

The distribution of turbulence driven wind speed extremes; a closed form asymptotic formulation

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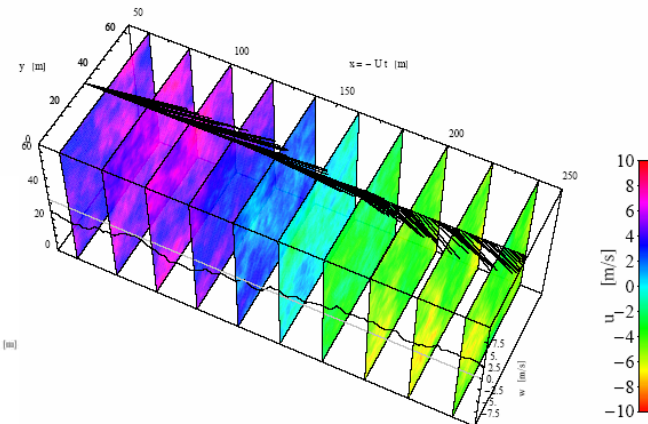
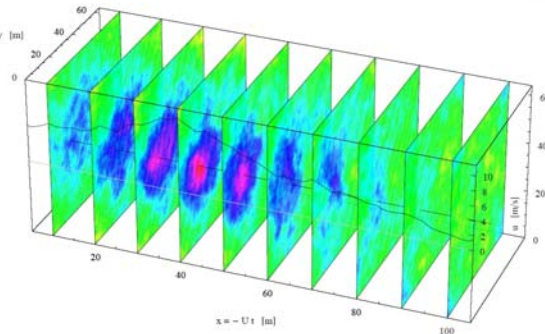
Outline

- Introduction
- Modeling
 - The classical approach - Cartwright /Longuet-Higgins [1]
 - An approach based on a non-Gaussian tail behavior
 - ... with an empirical distribution parameter [3]
 - ... with the requested asymptotic tail behavior derived from a subclass of the GH distribution
- Conclusion
- Outlook
- References

Introduction

- Wind sensitive structures ... in particular wind turbines
- Extreme wind events ... driven by turbulence
- “Gust-generator” for generation of stochastic turbulence fields with specified gust events consistently embedded ... magnitudes of gust events

(e.g. in an optimization context)



- ... Relevant for aeroelastic design computations of wind turbines as well as structural reliability considerations

Introduction

- Focus on the simplest possible class of gust events ... characterized by *wind speed increase* (coherent analogy: IEC 64100-1; extreme load case EOG)
- Aim: Asymptotic closed form solution for the distribution of the *largest* turbulence driven wind speed excursion within a specified span of time ... both turbulence generated excursions and recurrence period are assumed to be large (but otherwise arbitrary)

Cartwright /Longuet-Higgins

- Based on pioneering work of Rice [2]
- Basic assumptions
 - Stationary process with Gaussian “parent distribution”
 - Independent local extremes
 - Large magnitudes ... in terms of process standard deviations
 - Large number of local extremes contribution to the global extreme
- Approach
 - Distribution of local extremes
 - Distribution of the global extreme

Cartwright /Longuet-Higgins

- Result (normalised with process root mean square)

- Distribution
$$f_{\max}(\eta_m) = \eta_m \text{Exp} \left\{ -e^{-\frac{1}{2}\eta_m^2 + \ln(T\nu)} \right\} e^{-\frac{1}{2}\eta_m^2 + \ln(T\nu)} .$$

- Mean
$$E(\eta_m) = \sqrt{2\ln(\nu T)} + \frac{\gamma}{\sqrt{2\ln(\nu T)}} ,$$

- Root mean square
$$\sigma(\eta_m) = \frac{\pi}{\sqrt{12\ln(\nu T)}} ,$$

- Mode
$$m(\eta_m) = \sqrt{2\ln(\nu T)} .$$

- ... with
$$\nu = \sqrt{\frac{m_2}{m_0}} \quad \gamma \approx 0.5772$$

$$m_i = \int_0^{\infty} S(f) f^i df ,$$

Cartwright /Longuet-Higgins

- Characteristics:
 - Distribution resemble (some of) the functional characteristics of the EV1 distribution
 - Mean increases with increasing time span T
 - Mode increases with increasing time span T
 - Root mean square decreases with increasing time span T
- Performance ... comparing with data
 - Good for small/moderate recurrence periods
 - May underestimate substantially for large recurrence periods

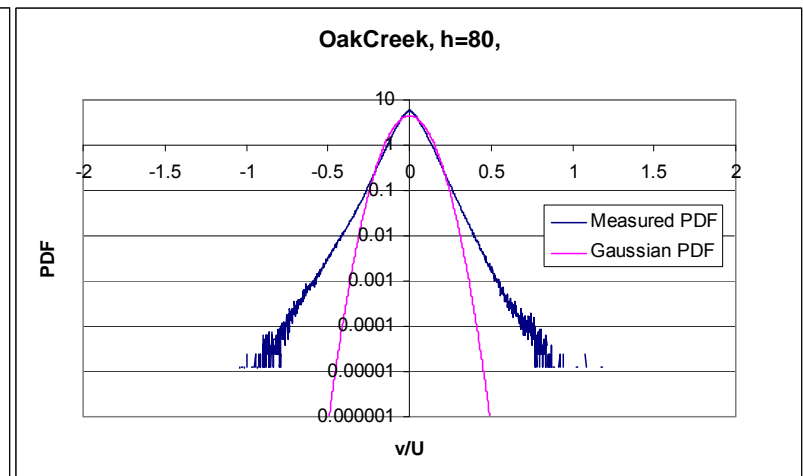
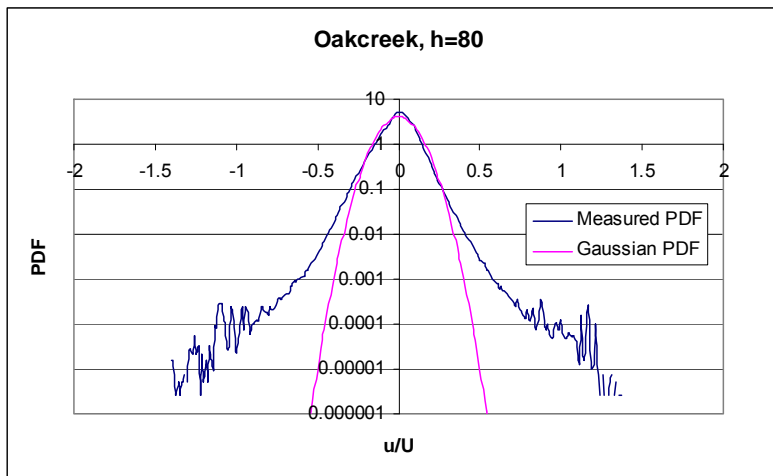
Cartwright /Longuet-Higgins

