

# A combo (Sonic & 2 x-hot-films) setup for atmospheric turbulence measurements

**Eliezer Kit**

*School of Mechanical Engineering,  
Tel-Aviv University*

*In collaboration with: Joe Fernando*

*Tomas Sant*

*Boris Gritz*

*Dan Liberzon*

*Chris Hocut*

# Motivation

- Fine resolution measurements of atmospheric turbulence, which enable to determine dissipation, velocity derivatives etc. is an important task.
- The standard instruments used for velocity field measurements such as Sonic anemometer and Lidar have a low temporal and spatial resolution.
- Miniature hot-wires or films are suitable for these purposes, however, they require frequent calibrations of the wires/films.
- The calibration using a specially devised calibrator is a cumbersome procedure in the Laboratory conditions and becomes practically inapplicable in the field.
- The use of in-situ calibration by utilizing a low resolution data from Sonic appears to be very attractive but only in case that an appropriate procedure is developed.

# Layout of the talk

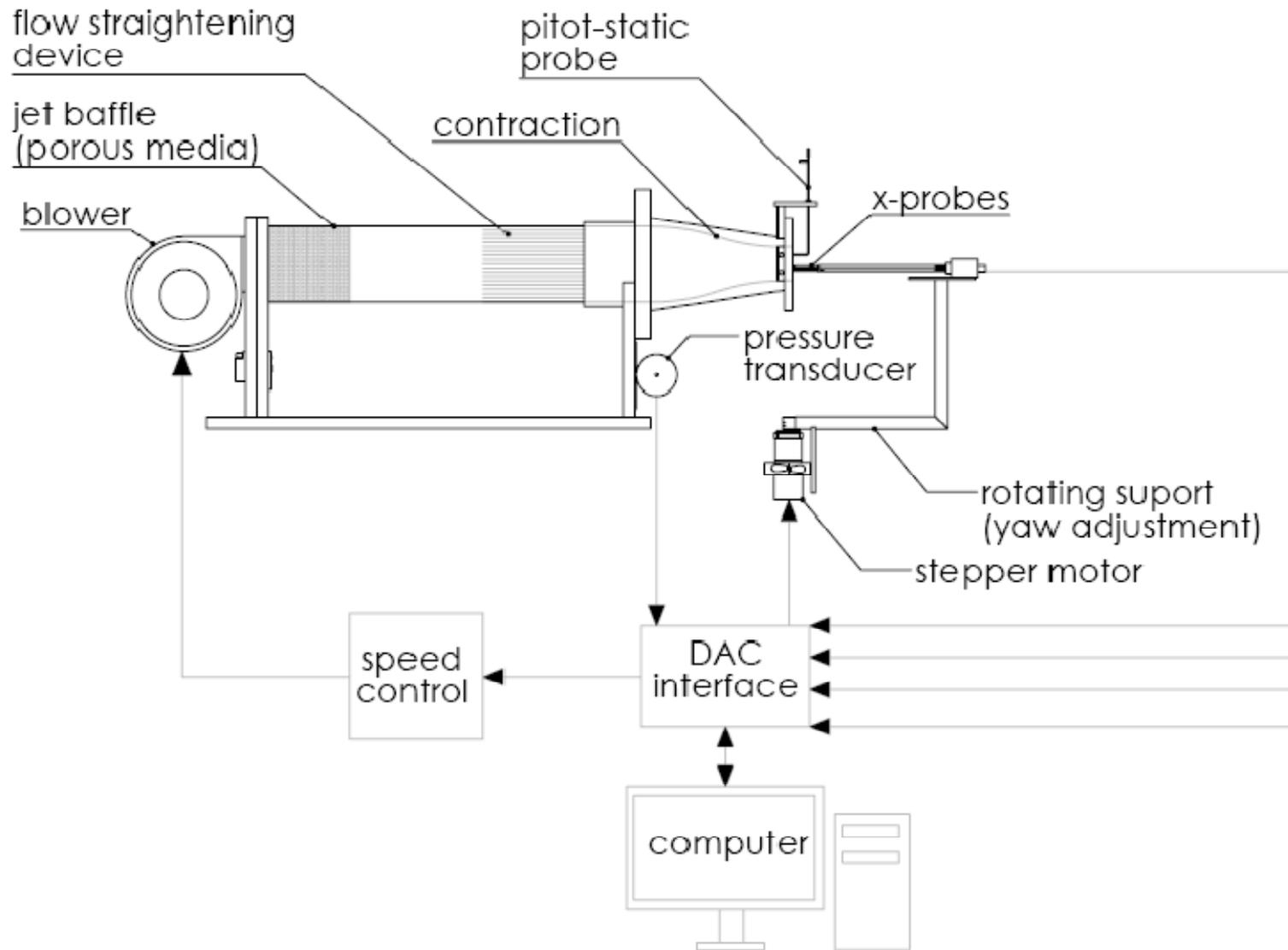
- **Part 1:** Feasibility Study (Work made in ASU)
- Jet facility – calibrator
- Probe yawing for calibration and feedback purposes
- Hot-film and sonic: calibration datasets
- Approximations of input/output relations:  
Polynomial least square Fit and Neural Network
- Results: Laboratory and Field
- **Part 2:** Angular probability distribution (Recent)
- **Future plans:** the use of UAV and combo setup in mountain terrain turbulence measurements ,  
Three-dimensional calibration (ND)
- Conclusions

# Relevant Papers

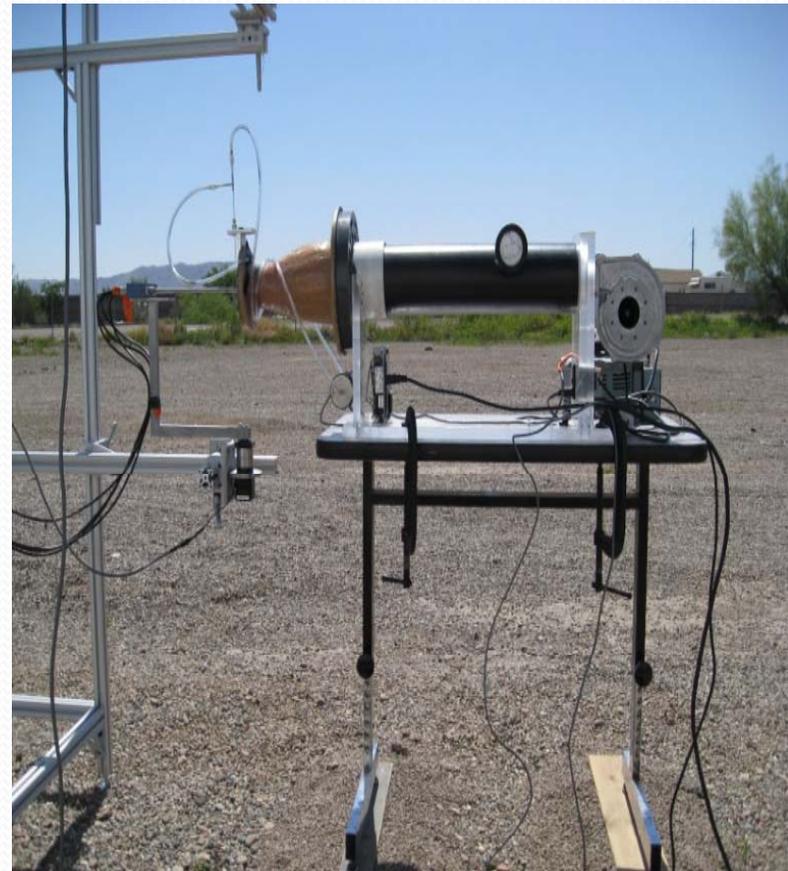
- E. Kit, A. Cherkassky, T. Sant, H.J.S. Fernando. *In-situ* calibration of hot-film probes using a co-located sonic anemometer: Implementation of a neural network. **Journal of Atmospheric and Oceanic Technology-AMS**, Vol. 27, No. 1, 23-41 (2010).
- E. Kit and B. Gritz. *In-situ* calibration of hot-film probes using a co-located sonic anemometer: angular probability distribution properties. **Journal of Atmospheric and Oceanic Technology-AMS**, Vol. 28, 104-110 (2011).

