line) with the Kaimal spectrum as input and z_i = 1000 m.

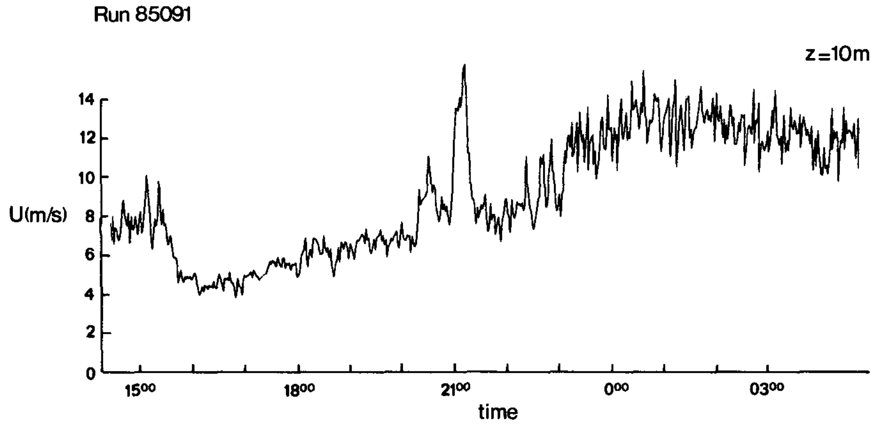

FIG. 5. Time evolution of the wind signal for Run 85091. To reduce the noise in the figure the signal has been filtered by averaging over 180 samples that are 0.5 sec apart. One point has been plotted every 90 sec. At about 2100 a shower starts with suddenly increasing wind.

more complex systems, model computations have to be carried out to find t_G.

In principle a number of unknown parameters in the wind spectrum are needed, namely z, $\bar{U}$, z_i and L. It has been shown, however, that the dependence on L and z_i can be neglected for strong wind cases. Although the dependences on $\bar{U}$ and z are incorporated in the model calculations of section 3, they only have a minor influence on the predicted gusts. For many purposes it is sufficient to use the spectrum and filters with fixed values for z, $\bar{U}$, z_i and L. For a standard station we choose $z = 10$ m, $\bar{U} = 10$ m s^{-1}, $z_i = 1000$ m and $-L \rightarrow \infty$.[1] In Fig. 10, model simulations are

[1] It should be noted that spectrum and parameters are different from those in Beljaars and Wieringa (1984). Although the results are quite similar, the present model is easier to use because of the insensitivity to z and U.

