

# On the estimation of ocean engineering design contours

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## Motivation

- Environmental design contours required for structural design
- FORM approach available
  - Assumptions might be unrealistic
  - Uncertainty not usually quantified
- Statistical modelling offers an alternative approach to estimate design contours
  - Conditional extremes modelling based on work of Heffernan & Tawn (2004)
- Different forms of design contours are possible
  - Contours of constant probability density
  - Contours of constant exceedence probability

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## Objectives

- Evaluate different options for design contour estimation
  - ▶ By analogy with 1-D, more natural to use constant exceedence probability P(X<sub>1</sub> > x<sub>1</sub>, X<sub>2</sub> > x<sub>2</sub>) than constant probability density
  - FORM provides contours of constant probability density
- Evaluate performance of design contour estimation for simulated data
- Estimate design contours for measured and hindcast applications
- Evaluate uncertainty of estimated design contours

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#### Content

- Introduction to FORM
- Introduction to Conditional Extremes modelling
- Illustration of different types of design contours
- ▶ Applications to estimation of (*H<sub>S</sub>*, *T<sub>P</sub>*) contours for
  - Measured Northern North Sea
  - Hindcast Northern North Sea
  - Measured Gulf of Mexico
  - Hindcast North-West Shelf of Australia
- Conclusions and recommendations

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# FORM in outline

- Joint estimation of contours for 2 or more environmental variates
- Independent of structural loading and response
- Used to define design point for structural reliability
- Probability integral transform (PIT) used to derive independent random variables to derive surface of constant probability density
- For example, in the case of 2 variates:
  - $H_S \sim$  Weibull  $\stackrel{PIT}{\Rightarrow} U_1 \sim$  standard Normal
  - $T_P|H_S \sim log-Normal \stackrel{PlT}{\Rightarrow} U_2 \sim standard Normal$
  - **Circle**  $u_1^2 + u_2^2 = \beta^2$  gives constant probability density
  - $(U_1, U_2) \stackrel{PIT}{\Rightarrow} (H_S, T_P)$  to get contours on original scale

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## FORM characteristics

- ► FORM assumes we can transform to **independent** random variables
- ► FORM assumes prior knowledge of the distribution of X<sub>1</sub> and (X<sub>2</sub>|X<sub>1</sub>)
  - Usually based on empirical fitting not physics
  - $T_P|H_S \sim log-Normal$  commonly used.
    - What about parameters of distribution?
    - Do they vary with location, with time?
  - ▶ What about other variates, e.g. *Current speed* |*H<sub>S</sub>*?
    - Can we treat current speed and H<sub>S</sub> as independent?
    - If not, which functional form for distribution? Parameters?
- Model explains body of distribution, not necessarily tail of distribution
  - $T_P|H_S \sim log-Normal$  may be appropriate for body but not tail of distribution
- Difficult in practice to extend beyond 2 variates

#### Conditional extremes modelling in outline

- Model the conditional distribution of  $Y_2$  given a large value of  $Y_1$
- ► (X<sub>1</sub>, X<sub>2</sub>) need to be transformed to (Y<sub>1</sub>, Y<sub>2</sub>) on the same standard Gumbel scale
- Asymptotic argument relies on  $X_1$  (and  $Y_1$ ) being large
- In a nut shell:
  - $\blacktriangleright (X_1, X_2) \stackrel{PIT}{\Rightarrow} (Y_1, Y_2)$
  - $(Y_2|Y_1 = y_1) = ay_1 + y_1^b Z$  for large values  $y_1$
  - $\blacktriangleright (Y_1, Y_2) \stackrel{PIT}{\Rightarrow} (X_1, X_2)$
  - ▶ Simulation to sample joint distribution of (Y<sub>1</sub>, Y<sub>2</sub>) (and (X<sub>1</sub>, X<sub>2</sub>))
- Marginal generalised Pareto modelling for  $(X_1, X_2)$ :

• 
$$F_{GP}(x_1;\xi,\beta,u) = 1 - (1 + \frac{\xi}{\beta}(x_1 - w_{X1}))_+^{-\frac{1}{\xi}}$$

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#### Conditional extremes modelling characteristics

- Value of conditioning variate must be large for conditional extremes model to apply
- ▶ No prior knowledge of form of distribution of  $X_1$  and  $X_2|X_1$  required
- Models tail of distribution using conditional extremes
- Models body of distribution empirically

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#### Exceedence contours explained



Figure: Contours of constant exceedence probability (C2-C4) radiate outwards from reference location  $r_{M0}$ 

• 
$$Pr(\bigcap_{j=1}^{2}(r_{Mj}(\theta; r_{M0})M_{j} > r_{Mj}(\theta; r_{M0})m_{j}(\theta))) = \alpha$$

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#### Constant density contours explained



**Figure:** Contours of constant probability density (C1) are circles in U-space. Density is constant **on the contour only** 