# 1. Feasibility Study

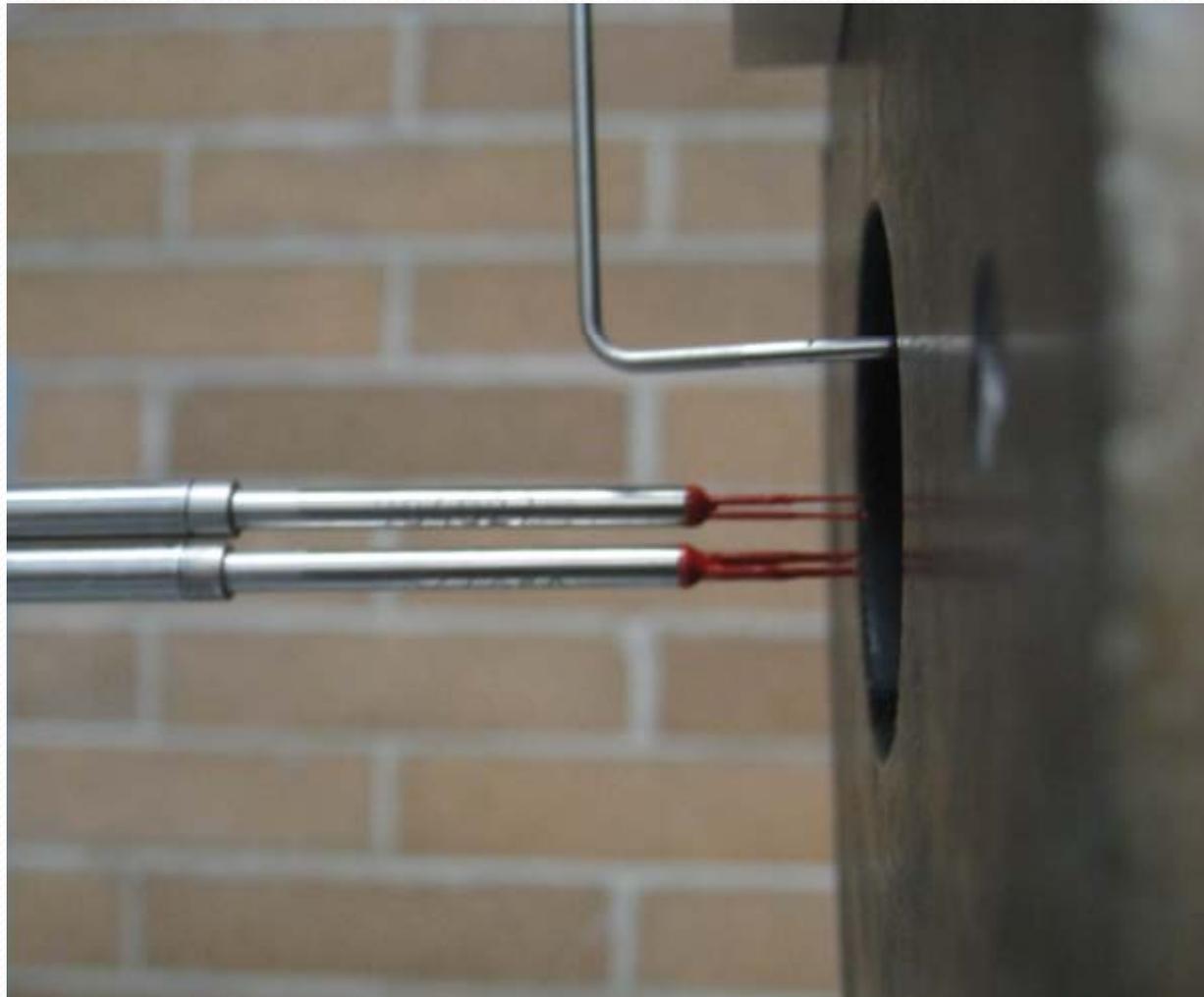
# Jet Facility and traverse for probe yawing



**Left: Laboratory - set-up for probe yawing**  
**Right: Calibration in the field - general view**



- **Hot-films (x-probes) at the jet exit.**  
**Miniature Pitot tube for simultaneous mean velocity measurements**



# Presentation of velocity components as polynomials of voltages across the wires.

## TKE dissipations and skewness of velocity derivatives

$$U_i = f_i(E_1, E_2)$$

$$f_i(E_1, E_2) = \sum_{kl} c_{ikl} P_k(E_1) P_l(E_2); \quad P_k(E) = E^k, \quad 0 \leq k, l \leq 4, \quad k + l \leq 4$$