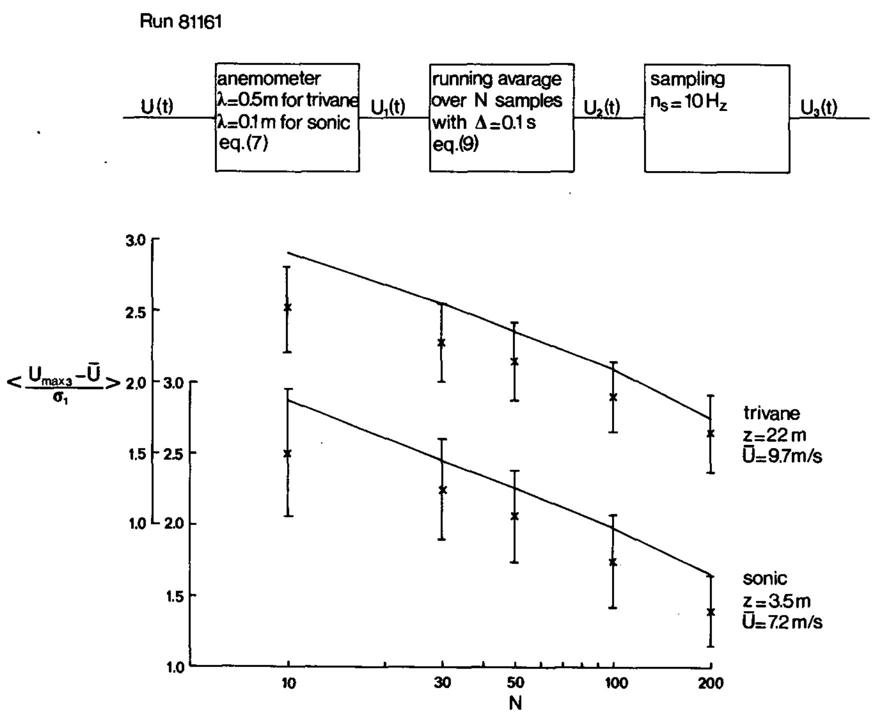

FIG. 6. Normalized gusts (Run 81161 at Cabauw) averaged over 18 ten-minute values (×) with standard deviations (errorbars) as a function of the number of samples N over which has been averaged. The solid lines are model calculations.

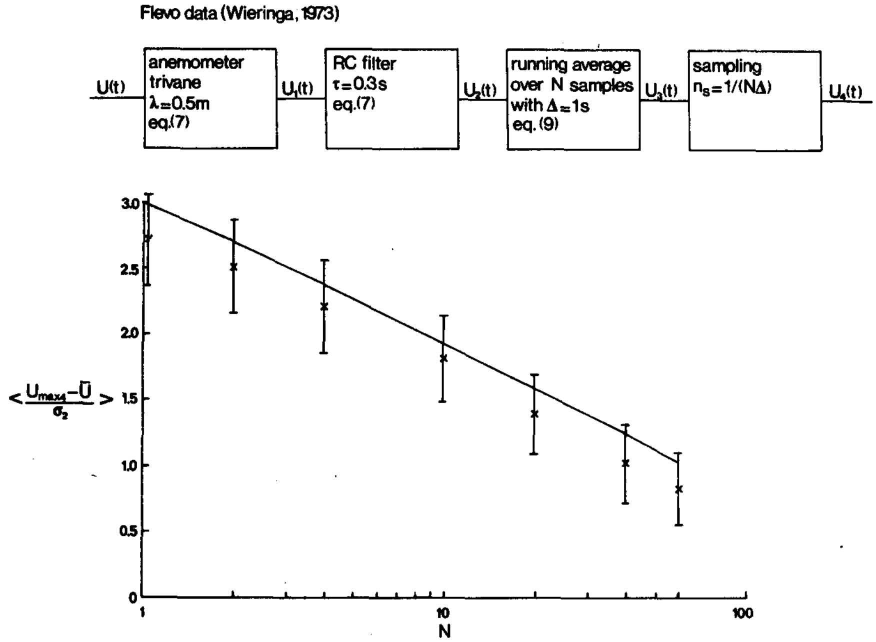

FIG. 7. Normalized gusts (×) averaged over 34 10-minute intervals. The data are taken over from Wieringa (1973) and were obtained with a trivane at 8 m height above Lake Flevo. Model calculations (solid line) were done with the Kaimal spectrum and the filters correspond to the indicated measuring chain.