• 
$$f(u_1, u_2) = (2\pi)^{-1/2} \exp(-\frac{1}{2}(u_1^2 + u_2^2))$$

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## Contour types C1-C3

- All of C1-C3 use the conditional extremes model to transform: (H<sub>S</sub>, T<sub>P</sub>|H<sub>S</sub>) ⇒ (U<sub>1</sub>, U<sub>2</sub>) ~ standard Normal as a first step
- C1: Constant probability density, standard Normal scale
  - Contours are circles  $u_1^2 + u_2^2 = \beta^2$
- C2: Constant exceedence probability, standard Normal scale
  - Contour  $(u_1, u_2)$  such that:  $Pr(\bigcap_{j=1}^2 (r_{Uj}(\theta; (0,0))U_j > r_{Uj}(\theta; (0,0))u_j(\theta))) = \alpha$
- C3: Constant 1-sided exceedence probability, standard Normal scale
  - Contour  $(u_1, u_2)$  such that:  $Pr(\bigcap_{j=1}^2 (r_{Uj}(\theta; (-\infty, 0))U_j > r_{Uj}(\theta; (-\infty, 0))u_j(\theta))) = \alpha$
- ► All of C1-C3 transform contour in U-space to contours in (H<sub>S</sub>, T<sub>P</sub>)-space as a final step

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#### Contour type C4

- C4: Constant 1-sided exceedence probability on original scale
  - Direct simulation using full conditional extremes model
  - Contour  $(x_1, x_2)$  such that:  $Pr(\bigcap_{j=1}^2 (r_{X_j}(\theta; (-\infty, 0))X_j > r_{X_j}(\theta; (-\infty, 0))X_j(\theta))) = \alpha$

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#### Illustration using model of Haver and Nyhus



**Figure:** Contours C1-C4 corresponding to the  $H_{S}$ - $T_P$  model of Haver & Nyhus (equivalent to a 1 in 1000 event of  $H_S$  marginally): C1 (dashed black), C2 (solid grey), C3 (dashed grey) and C4 (solid black).

• Haver-Nyhus model:  $H_S \sim Weibull$ ,  $T_P | H_S \sim log-Normal$ 

## Confidence limits



C1: Constant probability density, standard normal scale



C2: Constant exceedence probability, standard normal scale



C3: Constant 1-sided exceedence probability, standard normal scale



C4: Constant 1-sided exceedence probability, original scale

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• Grey: truth. Black: estimated with 95% bands. Dashed:  $T_P$ . Solid:  $H_S$ .

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- Storm peak  $(H_S, T_P)$  samples from 4 sources
- Northern North Sea measured
  - Laser: 620 storm peak events (March 1973 December 2006)
- Northern North Sea hindcast
  - 827 storm peak events (November 1964 April 1998)
- Gulf of Mexico measured
  - NDBC buoy 42002: 505 storm peak events (January 1980 -December 2007)
- North West Shelf of Australia hindcast.
  - 145 storm peak events (February 1970 April 2006)
- > All samples exhibit positive dependence between  $H_S$  and  $T_P$

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### **NNS** measured



Figure: C4 contours of constant exceedence probability, 1-sided in  $H_S$ , (equivalent to 10-, 100- and 1000-year  $H_{\rm S}$  marginally), for measured Northern North Sea data. Also shown is the sample.

Contour is not closed since it is 1-sided

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# **NNS** hindcast



Figure: C4 contours, one-sided in  $H_S$ , (equivalent to 10-, 100- and 1000-year  $H_{\rm S}$  marginally), for hindcast Northern North Sea data. Also shown is sample.

Contours are qualitatively similar to those of measured NNS data

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### GoM measured



Figure: C4 contours, one-sided in  $H_S$ , (equivalent to 10-, 100- and 1000-year  $H_{\rm S}$  marginally), for measured Gulf of Mexico data. Also shown is sample.

 $\blacktriangleright$  T<sub>P</sub> has a longer tail than for NNS

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## NWS hindcast



**Figure:** C4 contours, one-sided in  $H_S$ , (equivalent to 10-, 100- and 1000-year  $H_S$  marginally), for hindcast North West Shelf data. Also shown is sample.

- $T_P$  not obviously increasing with  $H_S$
- Clear lack of symmetry with respect to T<sub>P</sub>

# C4 confidence limits



► C4: Constant 1-sided exceedence probability, original scale, corresponding to 100-year  $H_S$  marginally <ロ> <同> <同> < 回> < 回> э

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## Estimating C1 contours



100-year  $H_S$  marginally

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### Conclusions

- Conditional extremes model:
  - Applicable to all contour estimation provided conditioning variate is large
  - Provides quantification of uncertainty in contour location
- Method has been generalised to p (p > 2) dimensions
  - Difficult using FORM
- Failure probability can be estimated directly
  - Rather than using a 'design point' as in FORM
- Further work on incorporating covariate effects (e.g. seasonality, directionality) within conditional extremes model is in progress

#### Thanks

Thanks for listening.

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