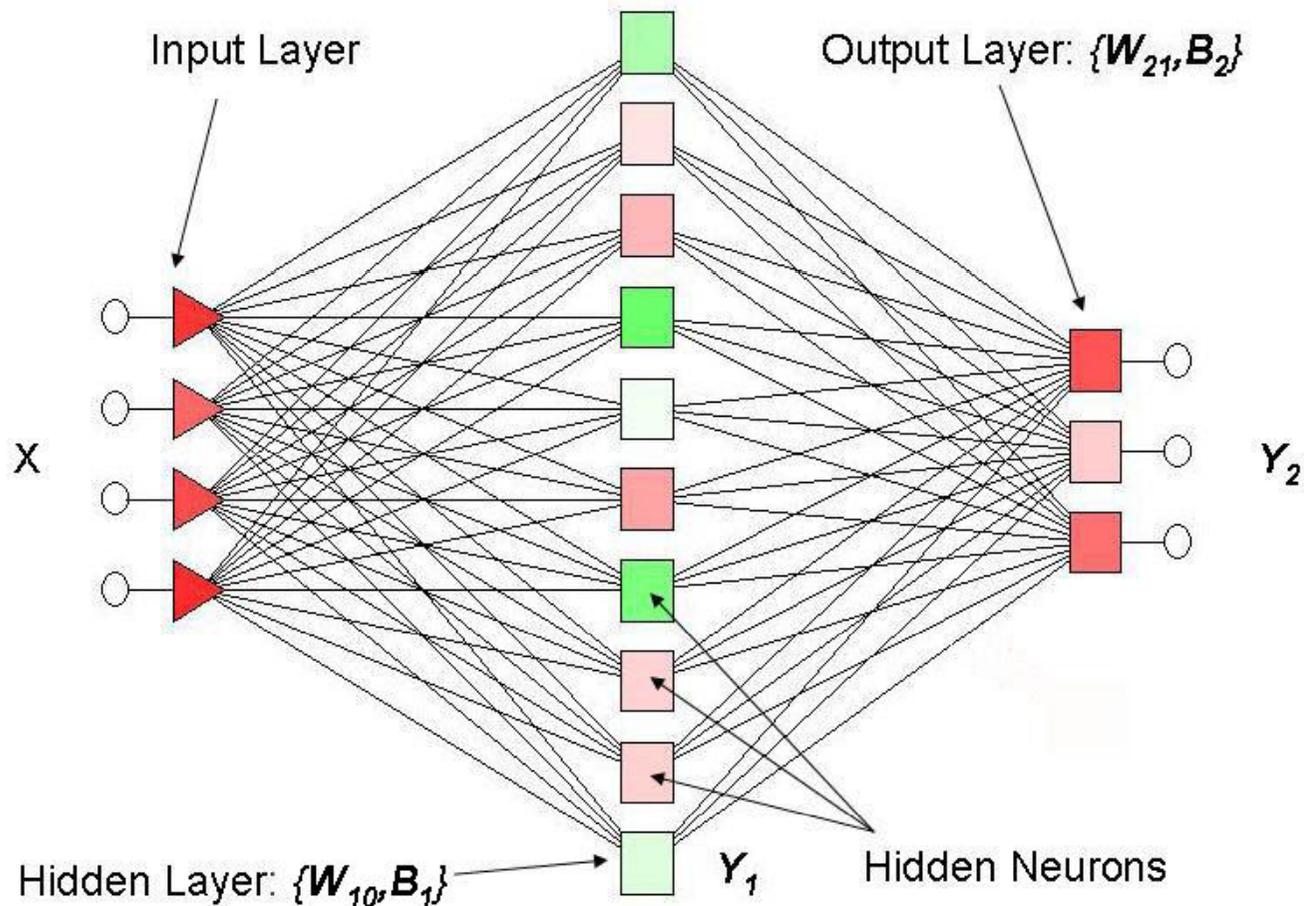
Linear system for determination of polynomial coefficients  $c$  is obtained from calibration data using the least square fit.

Dissipation:  $\epsilon = 15\nu \overline{\left(\frac{\partial u}{\partial x}\right)^2}; \quad \partial x = -U\partial t$

Skewness of velocity derivative:  $Sk = \overline{\left(\frac{\partial u}{\partial x}\right)^3} / \left(\overline{\left(\frac{\partial u}{\partial x}\right)^2}\right)^{3/2}$

# Neural Network

## The structure of the generated neural network (3-layer Perceptron)



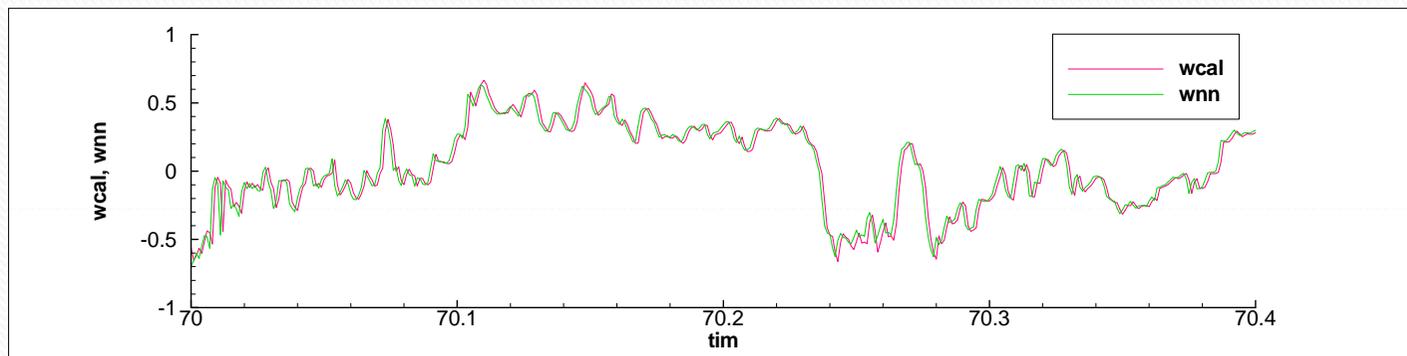
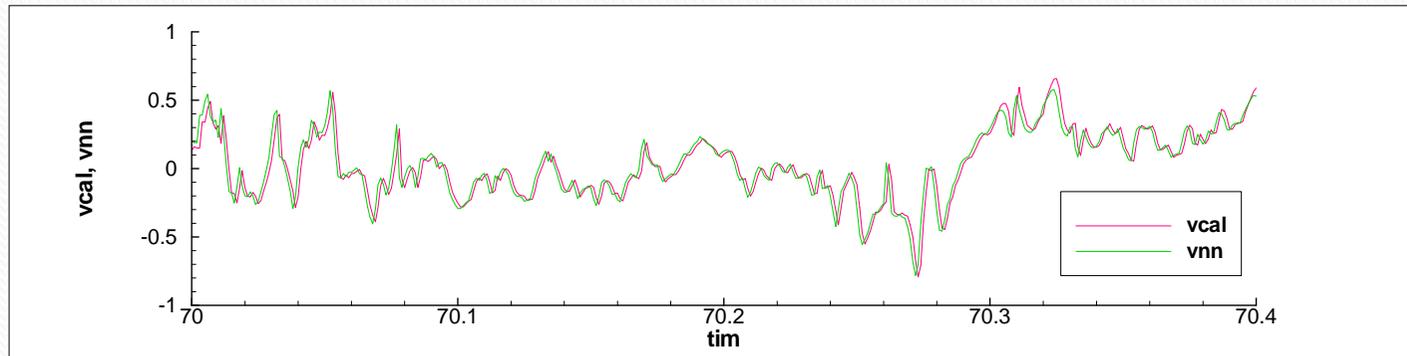
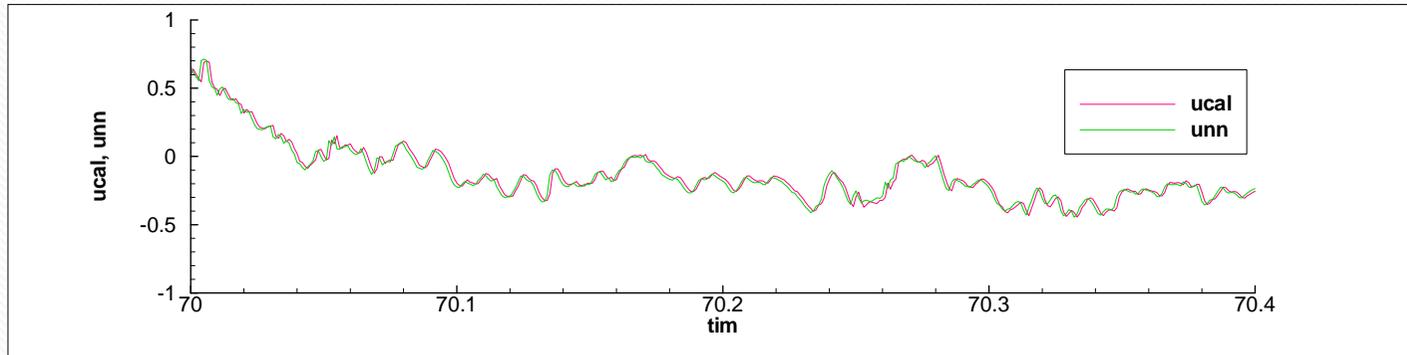
# Calibration Data Sets and Approximations