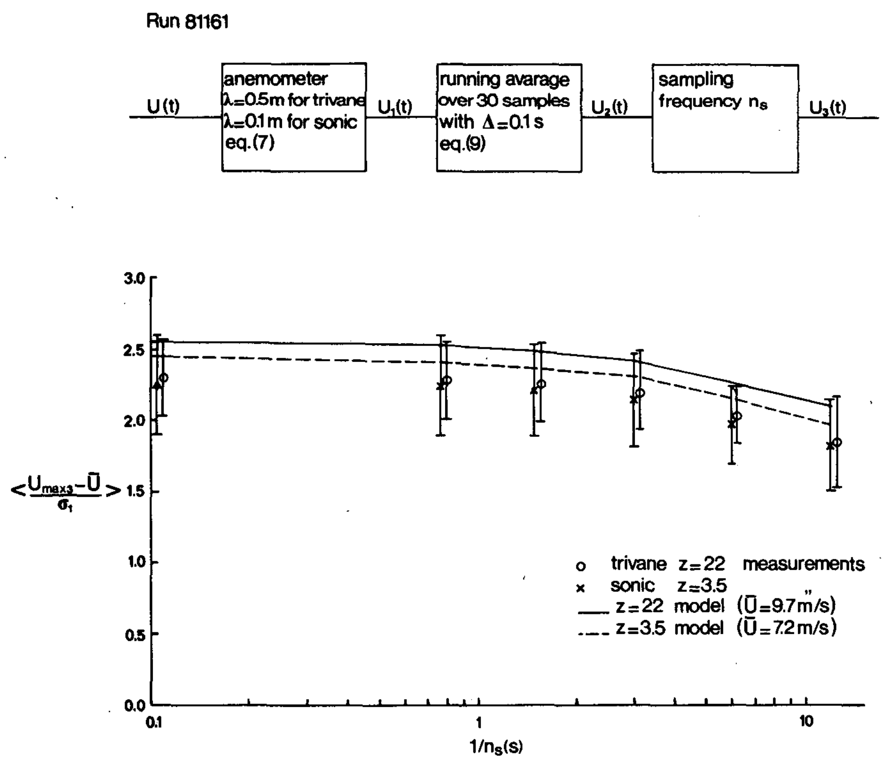

FIG. 8. The average normalized gust as a function of the time interval between samples, in comparison with model calculation for Run 81161.

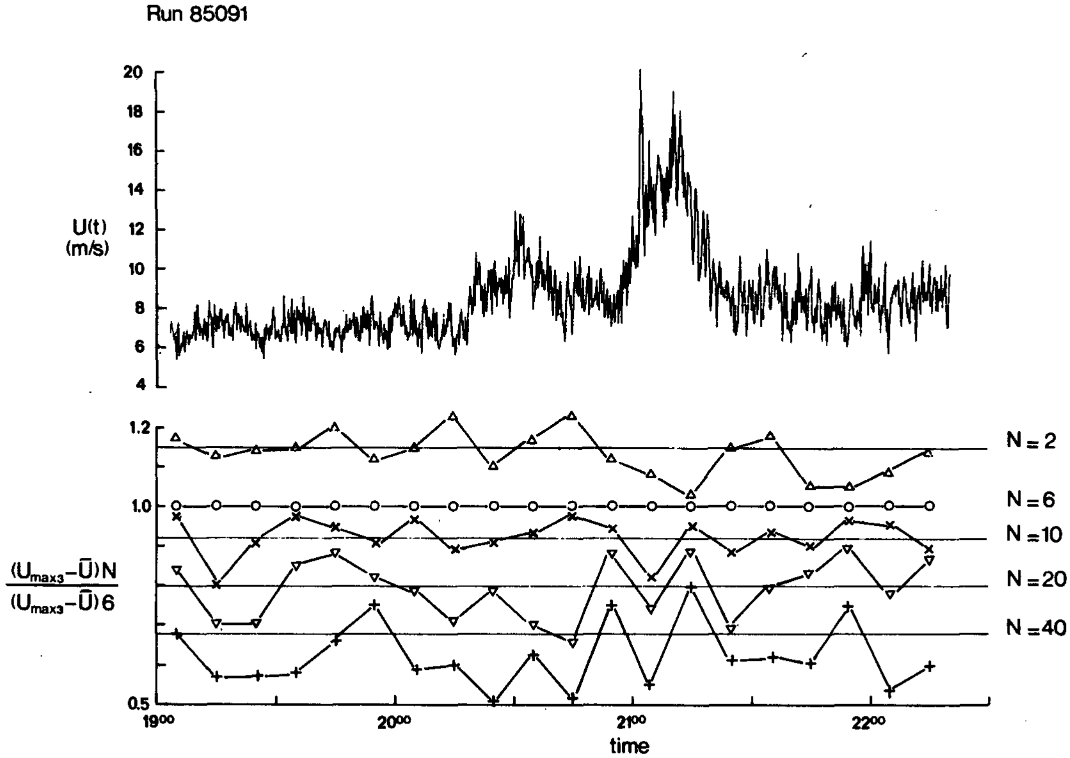

FIG. 9. Time evolution of the wind signal for Run 85091, filtered by averaging over 20 samples that are 0.5 sec apart. One point has been plotted every 10 sec (upper figure). In the lower figure the ratio of $(U_{max3} - \bar{U})$, measured with two integration times is shown. The reference filter averages over six samples and the other filter over N samples with N = 2, 6, 10, 20 or 40 (cf. Fig. 1 for the measuring chain). Each 10-minute interval results in one value, the connection lines are drawn for clarity. The horizontal lines represent the model output.