- Performance ... an example

Site	Cartwright/ Longuet- Higgins	Extreme value analysis of measurements
Skipheia; 101m; 1 month	4.9 m/s	7.5 ± 0.1 m/s
Skipheia; 101m; 1 year	5.4 m/s	9.1 ± 0.2 m/s
Skipheia; 101m; 50 year	6.1 m/s	11.7 ± 0.2 m/s
Näsudden; 78m; 1 month	5.0 m/s	7.7 ± 0.2 m/s
Näsudden; 78m; 1 year	5.4 m/s	9.3 ± 0.3 m/s
Näsudden; 78m; 50 year	6.1 m/s	11.9 ± 0.4 m/s
Oak Creek; 79m; 1 month	7.9 m/s	12.4 ± 0.2 m/s
Oak Creek; 79m; 1 year	8.6 m/s	15.2 ± 0.2 m/s
Oak Creek; 79m; 50 year	9.6 m/s	19.6 ± 0.3 m/s

Prelude to non-Gaussian tail behavior approach

- Two observations:
 1. Conventional Gaussian assumption is inadequate for description of events associated with large excursions from the mean



2. Extremes, associated with turbulence driven full-scale events in the atmospheric boundary layer, usually seems to be well described by a Gumbel EV1 distribution
- ... the suggested model aims at providing the link between these observations

Model

Key elements:

- Assumptions
- Monotonic transformation
- Distribution of local extremes in transformed domain
- Distribution of the global extreme in transformed domain
- Number of local extremes as function of recurrence period
- Synthesis
- Resulting distribution expressed in the physical domain
- Parameter estimation

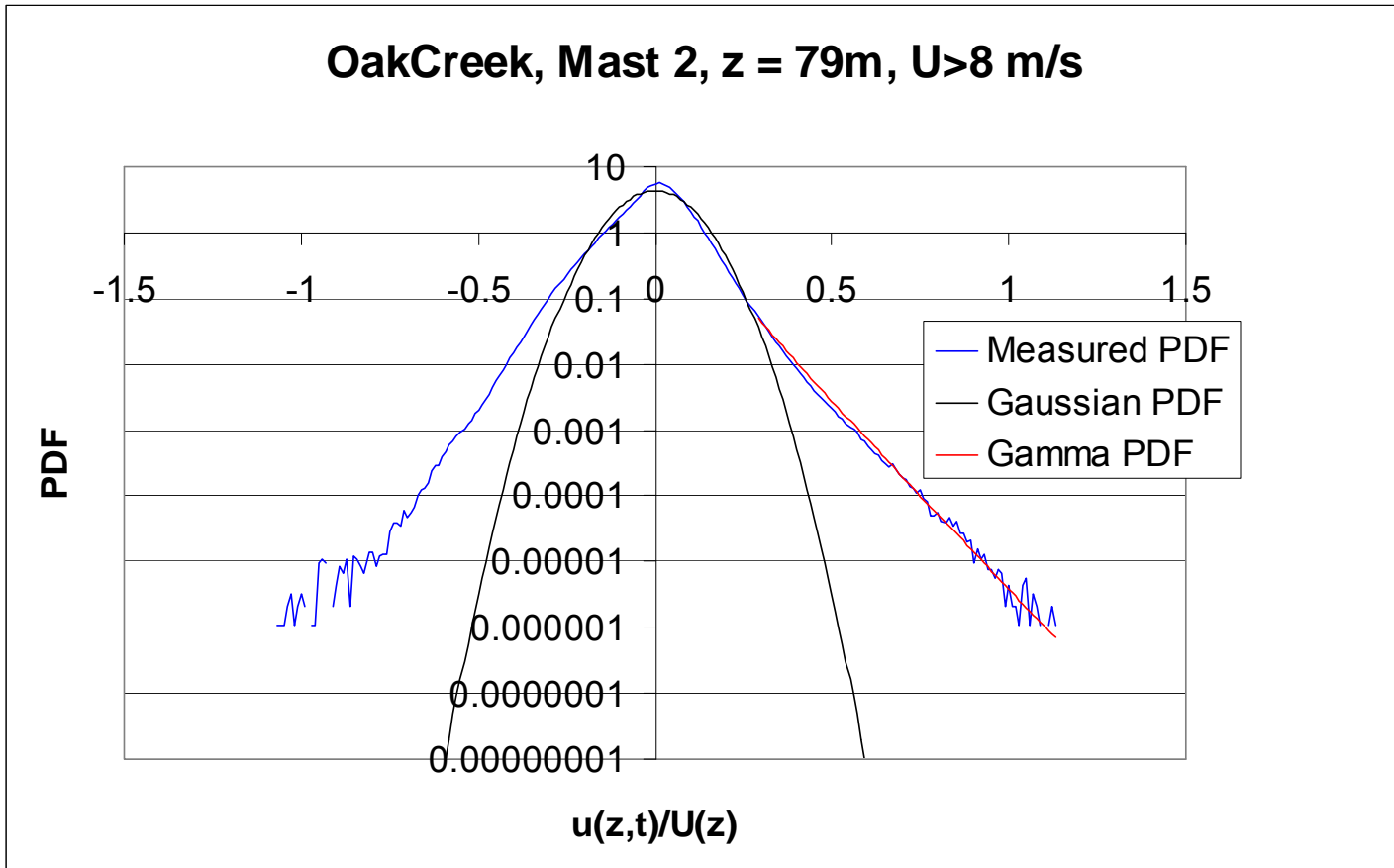
Model - Assumptions

- We postulate the following distribution of turbulence driven *large* excursions from mean (double sided Gamma dist.; shape par. =1/2):

$$f_{u_e}(u_e(z); \sigma(z), C(z)) = \frac{1}{2\sqrt{2\pi C(z)\sigma(z)}\sqrt{|u_e(z)|}} \text{Exp}\left(-\frac{|u_e(z)|}{2C(z)\sigma(z)}\right),$$

- $\sigma(z)$ is the standard deviations of the *total* data population measured at altitude z
- $C(z)$ is a dimensionless, but site- and height-dependant, *positive* constant

Model – ex. distribution fit in the asymptotic regime



Model - Monotonic transformation

- We introduce the *monotonic* transformation:

$$v_e = g(u_e) = \text{sign}(u_e) \sqrt{\frac{\sigma}{C(z)}} \sqrt{|u_e|}$$

- The (standard) “trick” is:
 - A monotonic transformation will transform local extremes in the physical domain into local extremes in the transformed domain
 - Thus, the number of local extremes (and their position on the time-axis) is invariant with respect to (strictly) monotone transformations
 - Therefore, *global* extremes may be analyzed in the transformed domain and subsequently transformed back to the physical domain