Table 1 List of calibration datasets and procedures.

Calibration datasets/Approximations	Polynomial Fit	Neural Network
<b>CBS</b> (Calibrator Based dataSet)	<b>1 – PF (CBS)</b>	<b>2 – NN (CBS)</b>
<b>SBS</b> (Sonic Based dataSet)	<b>3 – PF (SBS)</b>	<b>4 – NN (SBS)</b>

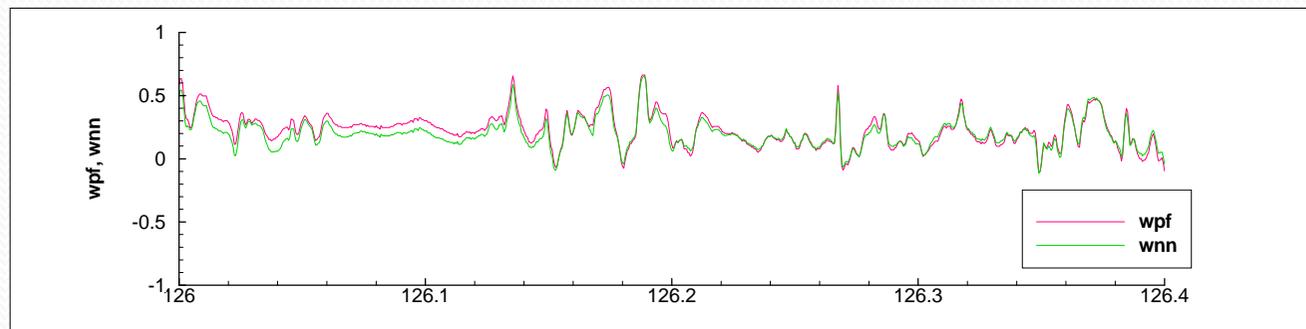
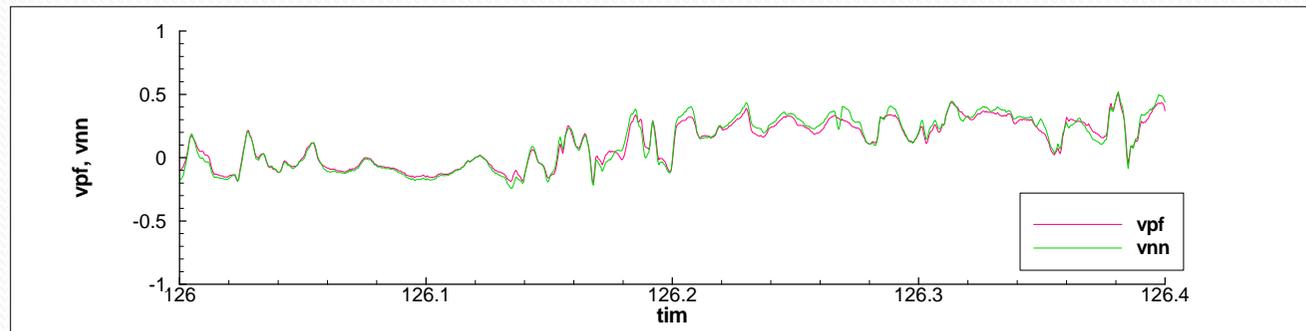
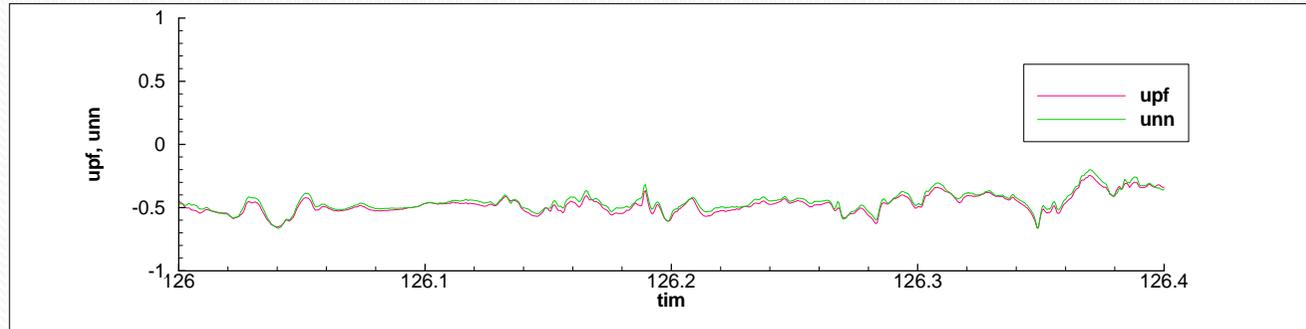
# Lab\_Exp# 01 L = 3m

Upper: streamwise, mid plot: crosswise, lower: vertical  
red-PF (CBS), green-NN (CBS).

