# Heep Least Squares Analysis For Coincidence Data

**September 27, 2019** 

**Carlos Yero** 

## System of Linear Equations for H(e,e'p)

$$dW^{calc} = \frac{\partial W}{\partial E_b} E_b \mathbf{a_0} + \frac{\partial W}{\partial E_f} E_f \mathbf{a_1} + \frac{\partial W}{\partial \theta_e} \mathbf{a_2} = dW_{obs} + \epsilon_{dW}$$

$$dE^{calc}_m = \frac{\partial E_m}{\partial E_b} E_b \mathbf{a_0} + \frac{\partial E_m}{\partial E_f} E_f \mathbf{a_1} + \frac{\partial E_m}{\partial \theta_e} \mathbf{a_2} = dE_{m_{obs}} + \epsilon_{dE_m}$$

$$a_1 = \frac{dE_f}{E_f}$$

$$dP^{calc}_{mx} = \frac{\partial P_{mx}}{\partial E_b} E_b \mathbf{a_0} + \frac{\partial P_{mx}}{\partial E_f} E_f \mathbf{a_1} + \frac{\partial P_{mx}}{\partial \theta_e} \mathbf{a_2} = dP_{mx_{obs}} + \epsilon_{dP_{mx}}$$

$$a_2 = d\theta_e$$

$$dP^{calc}_{mz} = \frac{\partial P_{mz}}{\partial E_b} E_b \mathbf{a_0} + \frac{\partial P_{mz}}{\partial E_f} E_f \mathbf{a_1} + \frac{\partial P_{mz}}{\partial \theta_e} \mathbf{a_2} = dP_{mz_{obs}} + \epsilon_{dP_{mz}}$$

$$\mathbf{Measured}_{variations} \mathbf{Predicted}_{variations}$$

$$\mathbf{Re-write}_{and} \mathbf{Parameters}_{in} \mathbf{matrix}$$

$$\mathbf{Measured}_{variations} \mathbf{Predicted}_{observed}$$

$$\mathbf{Measured}_{variations} \mathbf{Predicted}_{observed}$$

- To further constrain the beam energy, final electron energy and angle, in addition to the variations in W, the variations in missing energy and momenta were also considered.
- ONLY variations in W from beam energy, e- momentum and angle were considered

## In Matrix Notation: (Over-Determined System)

$$\begin{bmatrix} \frac{\sum \partial W}{\partial E_b} E_b & \frac{\sum \partial W}{\partial E_f} E_f & \frac{\sum \partial W}{\partial \theta_e} \\ \frac{\sum \partial E_m}{\partial E_b} E_b & \frac{\sum \partial E_m}{\partial E_f} E_f & \frac{\sum \partial E_m}{\partial \theta_e} \\ \frac{\sum \partial P_{mx}}{\partial E_b} E_b & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \\ \frac{\sum \partial P_{mx}}{\partial E_b} E_b & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \\ \frac{\sum \partial P_{mz}}{\partial E_b} E_b & \frac{\sum \partial P_{mz}}{\partial E_f} E_f & \frac{\sum \partial P_{mz}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mobs}}{\partial P_{mobs}} \\ \frac{\sum \partial P_{mx}}{\partial E_b} E_b & \frac{\sum \partial P_{mz}}{\partial E_f} E_f & \frac{\sum \partial P_{mz}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dE_{mobs} \\ \frac{\sum \partial P_{mz}}{\partial P_{mz}} E_b & \frac{\sum \partial P_{mz}}{\partial E_f} E_f & \frac{\sum \partial P_{mz}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_b & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_b & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_b & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial E_f} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial \theta_e} \end{bmatrix} \begin{bmatrix} \mathbf{a_0} \\ \mathbf{a_1} \\ \mathbf{a_2} \end{bmatrix} = \begin{bmatrix} \sum_{rus} dW_{obs} \\ \frac{\sum \partial P_{mx}}{\partial P_{mx}} E_f & \frac{\sum \partial P_{mx}}{\partial P_{mx}} E$$

The coefficients are summed over all runs (only 3 in this case)