Model - Monotonic transformations

- In the transformed domain we obtain the following Gaussian PDF

$$f_{Gauss}(v_e; \sigma) = \frac{1}{\sqrt{2\pi}\sigma} \text{Exp}\left(-\frac{v_e^2}{2\sigma^2}\right).$$

... and the analysis of the extremes in this domain can take advantage of a Gaussian variable having a *tractable joint Gaussian distribution* of the variable and its associated *first* and *second* order derivatives (required for formulation of conditions for an extreme occurrence)

Model - Distribution of local extremes

- Rice [2] has established the statistics of local extremes, η_e , for a Gaussian process (normalized with σ):

$$f_{\eta}(\eta_e; \delta) = \frac{1}{\sqrt{2\pi}} \left[\delta e^{-\frac{\eta_e^2}{2\delta^2}} + \eta_e \sqrt{1-\delta^2} e^{-\frac{\eta_e^2}{2}} g(\eta_e, \delta) \right],$$

$$g(\eta_e, \delta) = \sqrt{\frac{\pi}{2}} \left(1 + \text{sign}(\eta_e) \text{Erf} \left(\frac{|\eta_e| \sqrt{1-\delta^2}}{\sqrt{2} \delta} \right) \right),$$

... the statistics depends only on the *band width parameter*, which may be expressed in terms of process spectral moments as

$$\delta = \sqrt{\frac{m_0 m_4 - m_2^2}{m_0 m_4}},$$

Model - Distribution of the global extreme

- We assume the *local extremes to be statistical independent*
- D.E. Cartwright and M. S. Longuet-Higgins derived the following *asymptotic* expression (i.e. *large* excursions) for the largest among N independent local maxima:

$$f_{\max \eta}(\eta_{em}; N, \delta) = N \sqrt{1 - \delta^2} \eta_{em} \text{Exp} \left[- N \sqrt{1 - \delta^2} e^{-\frac{1}{2} \eta_{em}^2} \right] e^{-\frac{1}{2} \eta_{em}^2},$$

... which for *large* N can be approximated as

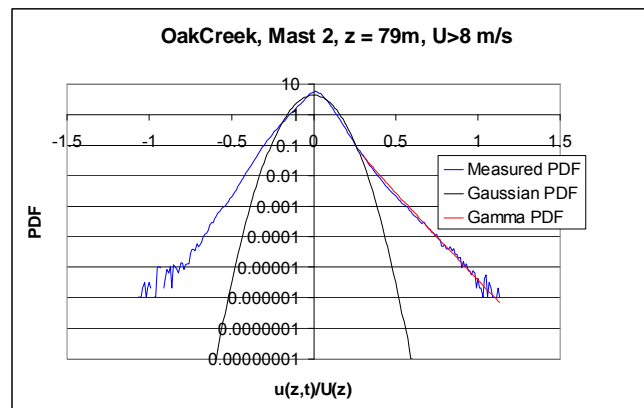
$$f_{\max \eta}(\eta_{em}; N, \delta) = \eta_{em} \text{Exp} \left[- e^{-\frac{1}{2} \eta_{em}^2 + \ln(N \sqrt{1 - \delta^2})} \right] e^{-\frac{1}{2} \eta_{em}^2 + \ln(N \sqrt{1 - \delta^2})}.$$

Model - Number of local extremes

- In the pure Gaussian case, N was obtained from Rice's estimate for the expected number of maxima [2]

$$N = \sqrt{\frac{m_4}{m_2}} T .$$

- Not* consistent within this approach



- The *expected number* of extremes of the process should include only contributions from large extremes (i.e. extremes exceeding $\sim 2\sigma$ in the physical domain)

Model - Number of local extremes

- A large extreme in the transformed (Gaussian) domain is accordingly

$$V_0 = \sqrt{\frac{2}{C}} \sigma$$

- Closed form (asymptotic) expression for the expected number of maxima exceeding V_0 obtained using Rice's asymptotic result for expected number of excursions above a pre-defined threshold

$$N = \kappa T; \quad \kappa \equiv \text{Exp}\left(-\frac{1}{C}\right) \sqrt{\frac{m_2^3}{m_0^2 m_4}} .$$

Model - Synthesis

- Combine expressions for extreme PDF, bandwidth parameter, and rate of local (large) maxima to obtain

$$f_{\max \eta}(\eta_{em}; T, \kappa) = \eta_{em} \text{Exp} \left[-e^{-\frac{1}{2}\eta_{em}^2 + \ln(\kappa T)} \right] e^{-\frac{1}{2}\eta_{em}^2 + \ln(\kappa T)} .$$

- Transformation to the normalized *physical* domain

$$f_{\max \mu}(\mu_m; T, \kappa, C) = \frac{1}{2C} \text{Exp} \left(-e^{-\frac{1}{2C}|\mu_m| + \ln(\kappa T)} \right) e^{-\frac{1}{2C}|\mu_m| + \ln(\kappa T)} .$$

Model – Characteristics

- Gumbel EV1 type of distribution ... as “requested”

- Mean
$$E(\mu_m) = 2C(\gamma + \ln(\kappa T)) ,$$

- Root mean square
$$\sigma(\mu_m) = \pi C \sqrt{\frac{2}{3}} ,$$

- Mode
$$m(\mu_m) = 2C \ln(\kappa T) .$$

- Comparison with C/LH: We predict faster increase in mean and mode with T, and our root mean square is *independent* of T

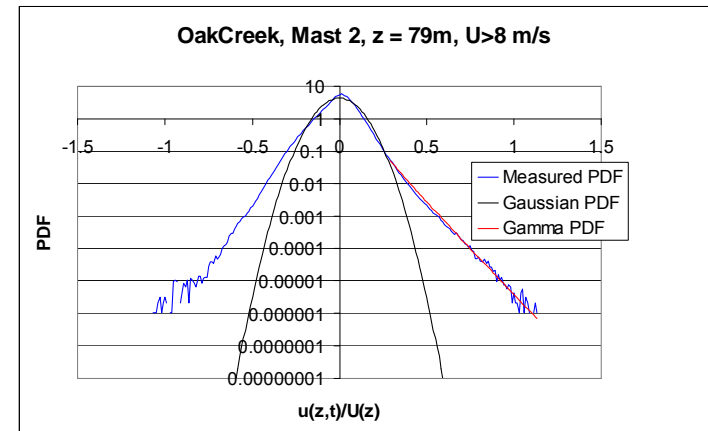
Model – Required parameters

- Required parameters:
 - Standard deviation of the driving process σ
 - Spectral moments (m_2 and m_4): from measurements *or* closed form expressions based on generic wind spectra as specified in codes (including length scale specifications) – e.g. Kaimal spectrum
 - $C(z)$... requires a huge number of fast sampled data (which is seldom available), or an empirical “pre-calibration”

