

Method for Comparison of Large Eddy Simulation-Generated Wind Fluctuations with Short-Range Observations



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Introduction

The often prohibitive costs of comprehensive field trials coupled with relatively cheap and abundant computational power leads to a strong desire to use modeling tools to supplement field testing of system components. These modeling tools must be capable of reproducing key environmental variables present during field testing and require rigorous validation.

The Virtual Threat Response Emulation and Analysis Testbed (VTHREAT) modeling system is composed of a suite of models designed to provide a virtual Chemical, Biological, Radiological and Nuclear release environment. Two key variables that VTHREAT is designed to realistically simulate are agent concentration and wind velocity. A key feature of VTHREAT is the potential to produce realistic, representative, meteorological fields and threat clouds that include *fluctuating and meandering components*. Typical validation studies compare mean predicted and observed quantities of interest such as mean concentration and mean wind speed and direction. This poster attempts to develop techniques to evaluate fluctuations – in particular, **two-dimensional wind vector fluctuations**.

Typically a large number of simulated realizations are available but few actual observations.

Notional Application of P-values Methodology to Scalars

Suggests observations could have come from associated predicted distributions

Intuitive Extension of P-values Methodology to Vectors

P-Value is the Integrated Probability Outside the Contour

Suggests observations could have come from associated predicted distributions

Predictions and Observation are Drawn from Normal Bivariate

Predictions

Observations

P-values are Uniformly Distributed

Predictions are Normal Bivariate and Observations are Rayleigh

Predictions Normal Bivariate

Observations Rayleigh

P-values are Still Uniformly Distributed

Notes on Potential Problems with Intuitive P-value Methodology (in 2D)

To better understand this example, we note that individual scalar p-values based on contouring the two-dimensional probability density function do not vary along equal probability contour lines.

This allowed us to construct a one-dimensional illustration by specifically selecting observations along a ray emanating from the origin with a probability density function defined by angular projection of circular contours of normal bivariate distribution onto the radial ray.

These examples need not be one-dimensional – one could easily construct two-dimensional observations by allowing some variation in angle along circular contours that would still yield a uniform distribution of p-values.

2D P-values When Predictions are Normal Bivariate

P_x-values Direction

P_y-values Direction

P_x-values

P_y-values

2D P-values When Predictions are Normal Bivariate and Observations are Rayleigh

P_x-values Direction

P_y-values Direction

P_x-values

P_y-values

2D P-Value Methodology

Intuitively, one needs to extend the definition of scalar p-values to two-dimensional p-values to be able to capture the full dynamics of potential two-dimensional distribution functions.

Given a large finite set of VTHREAT predicted wind vector fluctuations $w_i = (u_i, v_i)$ that could be used to define a continuous probability density function for two random variables (U, V) and another set of observed wind vector fluctuations (e.g., samples) s_j , the following procedure to ascertain whether or not samples s_j are consistent with being drawn from random variables (U, V) is proposed:

1. Find a rotation matrix R that decorrelates predictions w_i . Apply this rotation matrix R to both predictions w_i and samples s_j . For simplicity, assume that the new decorrelated sets use the same name.
2. Test transformed $w_i = (u_i, v_i)$ to see if u_i and v_i are independent

 - Modified 2D Kolmogorov-Smirnov test might be used
 - If u_i and v_i are not independent then the procedure to calculate two-dimensional p-values might not be applicable.

3. Calculate two-dimensional p-values using transformed samples s_j .
4. Test to see if two-dimensional p-values are uniformly distributed in $[0,1] \times [0,1]$

 - 2D Kolmogorov-Smirnov test might be used

Sample VTHREAT Wind Vector Fluctuations Comparison with Observations

For a given snapshot in time • single "observation" • 20 VTHREAT realizations

Each observed "red" wind arrow has 20 VTHREAT predicted wind vectors

Wind Fluctuations at Selected Times

600 sec 1200 sec 1800 sec

Black - observations
Red - predictions

P-values Based on Preliminary VTHREAT Predictions

Scalar P-values Based on Distance

2D P-values

P_x-values

P_y-values

P-values Frequency Table

Boundary cells shaded in gray are low values, cells shaded in black read are top 20 values and cells shaded in dark red are frequencies whose count exceeds 20

Notes on VTHREAT Application

- VTHREAT was used to simulate continuous trial 54 from the Fusing Sensor Information from Observing Networks (FUSION) Field Trial 2007
- VTHREAT predictions, including wind speed and direction at PWIDS locations, covered 1200 seconds duration of trial 54
- Twenty VTHREAT realizations of trial 54 were performed.
- There are a total of 4719 observed wind speed and direction measurements available for the comparison (i.e., number of p-values that could be calculated)
 - Only 39 out of 40 PWIDS recorded wind measurements for trial 54
- For simplicity, we assume that the VTHREAT-based fluctuations are drawn from an elliptical-normal distribution
- While 2D P-values seems to indicate uniformly distributed two dimensional p_x and p_y values, individual histograms of p_x and p_y values indicate a slight peak in the distribution near the origin which could be confirmed with a frequency count table

References

1. Bieberbach, G., Bieringer, P.E., Wyszogrodzki, A., Weil, J., Cabell, R., Hurst, J., and J. Hannan. 2010. Virtual chemical and biological (CB) agent data set generation to support the evaluation of CB contamination avoidance systems. The Fifth Symposium on Computational Wind Engineering (CWE 2010), Chapel Hill, North Carolina.
2. Corbett, G.C., Rouse, A.R., and A. Prater. 2001. Probabilistic Evaluation of Models for the Atmospheric Dispersion of Effluents Released from a Complex Site. Proceedings of the 8th Int. Conf. on Harmonization within Atmospheric Dispersion Modeling for Regulatory Purposes, Sofia, Bulgaria.
3. Fries, A. 2000. Another "New" Approach For "Validating" Simulation Models. American Statistical Association 2000 Proceedings of the Section on Physical and Engineering Sciences, Indianapolis, IN, August 13-17, pp. 61-66.
4. Press, W.J., Teukolsky, S.A., Vetterling, W.T., and B.P. Flannery. 1992. Numerical Recipes in Fortran, The Art of Scientific Computing, Second Edition, Cambridge University Press.
5. Stowick, D.P. 2007. Detailed test plan for the Fusing Sensor Information from Observing Networks (FUSION) Field Trial 2007 (FT 07). West Osborn Test Center, U.S. Army Dugway Proving Ground, WDTC Document No. WDTC-TP-07-078.

Conclusions

In this poster we demonstrated a potential extension of a scalar p-value methodology to statistically compare predicted distributions with a limited set of observations to two-dimensional (p_x, p_y) p-values. An initial application of these techniques to help validate wind fluctuations predicted by VTHREAT is shown as well. The distribution of VTHREAT predicted wind fluctuations visually appears close to the observed fluctuations (i.e., it appears that the observations could have been randomly drawn from the predicted distributions). Nevertheless, two-dimensional (p_x, p_y) p-values indicate a slight diversion from a uniform distribution in the unit square $[0,1] \times [0,1]$ around the edges and the origin.

Future work with VTHREAT-simulated results will replace the elliptical-normal distribution assumption with a non-parametric estimation of the cumulative probability function that will be used to estimate p-values.

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