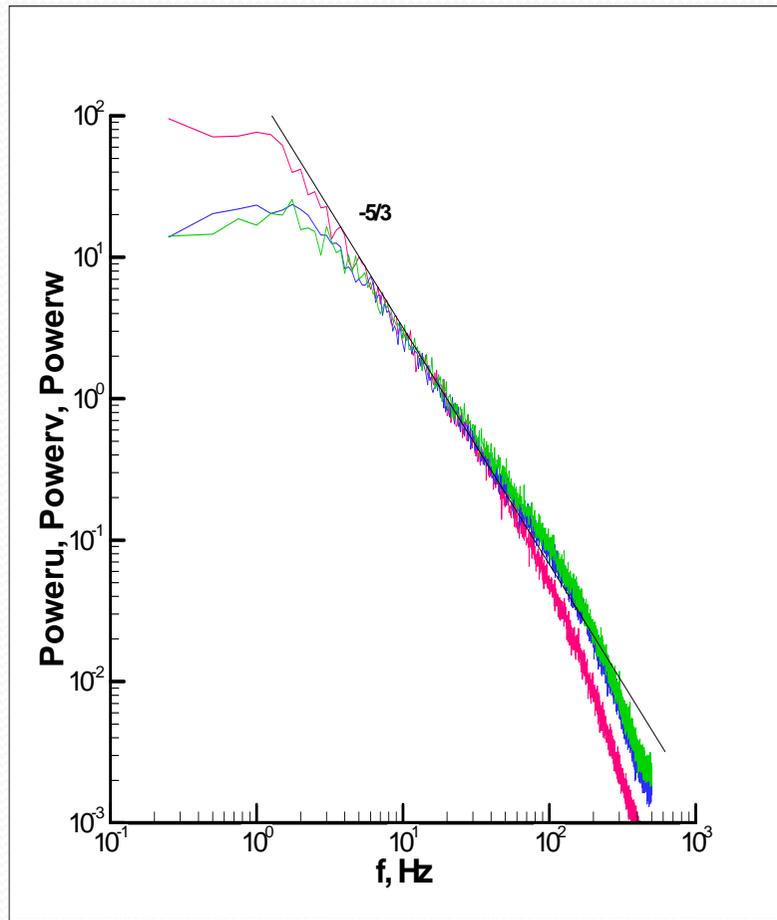


# Field\_Exp# 02 Night

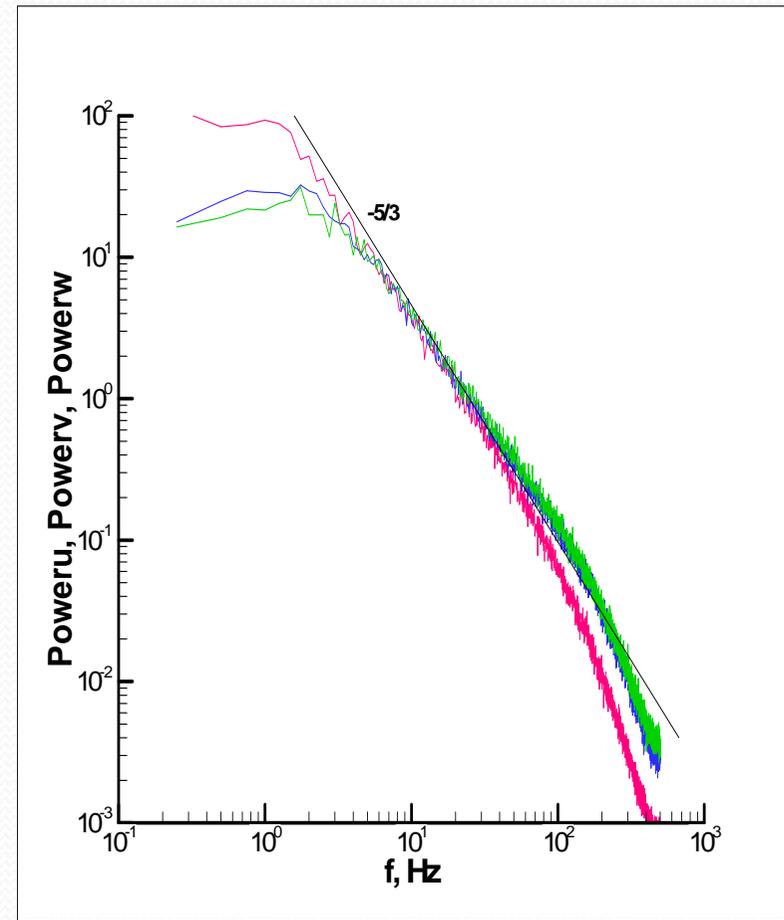
Upper: streamwise, mid plot: crosswise, lower: vertical  
red-PF (CBS), green-NN (SBS).



# Spectra of u-red, v-blue, w-green: a-using NN procedure, b-using PF procedure. Lab\_Exp# 1

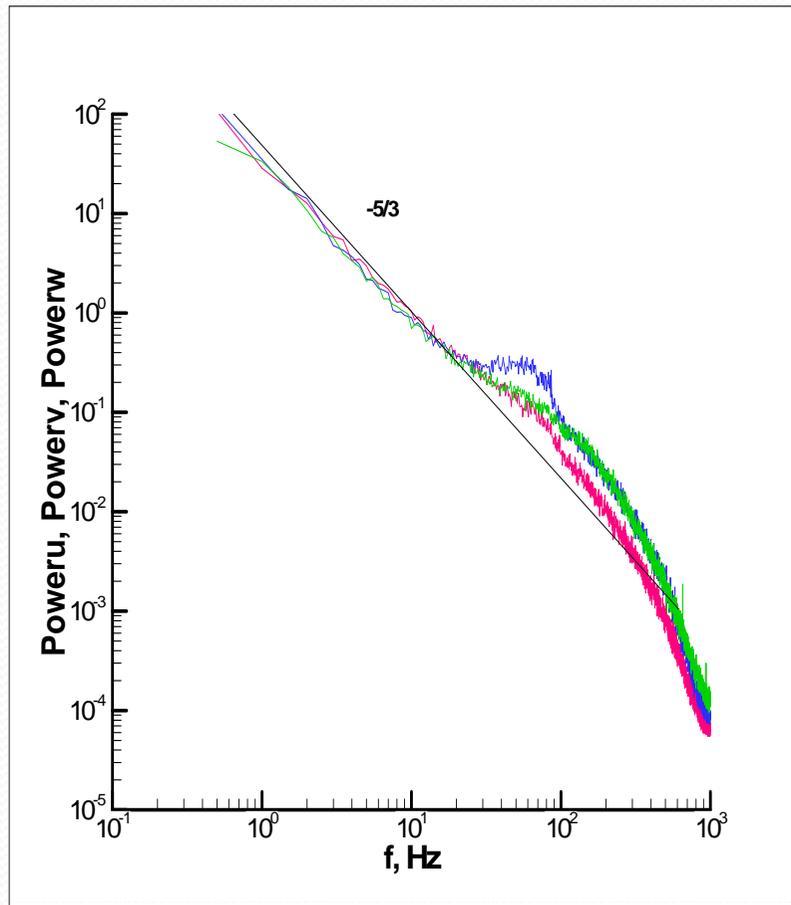


a)