Model – Calibration of $C(z)$

- The “constant” $C(z)$ is calibrated using a huge fast sampled data material representing three different terrain categories
 - offshore/coastal
 - flat homogeneous terrain, and
 - hilly scrub terrain
- ...by minimizing the functional

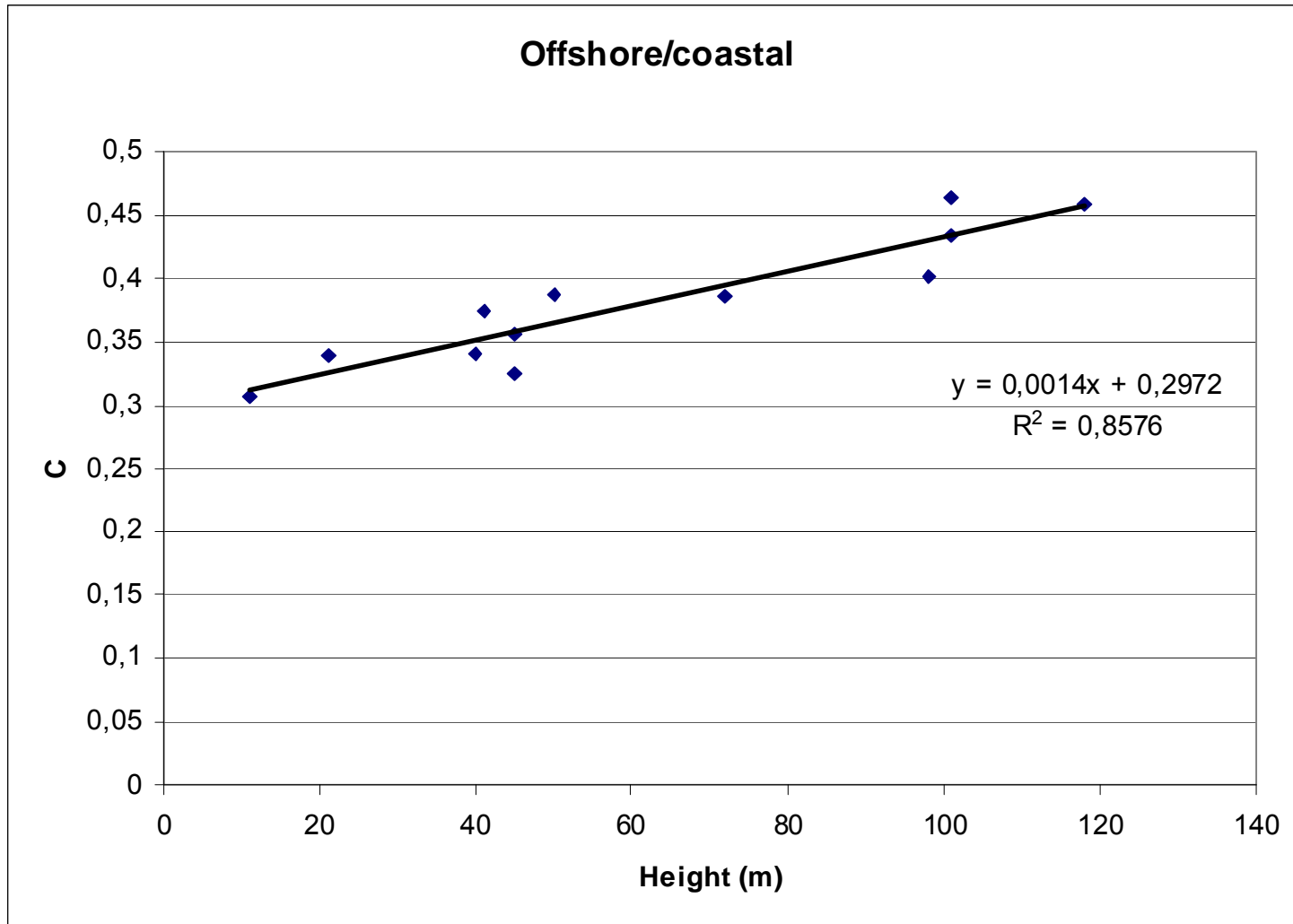
$$\Pi(C(z)) = \int_{2\sigma}^{+\infty} du(z) \left(f_{u_e}(u_e(z); \sigma(z), C(z)) - f_m(u_e(z)) \right)^2 .$$