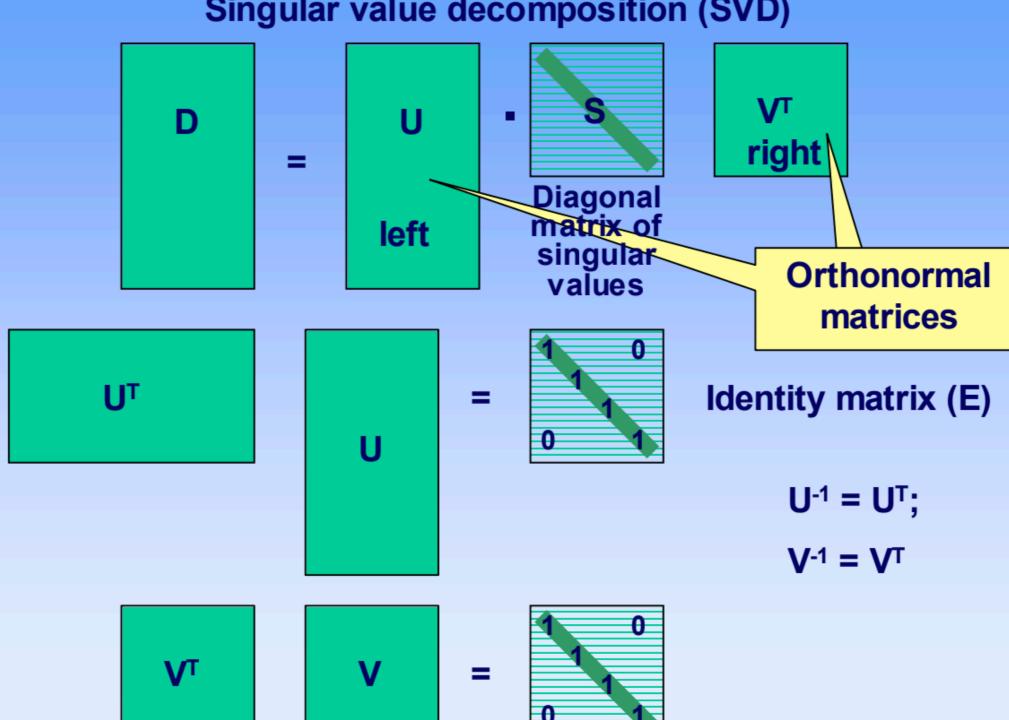
$$\mathbf{C}\overrightarrow{\mathbf{a}} = \overrightarrow{\mathbf{b}} + \hat{\epsilon}$$

Solve for:  $\overrightarrow{Ca} \cong \overrightarrow{b}$  via Single-Value Decomposition

(SEE NEXT TWO SLIDES FOR OVERVIEW OF SVD)

## Solution of systems of linear equations





**Author: Vladimir Volkov** 

## Solution of systems of linear equations

Solution by least squares using normal equations:

$$D^TD A = D^T B$$
,  
 $A=(D^TD)^{-1} D^T B$ 

**Errors** 

Solution by least squares using SVD:

$$D = U S V^{T};$$

 $U^{T} U S V^{T} A = U^{T} B$ ; because  $U^{T}U = E$ , and E play role of a unity in multiplications:

$$S V^T A = U^T B;$$
  $S^{-1}S = E$ , then

 $V^T A = S^{-1} U^T B$ ; critical operation - inversion of  $S_{ii}$ 

$$A = V S^{-1} U^T B$$
 because  $V V^T = E$ 

 $\mathbf{A} = \sum_{i=1}^{M} \left( \frac{\mathbf{U}_{(i)} \cdot \mathbf{B}}{S_i} \right) \mathbf{V}_{(i)} \pm \frac{1}{S_1} \mathbf{V}_{(1)} \pm \dots \pm \frac{1}{S_m} \mathbf{V}_{(m)} \qquad \boldsymbol{\sigma}_{a_j}^2 = \sum_{i=1}^{M} \left( \frac{\mathbf{V}_{ji}}{S_i} \right)^2$ 

**Author: Vladimir Volkov** 

### Getting the Residuals and Chi2

• Once the optimum parameters, (vector a) have been determined by SVD, the residuals and chi2 can be calculated as follows:

$$\hat{\epsilon} = \mathbf{C} \overrightarrow{\mathbf{a}} - \overrightarrow{\mathbf{b}} \longrightarrow \mathbf{Residuals} \qquad \text{One can think of this matrix as the inverse of the covariant matrix} \\ \chi^2 \equiv \hat{\epsilon}^T \mathbf{N}^{-1} \hat{\epsilon} \longrightarrow \begin{bmatrix} \epsilon_{dW} \\ \epsilon_{Em} \\ \epsilon_{Pm_z} \\ \epsilon_{Pm_z} \end{bmatrix} \qquad \qquad 0 \qquad 0 \qquad 0 \\ \mathbf{N}^{-1} = \begin{bmatrix} 1/\sigma_{dW_{obs}}^2 & 0 & 0 & 0 \\ 0 & 1/\sigma_{dEm_{obs}}^2 & 0 & 0 \\ 0 & 0 & 1/\sigma_{dPmx_{obs}}^2 & 0 \\ 0 & 0 & 0 & 1/\sigma_{dPmx_{obs}}^2 \end{bmatrix}$$

where the  $\sigma_{i_{abs}}$  are the measured errors and assumed to be independent of each other