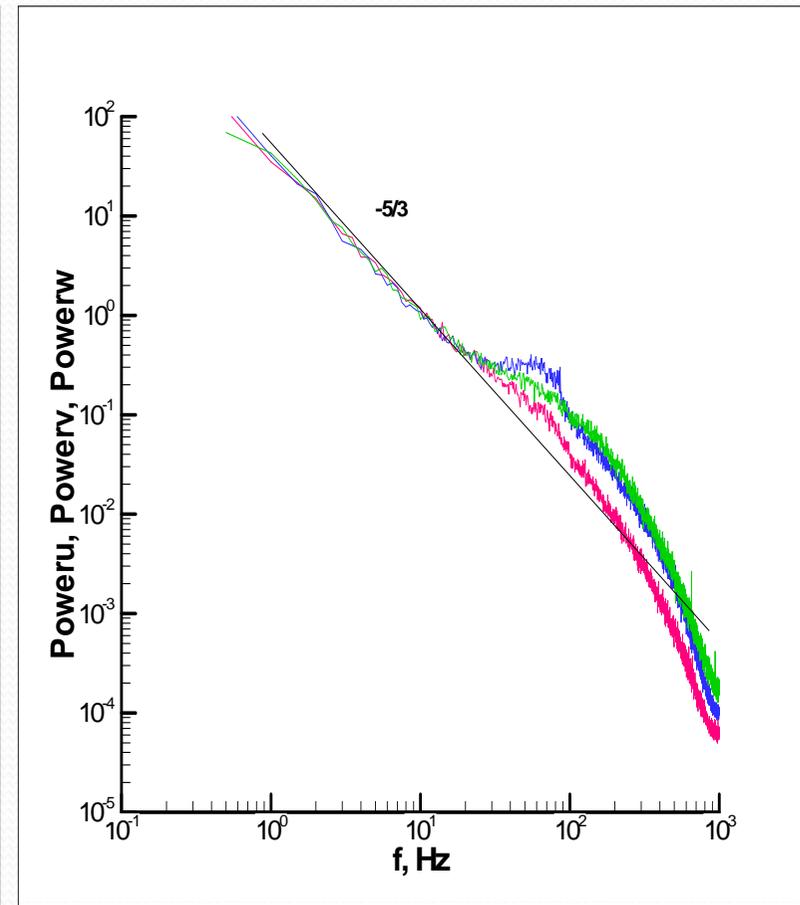


b)

# Spectra of u-red, v-blue, w-green: a-using NN procedure, b-using PF procedure. Field\_Exp# 2



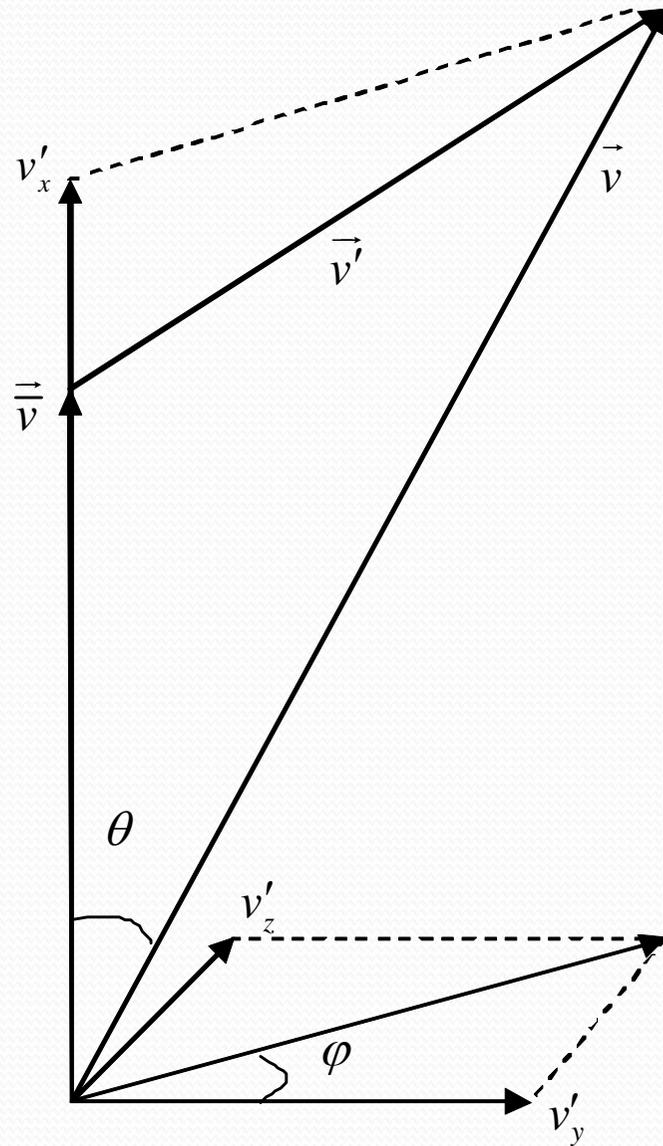
a)



b)

## **2. Angular Probability Distribution**

# Sketch of velocity vector, components and angles



Velocities and angles at a given point:

$\vec{v}$  - mean velocity,

$\vec{v}'$  - fluctuating part,

$\vec{v}$  - full velocity;

$\theta$  - the deviation angle of full velocity from mean velocity,

$\phi$  - the azimuth angle.

# Angular distribution - development

Assumptions:

- each velocity component obey a Gaussian distribution,
- correlation among components are relatively low

then the probability density for the full velocity

$$P(v'_x, v'_y, v'_z) = n \cdot \exp\left(-\frac{(v'_x)^2}{2\sigma_x^2}\right) \cdot \exp\left(-\frac{(v'_y)^2}{2k_y\sigma_x^2}\right) \cdot \exp\left(-\frac{(v'_z)^2}{2k_z\sigma_x^2}\right)$$

$n$  - a normalization factor

$k_y$  and  $k_z$  – coefficients for standard deviations in  $y$  and  $z$

Isotropic case:  $k_z = k_y = 1$

Axisymmetric case:  $k_z = k_y = k$

The integration in spherical coordinate system yields

$$n = \frac{1}{(2\pi)^{3/2} k \cdot \sigma_x^3}$$

## Angular distribution – development, cont...

- using the expressions  $(v'_x)^2 = (v \cdot \cos \theta - \bar{v})^2$ ,  $v'_y = v \cdot \sin \theta \cdot \cos \varphi$
- and  $v'_z = v \cdot \sin \theta \cdot \sin \varphi$
- The probability density function in spherical coordinate system

$$P(\varphi, \theta, x) = \frac{x^2 \sin \theta}{(2\pi)^{3/2} \bar{v} k \cdot \sigma_n^3} \cdot \exp\left(-\frac{(x \cos \theta - 1)^2 + x^2 \sin^2 \theta / k}{2\sigma_n^2}\right).$$