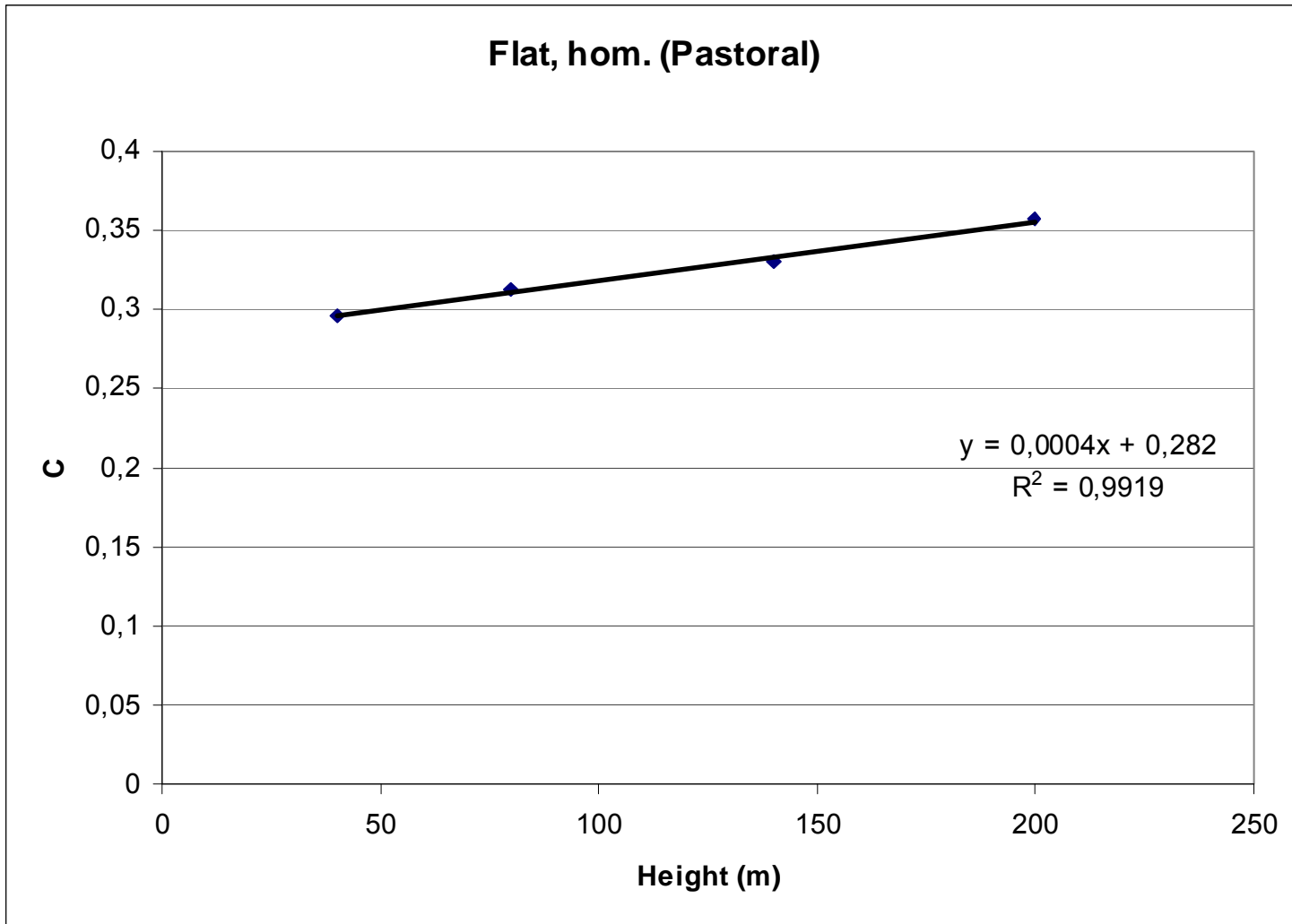


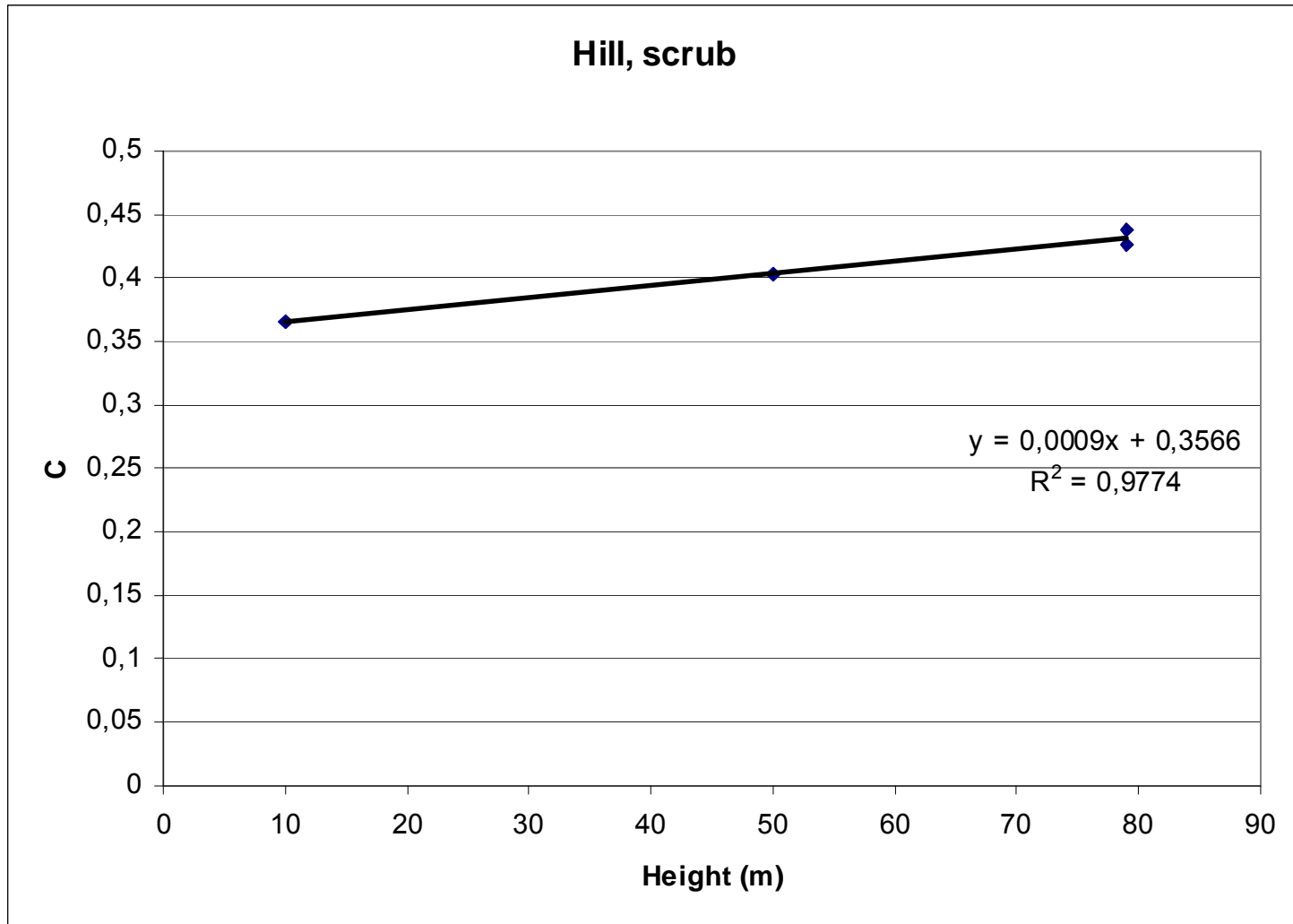
Model – Calibration of $C(z)$

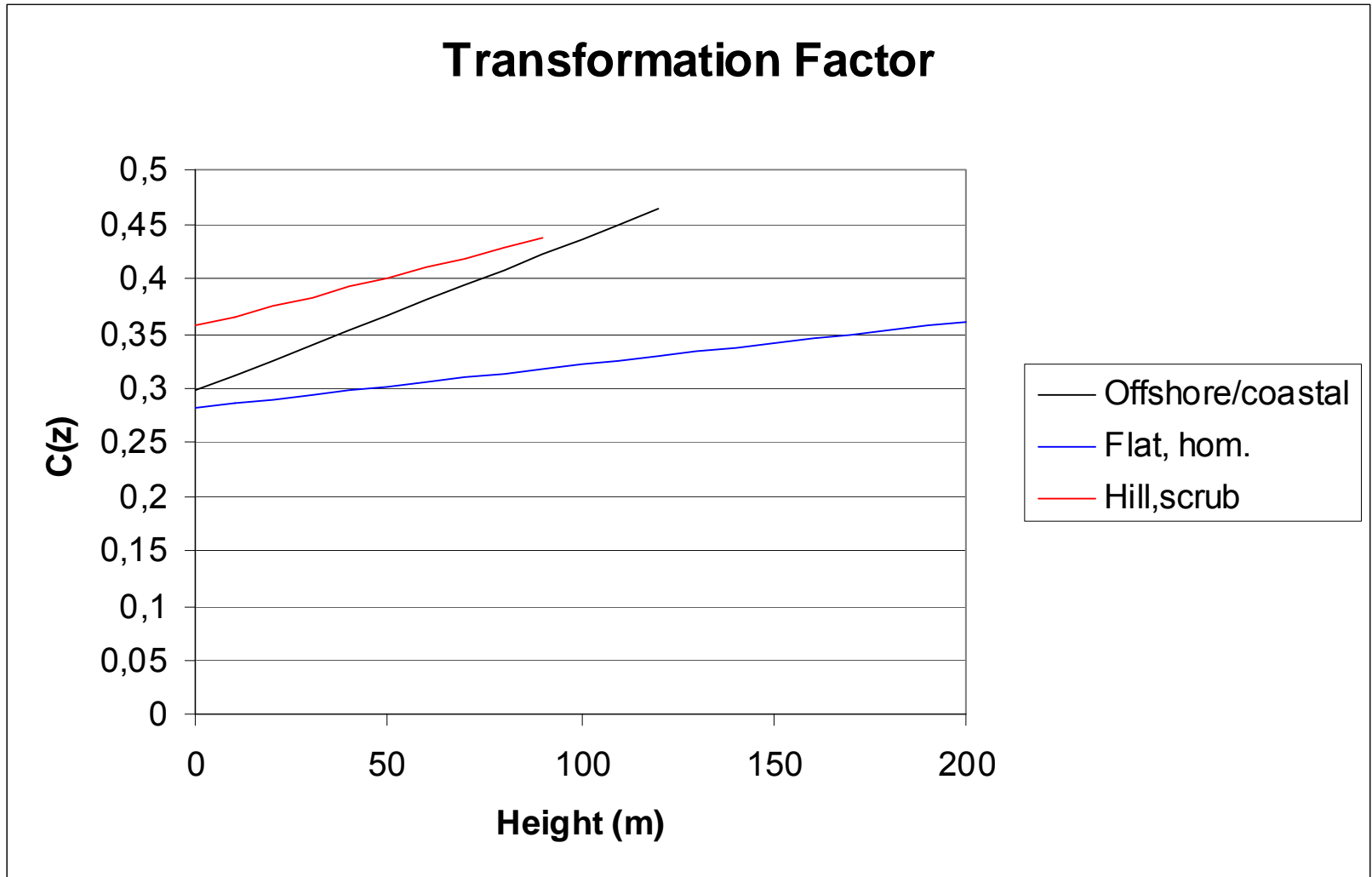
Site	Type of site	Obs. height [m]	No. hours	Scan freq. [Hz]	C
Gedser rev	Offshore	45	385	5	0.357
Rødsand	Offshore	45	390	5	0.325
Horns Rev	Offshore	50	629	20	0.387
Nasudden	Coastal; flat	40	1122	1	0.340
Nasudden	Coastal; flat	98	1548	1	0.401
Nasudden	Coastal; flat	118	1589	1	0.459
Skipheya	Coastal; roling hills	11	5200	0.85	0.307
Skipheya	Coastal; roling hills	21	5737	0.85	0.339
Skipheya	Coastal; roling hills	41	6408	0.85	0.373
Skipheya	Coastal; roling hills	72	4446	0.85	0.386