given for a running average filter with variable integration time. We see that the wind speed range from 5 to 20 m s^{-1} gives only minor changes in the gusts. The weak dependence of $(U_{max} - \bar{U})/\sigma$ on z_i, L and z has been shown already.

Figure 10 gives the explicit relation between normalized gust magnitude $(U_{max} - \bar{U})/\sigma$ and t_G. It can be used to determine t_G if the gust magnitude is known or vice versa. For a given measuring chain t_G can be calculated as follows. With the model and the filters in the chain we compute $(U_{max} - \bar{U})/\sigma$ where U_{max} is the extreme at the end of the chain and σ is the standard deviation of the wind. The gust duration t_G is derived now from Fig. 10 in such a way that the same gust magnitude is found on the ordinate as for the actual chain. This t_G is a characteristic of the measuring system; when gusts are recorded with this system we say they have duration t_G. When a system is characterized in this way, a user of gust data will know how to use the data and to correct it for certain applications.

Two examples are given now of wind measuring systems that are quite common in practice. The first is an anemometer producing a fixed number of pulses per turn, combined with a counter that is read and reset every t_0 seconds. This can be simulated as depicted in Fig. 11 by a running average over t_0 seconds and sampling with frequency $1/t_0$ (nonoverlapping averages). The second system consists of an anemometer followed by an RC-filter and sampling. The model results in Fig. 11 are given as "gust durations" instead of gust magnitudes. The conversion has been done by means of Fig. 10 with $\bar{U}$ = 10 m s^{-1}.

Two conclusions can be drawn from this figure: (i) The response length of the anemometer only plays a role if t_0 or τ is very small in the two examples respectively. In common situations with say t_0 = 3 s or τ = 1 s, the contribution to the filtering by the anemometer is relatively unimportant. For the usual sampling rates the curves for different anemometer response lengths almost coincide. (ii) The sampling part in the measuring chain contributes considerably to the gust duration for usual sampling rates (i.e., nonoverlapping averaging for which $n_s = 1/t_0$). If $n_s = \infty$ is compared with $n_s t_0$ = 1 in the left part of Fig. 11, it is seen that sampling makes the gust duration about 50% larger. The reduction of the gust magnitude can be derived from Fig. 10.

It is appropriate here to comment on the question of whether gusts should be seen as temporal or spatial structures. The scaling of turbulence spectra and the spatial filtering by the anemometer suggest a definition