Where  $x = v/\bar{v}$ ,  $\sigma_n = \sigma_x / \bar{v}$

For isotropic case  $k=1$ ,

$$P(\varphi, \theta, x) = \frac{x^2 \sin \theta}{(2\pi)^{3/2} \bar{v} \sigma_n^3} \cdot \exp\left(-\frac{(x - \cos \theta)^2 + \sin^2 \theta}{2\sigma_n^2}\right).$$

# Angular distribution – development, cont...

Integrating over  $x$  and over  $\varphi$  in axisymmetric case yields

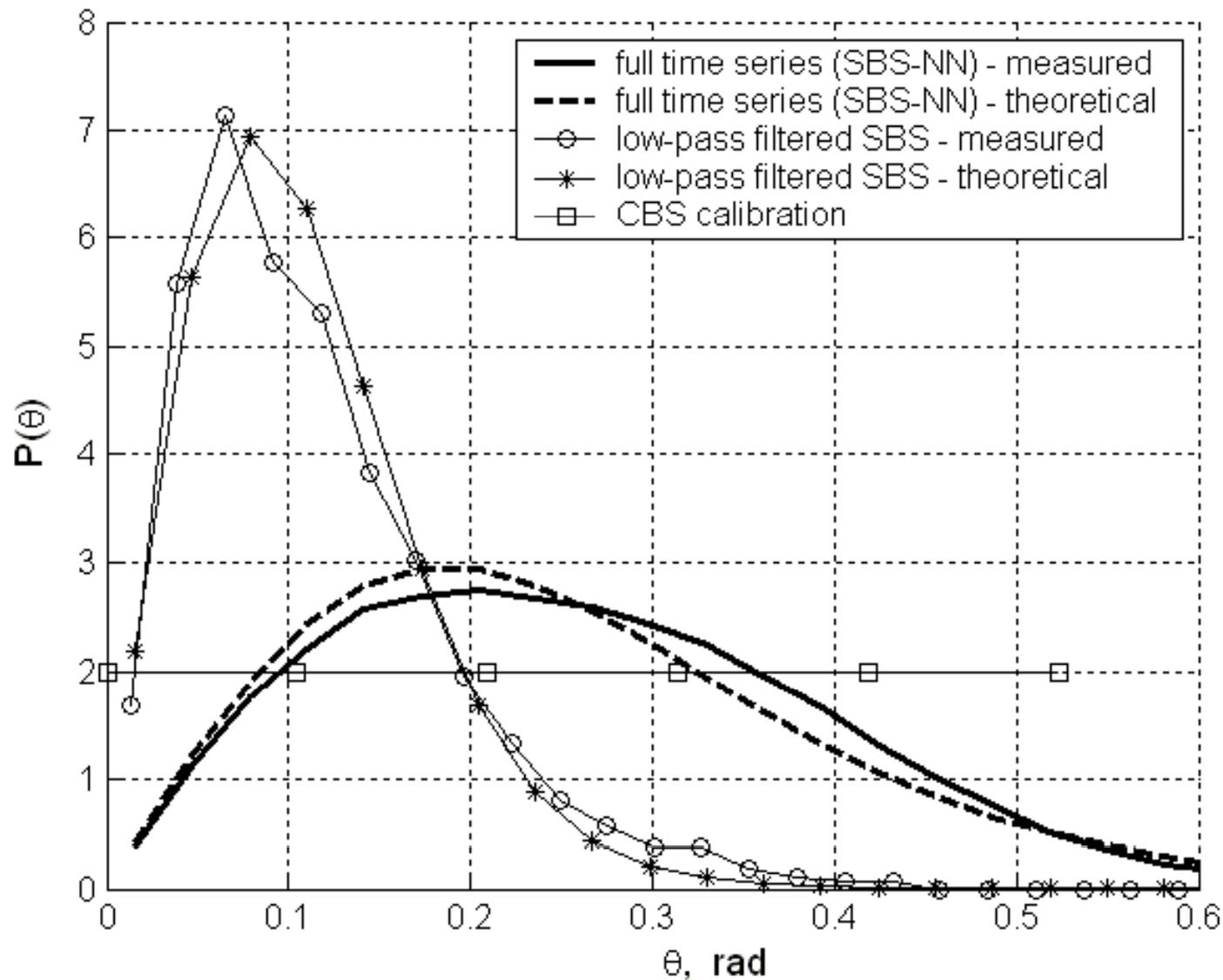
$$P(\theta) = \frac{\tan \theta}{k\sigma_n \cos^2 \theta \cdot f^2} \left\{ \frac{\exp\left(-\frac{1}{2\sigma_n^2}\right)}{\sqrt{2\pi}} + \frac{(f\sigma_n^2 + 1)\exp\left(\frac{f^{-1} - 1}{2\sigma_n^2}\right)}{2\sigma_n \sqrt{f}} \cdot \left[1 - \operatorname{erf}\left(-\frac{1}{\sqrt{2f}\sigma_n}\right)\right] \right\}$$

where  $f = 1 + \tan^2 \theta / k$

In the isotropic case ( $k=1$ ):

$$P(\theta) = \frac{\tan \theta}{\sigma_n} \cdot \left\{ \frac{\exp\left(-\frac{1}{2\sigma_n^2}\right)}{\sqrt{2\pi}} + \frac{(\sigma_n^2 + \cos^2 \theta)\exp\left(-\frac{\sin^2 \theta}{2\sigma_n^2}\right)}{2\sigma_n \cos \theta} \cdot \left[1 - \operatorname{erf}\left(-\frac{\cos \theta}{\sqrt{2}\sigma_n}\right)\right] \right\}$$

# Angular probability: Comparison of model prediction with experimental data



# Conclusions

- NN model works with calibration datasets with unevenly distributed data points, PF works only with evenly.
- Field: Nocturnal works best and recommended.
- Very interesting spectra in our short preliminary campaign.
- Model of Angular Density Probability (ADP) is developed based on Gaussian distribution of velocity components.
- Angular Probability Distribution for calibration dataset is twice as narrow as for full signal. PF fails, NN comes through.
- Studying of non-linearity defined as RMS to mean velocity ratio
- The installation of combo setup on UAV for mountain terrain to study the turbulent atmospheric boundary layer.
- Further development of the method: establishing of criteria for data quality.