Skipheya	Coastal; roling hills	101	3904	0.85	0.434
Skipheya	Coastal; roling hills	101	3550	0.85	0.463
Cabauw	Flat, hom. (Pastoral)	40	377	2	0.297
Cabauw	Flat, hom. (Pastoral)	80	421	2	0.313
Cabauw	Flat, hom. (Pastoral)	140	440	2	0.331
Cabauw	Flat, hom. (Pastoral)	200	404	2	0.358
Oak Creek (M1)	Hill, scrub	79	1671	8	0.437
Oak Creek (M2)	Hill, scrub	10	2593	8	0.366
Oak Creek (M2)	Hill, scrub	50	1916	8	0.404
Oak Creek (M2)	Hill, scrub	79	3210	8	0.426

Model – Calibration of $C(z)$



Model – Calibration of $C(z)$ 

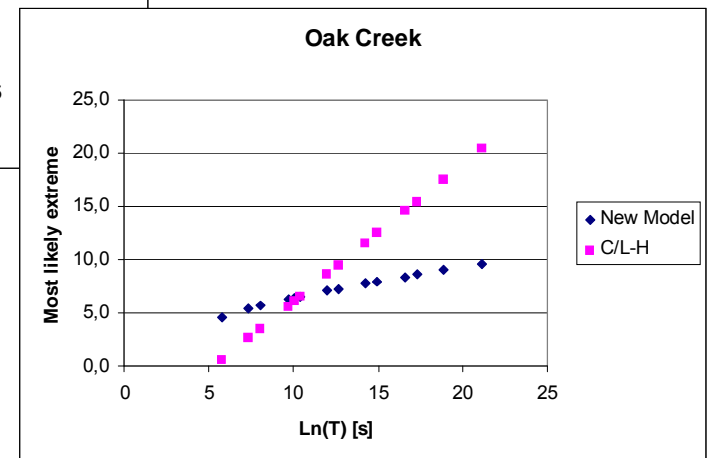
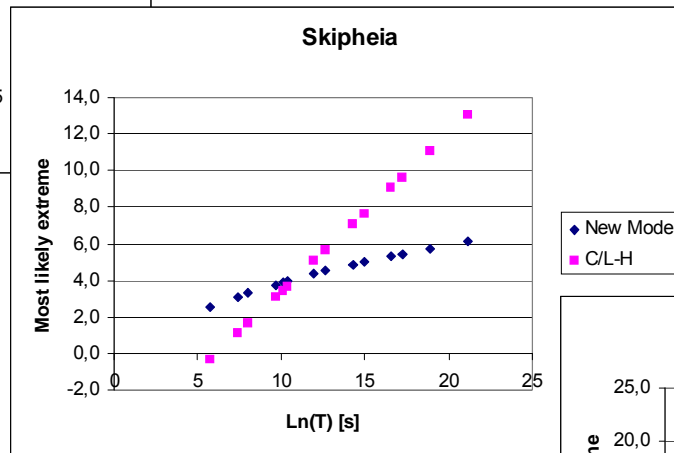
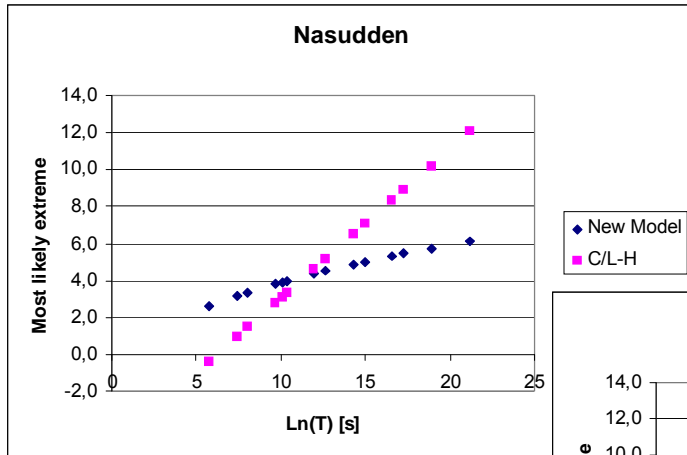
Model – Calibration of $C(z)$ 