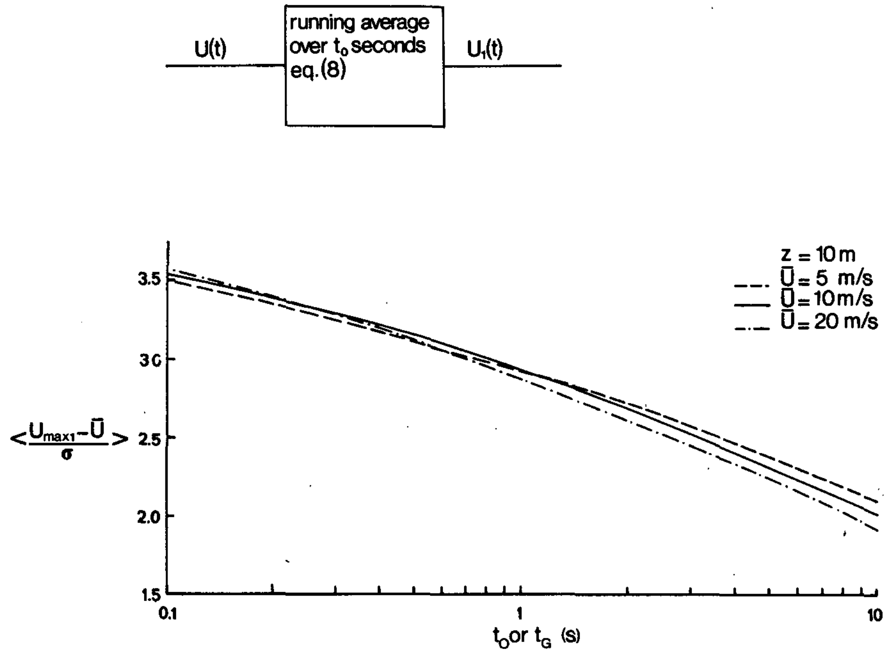

FIG. 10. Calculated gusts for a running average filter and the Kaimal spectrum as input with the following parameters: $T = 600$ s, $z = 10$ m, $z_i = 1000$ m and $-L \to \infty$. According to the definition, $t_G = t_0$ for this measuring chain.

of gust dimensions in terms of length rather than time. This would also be preferable for most applications where the spatial dimension of the gust has to be seen in relation to the size of the structure on which the load has to be evaluated. It has been shown, however, that the time filtering dominates in most operational measuring chains. The filtering by the anemometer can often be neglected and the sensitivity of the gust magnitude to the wind speed (to convert from space to time in the spectrum) is very weak (cf. Fig. 10). This implies that wind extremes observed with most operational systems have to be characterized by a duration rather than by a length. The duration is determined by the filtering in the measuring chain.

5. Conclusions

In this paper the effect of filtering and sampling on the measurement of standard deviations and gusts has been investigated. The theory for gusts is shown to compare well with experimental data for several different situations. The main conclusions are:

- The theory for gusts is applicable to an arbitrary measuring chain as long as the elements in the chain are approximately linear.
- The empirical form for the near-neutral wind spectrum as proposed by Kaimal (1978) is better than the form proposed by Højstrup (1982) in particular for the 10 m level. The Højstrup spectrum scales on $z/\bar{U}$ for the entire frequency range whereas the Kaimal spectrum scales on $z/\bar{U}$ for the high-frequency part only.
- The model computations for gusts in 10-minute intervals are insensitive to $\bar{U}$, z, z_i and L for near neutral cases with relatively strong winds.
- The model enables the definition of a "gust duration" that is a characteristic of the measuring chain. Measurement with a running average filter with an integration time of this "gust duration" would have resulted in the same gust.
- The gust duration as defined in section 4 has been computed for two quite common measuring chains. The effect of sampling turns out to be important.
- Even very nonstationary situations are well described by the model.

We return now to the basic problem of specifications for standard wind stations. The applicability of the climatology from such stations would be enlarged if it were known how the measurements were done and if the parameters in the measuring chain were specified. What kind of anemometers, filters and data reduction parameters have to be chosen? As pointed out in the introduction, we want the mean value, the standard deviation and a gust with a length of about 100 m (in strong wind cases) as the result of data reduction over 10 min intervals. For the standard deviation one would like to avoid any filtering in the measuring chain. Filtering reduces the measured values of the standard deviation and corrections become necessary (cf., Fig. 11).