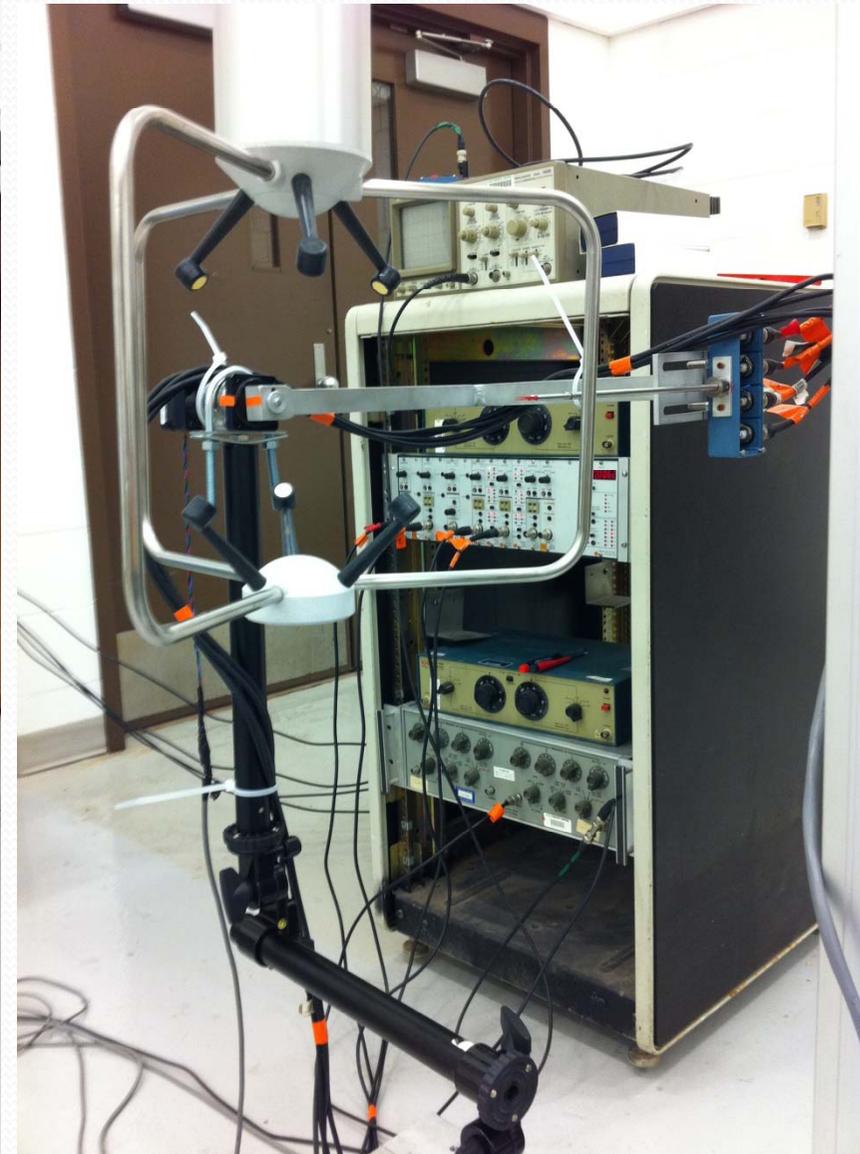
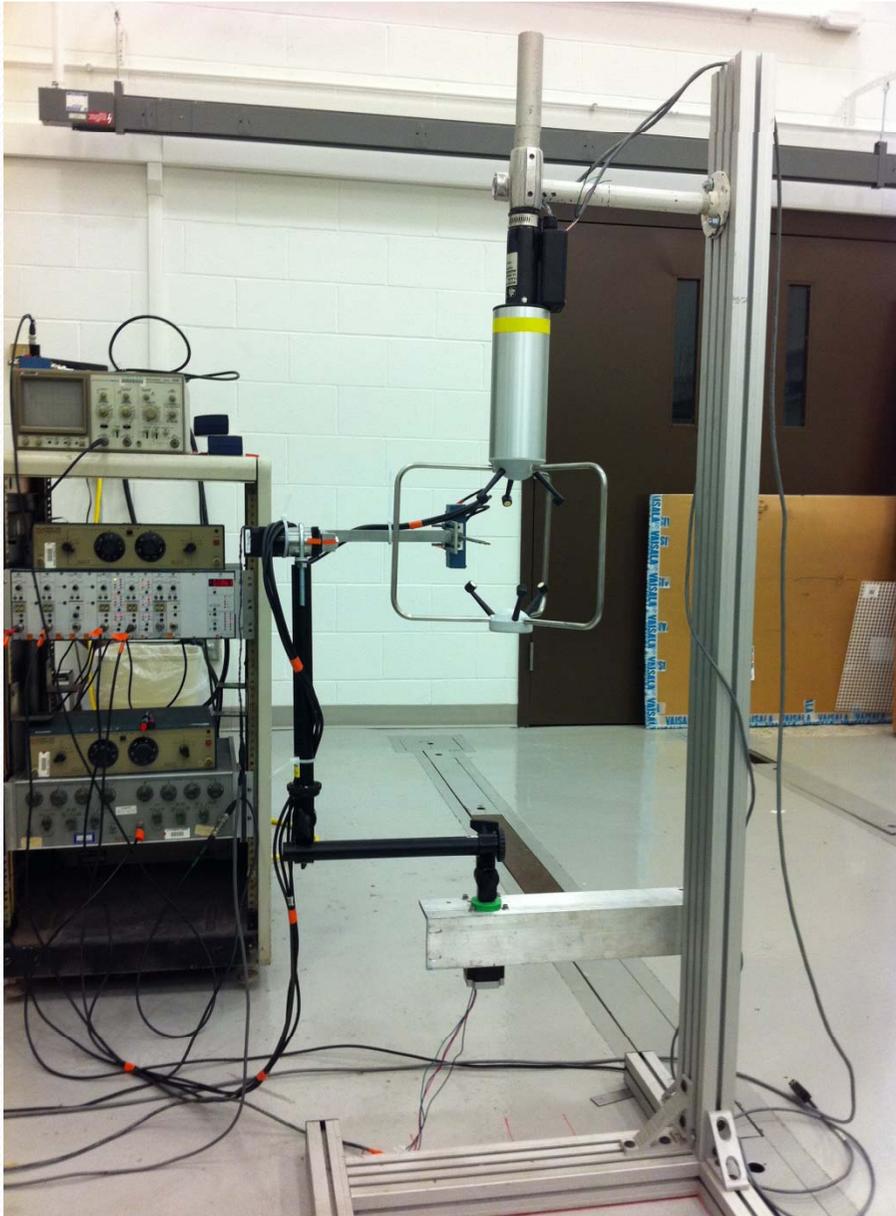
3. Future plans: the use of UAV and combo setup (pair of  $x$ -hot-films or a **triple-sensor fiber-film probe** & sonic) for turbulence atmospheric measurements in mountain terrain.

**Development of three-dimensional traversing and 3D calibration procedure**

**A small autonomous UAV: 30 pound  
payload capacity, airborne for two hours  
at 30-40 mph.**



# 3D-TRAVERSING & SONIC





**THANK YOU!**  
**THE END**