#### **Expanding chi2 in matrix form, one obtains:**

$$\chi 2 = \frac{\epsilon_{dW}^2}{\sigma_{dW_{obs}}^2} + \frac{\epsilon_{dE_m}^2}{\sigma_{dE_{m_{obs}}}^2} + \frac{\epsilon_{dP_{mx}}^2}{\sigma_{dP_{mx_{obs}}}^2} + \frac{\epsilon_{dP_{mz}}^2}{\sigma_{dP_{mz_{obs}}}^2}$$

## Getting the Covariance Matrix of the Parameters

The covariance matrix can be determined from:

- ${f C} \overrightarrow{a} = \overrightarrow{b} + \widehat{\epsilon}$
- $\cdot$  the inverse of the data error matrix  $N^{-1}$

$$\mathbf{COV_M} = (\mathbf{C^TN^{-1}C})^{-1}$$

The covariance matrix depends only on:

- The measured data errors
- The experimental model

## **Getting the Correlation Matrix**

The correlation matrix can be determined by dividing the covariance by the diagonal elements as follows:

$$ext{Cor}_{ij} = rac{ ext{Cov}_{ij}^{(i,j)} ext{ element of the Covariance Matrix}}{ ext{Cov}(i) ext{Cov}(j)}$$
Covariance
Diagonal elements (i), (j)

For the special case of i=j, the diagonal elements are 1 which indicates they are 100% correlated with themselves

## Results from H(e,e'p) Coincidence Data

Measured data and error for each of the 4 elastic runs (only the 1st three runs considered)

```
//Define the measured DATA, SIMC variables
Double_t Wdata[4] = {9.42152e-01, 9.40229e-01, 9.43825e-01, 9.55773e-01};
Double_t Wdata_err[4] = {9.71583e-05, 3.77469e-04, 6.01623e-05, 4.13486e-05};
Double t Wsimc[4] = \{9.44690e-01, 9.44480e-01, 9.43591e-01, 9.42933e-01\};
Double t Wsimc err[4] = \{1.38566e-04, 6.68696e-05, 2.81437e-05, 2.23158e-05\};
Double t Emdata[4] = \{6.58010e-03, 5.28983e-03, 6.26642e-03, 5.32021e-03\};
Double t Emdata err[4] = \{4.69566e-05, 1.47900e-04, 3.65940e-05, 4.14000e-05\};
Double t Emsimc[4] = \{5.51066e-03, 6.06886e-03, 6.58531e-03, 6.47356e-03\};
Double_t Emsimc_err[4] = {9.05496e-05, 3.84833e-05, 1.74941e-05, 1.37620e-05};
Double_t PmXdata[4] = \{-1.29097e-03, -9.93560e-04, -5.53961e-04, 7.13300e-03\};
Double_t PmXdata_err[4] = \{3.30069e-05, 1.75464e-04, 2.87979e-05, 2.08787e-05\};
Double t PmXsimc[4] = \{-5.88228e-04, -5.91870e-04, -6.80114e-04, -1.02935e-03\};
Double t PmXsimc_err[4] = \{7.19549e-05, 2.48719e-05, 2.31853e-05, 1.11287e-05\};
Double_t PmZdata[4] = {5.77521e-03, 5.42333e-03, 5.33585e-03, 3.43146e-03};
Double_t PmZdata_err[4] = \{7.85239e-05, 1.13337e-04, 3.97398e-05, 3.45173e-05\};
Double_t PmZsimc[4] = \{5.82773e-03, 6.50794e-03, 6.35112e-03, 6.02246e-03\};
Double_t PmZsimc_err[4] = \{1.06200e-04, 2.89548e-05, 1.55699e-05, 1.62459e-05\};
```

Data Errors Seem to be too small, which can make chi2 artificially large. Would it be better to consider the sigma from the gaussian fit as the error?

## Results from H(e,e'p) Coincidence Data

```
****COVARIANCE MATRIX****
3x3 matrix is as follows
           0
       5.858e-08 7.221e-08 -1.409e-08
       7.221e-08 8.904e-08 -1.738e-08
      -1.409e-08 -1.738e-08 3.419e-09
=== Optimized Parameters ===
total equations x total runs = 4x3 = 12 observations, # parameters = 3, dof = 9
chi2 = 126.145 chi2/dof = 14.0161
dEb / Eb = -0.000410038
dEf / Ef = -0.000448075
                                          The error on the electron
dth_e = 0.000164275
                                           Angle seems too good
                                         (This is probably related to
=== Uncertainty in Parameters ===
dEb / Eb = 0.000242029
                                   The unrealistically small data errors)
dEf / Ef = 0.000298391
dth_e [rad] = 5.84754e-05
                                     Could we use the sigma from the
                                        Fit as the error of the mean?
****CORRELATION MATRIX****
3x3 matrix is as follows
                                  2
           0
                                -0.9958
                      0.9999
   0
          0.9999
                                 -0.996
   2
         -0.9958
                      -0.996
```