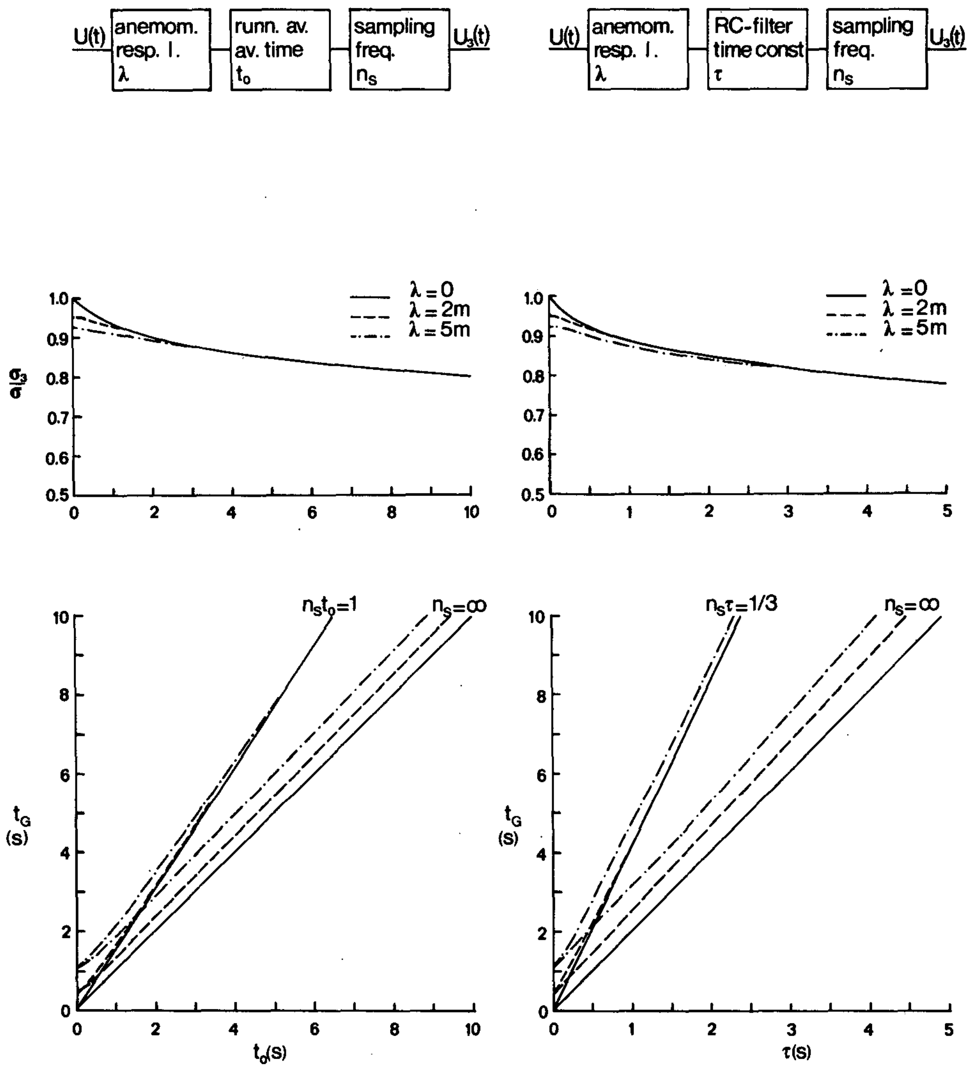

FIG. 11. Reduction of standard deviation (upper figure) and gust duration (lower figure) for two different measuring chains.

The gust length of about 100 m in strong wind situations, however, requires a filter that smooths the shortest spikes in the signal. This is in conflict with the optimal choice for the standard deviation. It seems unacceptable from the operational point of view to use different measuring systems for gusts and standard deviation. We therefore have to compromise here. It is proposed to choose the filtering in accordance with requirements of the gusts and to accept the errors in the standard deviations which can be corrected. In practice this results in counting pulses from an anemometer over nonoverlapping time intervals from 2 to 5 sec, which is equivalent with a running average filter with an integration time of 2 to 5 sec combined with sampling from 0.5 to 0.2 Hz. According to Fig. 11a the error in σ_u can go up to about 15% which can be easily corrected for. The gust duration for this filtering ranges from about 3 to 8 sec, which corresponds to gust lengths of 60 to 160 m at $\bar{U} = 20$ m s^{-1}. It is also clear from Fig. 11 that the response length of the anemometer has a minor influence. Even slowly responding anemometers are acceptable in this context (however, overspeeding errors might impose limitations). Wind measuring systems that use analog data transmission should use an RC-filter with $\tau = 0.7$–1.7 sec to produce reasonable gusts. Sampling frequency can be the same as for the pulse counting anemometer.

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