Model – Calibration of $C(z)$ 

Model – Performance

	Cartwright/ Longuet- Higgins	Proposed model	Extreme value analysis of measurements
Skipheia; 101m; 1 month	4.9 m/s	7.5 m/s	7.5 ± 0.1 m/s
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Näsudden; 78m; 1 month	5.0 m/s	6.9 m/s	7.7 ± 0.2 m/s
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Oak Creek; 79m; 1 month	7.9 m/s	12.2 m/s	12.4 ± 0.2 m/s
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Oak Creek; 79m; 50 year	9.6 m/s	20.5 m/s	19.6 ± 0.3 m/s

Model – The asymptotic constraint



Model – C based on GH distribution approach

- Strategy:
 - Assume turbulence excursions generalized hyperbolic (GH) distributed (fatter than Gaussian tails)
 - The distribution of the largest extreme is preferred evaluated in a Gaussian domain as GH distribution is not particularly analytically tractable (joint $\text{GH}(u, \acute{u}, \ddot{u})$ needed for extreme assessment)
 - When resulting EV1 is required constraints are imposed on the GH asymptotic behavior → specific GH subclass follows ...

Model – GH distribution

- Distribution of turbulent excursions

$$f_{GH}(u; \alpha, \beta, \lambda, \mu, \delta) = \frac{(\alpha^2 - \beta^2)^{\lambda/2} K_{\lambda-1/2}\left(\alpha\sqrt{\delta^2 + (u - \mu)^2}\right) \text{Exp}(\beta(u - \mu))}{\sqrt{2\pi} \alpha^{\lambda-1/2} \delta^\lambda K_\lambda\left(\delta\sqrt{\alpha^2 - \beta^2}\right) \left(\sqrt{\delta^2 + (u - \mu)^2}\right)^{1/2-\lambda}} .$$

$$\delta \geq 0 \wedge |\beta| < \alpha \text{ for } \lambda > 0$$

$$\delta > 0 \wedge |\beta| < \alpha \text{ for } \lambda = 0$$

$$\delta > 0 \wedge |\beta| \leq \alpha \text{ for } \lambda < 0$$

... with the requirement imposed that the asymptotic behavior resembles the characteristics of the Gamma distribution with shape parameter 1/2

Model – GH asymptotes

- GH subclass defined by subclass parameter $\lambda = 1/2$
- GG defined by

$$f_{GG}(u; \alpha, \beta, \mu, \delta) \equiv \frac{(\alpha^2 - \beta^2)^{1/4} K_0\left(\alpha\sqrt{\delta^2 + (u - \mu)^2}\right) \text{Exp}(\beta(u - \mu))}{\sqrt{2\pi\delta} K_{1/2}\left(\delta\sqrt{\alpha^2 - \beta^2}\right)},$$

$$\delta \geq 0 \wedge |\beta| < \alpha$$

- GG asymptotics

$$f_{GG}(u; \alpha, \beta, \mu, \delta) \propto \frac{\text{Exp}\left(\delta\sqrt{\alpha^2 - \beta^2} + \mu(\alpha - \beta)\right)\sqrt{\alpha^2 - \beta^2}}{\sqrt{2\pi\alpha}\sqrt{|u|}} \text{Exp}(-\alpha|u| + \beta u) \quad \text{for } u \rightarrow \pm\infty.$$

Model – GG symmetric

- First attempt ... assume symmetry of distribution of excursions
- Consequence $\beta = 0$
- Turbulent excursions have zero mean

$$E_{GG}[U] = \mu + \frac{\beta\delta}{\gamma} \frac{K_{3/2}(\delta\gamma)}{K_{1/2}(\delta\gamma)} = \mu = 0, \quad \gamma \equiv \sqrt{\alpha^2 - \beta^2}.$$

- With $\beta = 0$ and $\mu = 0$ GG asymptotes simplifies to

$$f_{GG,asympt}(u; \alpha, 0, 0, \delta) = \frac{\sqrt{\alpha} \text{Exp}(\delta\alpha)}{\sqrt{2\pi} \sqrt{|u|}} \text{Exp}(-\alpha|u|).$$

Model – Parameter match

$$f_{GG,asympt}(u; \alpha, 0, 0, \delta) = \frac{\sqrt{\alpha} \text{Exp}(\delta\alpha)}{\sqrt{2\pi} \sqrt{|u|}} \text{Exp}(-\alpha|u|) .$$

$$f_G(u; \sigma) = \frac{1}{2\sqrt{\pi} \sqrt{2C\sigma|u|}} \text{Exp}\left(-\frac{|u|}{2C\sigma}\right),$$

- $C = \frac{1}{2\sigma\alpha}$
- and $\sqrt{2}\text{Exp}(\delta\alpha) = 1$, or $\delta\alpha = -\frac{\text{Ln}(2)}{2}$.
- ... but $\delta \geq 0 \wedge |\beta| < \alpha$

Model – GG asymmetric

- *Symmetric* GG gives too fat tails compared to the requested Γ -behavior ... but $\beta \neq 0$ potentially opens for the needed affinity/scaling of the tail behavior
- Second (and last) attempt ... require asymmetry of the GG parent distribution by assuming $\beta \neq 0$... *even* in case a symmetric empirical distribution (engineering approach!)
- GG fit based on
 - Statistical moments (even order)
 - An additional parameter constraint arising from the requested type of asymptotic distribution behavior.

Model – GG fit

- Mean [4]

$$0 = \mu + \frac{\beta\delta}{\gamma} \frac{K_{3/2}(\delta\gamma)}{K_{1/2}(\delta\gamma)}, \quad \gamma \equiv \sqrt{\alpha^2 - \beta^2} .$$

- Variance [4]

$$\sigma^2 = \delta^2 \left(\frac{K_{3/2}(\delta\gamma)}{\delta\gamma K_{1/2}(\delta\gamma)} + \frac{\beta^2}{\gamma^2} \left(\frac{K_{5/2}(\delta\gamma)}{K_{1/2}(\delta\gamma)} - \left(\frac{K_{3/2}(\delta\gamma)}{K_{1/2}(\delta\gamma)} \right)^2 \right) \right),$$

Model – GG fit

- 4th order central moment

$$\mu_4 = \frac{\partial^4}{\partial \theta^4} C(\theta) \Big|_{\theta=0} + 3 \left[\delta^2 \left(\frac{K_{3/2}(\delta\gamma)}{\delta\gamma K_{1/2}(\delta\gamma)} + \frac{\beta^2}{\gamma^2} \left(\frac{K_{5/2}(\delta\gamma)}{K_{1/2}(\delta\gamma)} - \left(\frac{K_{3/2}(\delta\gamma)}{K_{1/2}(\delta\gamma)} \right)^2 \right) \right) \right]^2 .$$

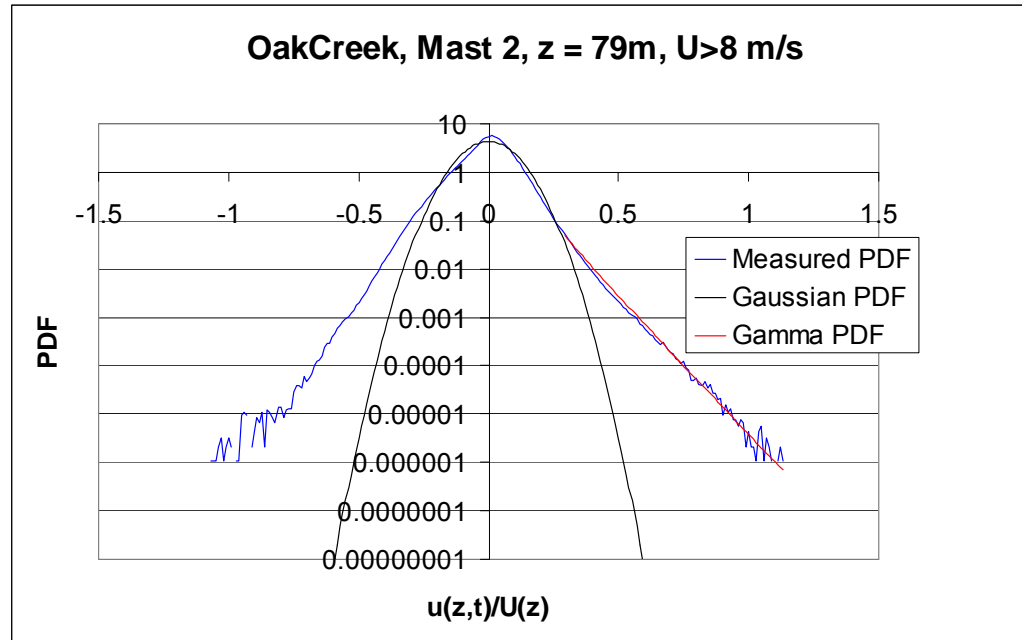
with the GG cumulant function $C(\Theta)$ given by [4]

$$C(\theta) = \frac{1}{4} \text{Ln} \left(\frac{\gamma}{\alpha^2 - (\beta + \theta)^2} \right) + \text{Ln} \left(\frac{K_{1/2} \left(\delta \sqrt{\alpha^2 - (\beta + \theta)^2} \right)}{K_{1/2} \left(\delta \sqrt{\alpha^2 - \beta^2} \right)} \right) + \frac{\theta}{2} ,$$

- Requested asymptotic match

$$\frac{\text{Exp} \left(\delta \sqrt{\alpha^2 - \beta^2} + \mu(\alpha - \beta) \right) \sqrt{2(\alpha + \beta)}}{\sqrt{\alpha}} = 1 .$$

Model – Definition of asymptotic regime



- Crossing between Gauss PDF and continuation of GG asymptote

$$\frac{u_0^2}{2\sigma^2} = \frac{u_0}{2C\sigma} + \frac{\text{Ln}(u_0)}{2} - \text{Ln}\left(\frac{\sqrt{\sigma}}{2\sqrt{C}}\right); \quad C = (2\sigma)^{-1}(\alpha - \beta)^{-1}$$

Model – Implication for local extremes to be counted

- Rate of extremes in the asymptotic regime (i.e. rate of extremes exceeding u_0)

$$\kappa \equiv \text{Exp}\left(-\frac{k}{2C}\right) \sqrt{\frac{m_2^3}{m_0^2 m_4}} ; \quad k = \frac{u_0}{\sigma} \quad C = (2\sigma)^{-1}(\alpha - \beta)^{-1}$$

Model – Syntheses

- Assume the existence of a monotonic memoryless (time independent) variable transformation that transforms the GG distribution onto a Gaussian distribution
- This transformation does not have to be known, except for its asymptotic properties

$$v = g(u) \propto g_{Asymp}(u) = \sqrt{\frac{\sigma}{C}} \sqrt{u} \quad \text{for } u \rightarrow +\infty ,$$

- The steps from here is analogue to the previous model with the empirical determination of C ...

Conclusions

- An *asymptotic* model for the PDF of the *largest* wind speed excursion is derived
- The model is based on a “mother” distribution that reflects the Exponential-like distribution behaviour of *large* wind speed excursions ... and is shown to be of the Gumbel EV1 type
- The recurrence period is assumed *large*, but may otherwise be arbitrary
- The model requires only a few, easy accessible, input parameters ... these are basic parameters characterizing the stochastic wind speed processes in the atmospheric boundary layer together with the recurrence period

Conclusions

- The model parameter, C , have been calibrated against a large number of full-scale time series wind speed measurements for application in three common terrain categories
- Model predictions have been successfully compared to results derived from full-scale measurements of wind speeds extracted from “Database on Wind Characteristics”
- A fit of the C parameter has been attempted by assuming a parent distribution as a subclass (GG) of the GH distribution family

Conclusions

- This approach in addition opens for a consistent definition of the asymptotic regime
- The *symmetric* version of the GG distribution inevitable results in too fat tails compared to the requested asymptotic behaviour
- This has lead to the proposal of a GG fit with the skewness parameter β *required* different from zero! ... but up to now it has not been investigated if this approach leads to parameter estimates within the allowable regime $\delta \geq 0 \wedge |\beta| < \alpha$

Outlook

- Analyze the monotony of the transformation
g: GG \rightarrow Gauss
- Analyze if the fitting system of equations can be solved within the allowable parameter regime

References

1. D.E. Cartwright and M. S. Longuet-Higgins (1956). The statistical distribution of the maxima of a random function, Proc. Royal Soc. London Ser. A 237, pp. 212-232.
2. S.O. Rice (1958). Mathematical analysis of random noise, Bell Syst. Techn. J., 23 ('44); Reprinted in N. Wax (ed.), Selected papers on noise and stochastic processes, Dover Publ..
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4. O.E. Barndorff-Nielsen and R. Stelzer (2005). Absolute moments of Generalized Hyperbolic distributions and approximate scaling of Normal Inverse Gaussian Lévy processes. *Scandinavian Journal of Statistics*, Vol. 32; 617-637.
5. Database on wind characteristics. <http://www.winddata.com>.