

# W mass studies - Kinematic Fit

WG1 & WG2 working meeting

**Marina Béguin**, Paolo Azzurri

February 6, 2018

# Kinematic Fit - Principle (1)

The aim is ...

...to improve the resolution of an object slightly changing the measured quantities (e.g four-vector) within their uncertainty to fulfil kinematic constraints.

To solve a problem with **n measured parameters y**, **p unmeasured parameters a** and **m constraints f**, a kinematic fit will determine the corrections  $\Delta y$  on parameters y, such that :

- 1  $S(y) = \Delta y^T V^{-1} \Delta y = \chi^2$  is minimal  $V = \text{cov. matrix y params.}$
- 2 All constraints are fulfilled :

$$f_1(a_1, \dots, a_p, y_1, \dots, y_n) = 0$$

$$f_2(a_1, \dots, a_p, y_1, \dots, y_n) = 0$$

⋮

$$f_m(a_1, \dots, a_p, y_1, \dots, y_n) = 0$$

## Kinematic Fit - Principle (2)

To determine the optimal  $\Delta y$ , the Lagrange Multipliers definition is used :

$$L(y, a, \lambda) = S(y) + 2 \sum_{i=1}^m \lambda_i f_i(y, a)$$

one multiplier by constraints

$L(y, a, \lambda)$  minimal when  $S(y)$   
minimal and  $f_i(y, a) = 0$

If the constraints are not linear, the minimization is done iteratively using the Taylor development at the first order :

$$f(y') \sim f_i(y^*) + \sum_{i=1}^4 \frac{\partial f_i}{\partial y_i} (\Delta y_i - \Delta y_i^*) \sim 0$$

Fit output :

- $\chi^2$  = probability that the event kinematic hypothesis are true
- Resolution improvement on reconstructed object

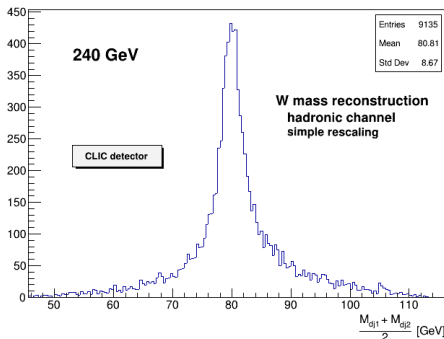
# Kinematic Fit - W mass reconstruction (1)

W mass reconstruction improvement in the *hadronic decay*

- **Samples** : Simulation with Pythia and reconstruction with HepPy (CLIC detector, ee-kt algorithm, 4 jets per event) at 162.3, 240 and 350 GeV.

- **Kinematic fit** :

- **Measured parameters** :  
rescaling coefficient  $\alpha$ , jets angles  $\theta$  and  $\phi$  and jets velocity  $v$
- **Constraints** :
  - energy-momentum conservation (4C) :  
 $\sum p_x = \sum p_y = \sum p_z = 0$  and  
 $\sum E = \sqrt{s}$
  - mass equality (1C) :  
 $M_{dj1} = M_{dj2}$



# Kinematic Fit - W mass reconstruction (2) - Likelihood

The likelihood is defined as follow :

$$L = \frac{\sum_{i=1}^4 (\alpha_i - \alpha_{i0})^2}{\sigma_\alpha^2} + \frac{\sum_{i=1}^4 (\theta_i - \theta_{i0})^2}{\sigma_\theta^2} + \frac{\sum_{i=1}^4 (\phi_i - \phi_{i0})^2}{\sigma_\phi^2} + \frac{\sum_{i=1}^4 (v_i - v_{i0})^2}{\sigma_v^2}$$
$$+ 2\lambda_X \Sigma p_x$$
$$+ 2\lambda_Y \Sigma p_y$$
$$+ 2\lambda_Z \Sigma p_z$$
$$+ 2\lambda_E (\Sigma E - \sqrt{s})$$
$$+ 2\lambda_M (M_{dj1} - M_{dj2})$$

# Kinematic Fit - W mass reconstruction (2) - Likelihood

The likelihood is defined as follow :

measured parameters  $y$

$$L = \frac{\sum_{i=1}^4 (\alpha_i - \alpha_{i0})^2}{\sigma_\alpha^2} + \frac{\sum_{i=1}^4 (\theta_i - \theta_{i0})^2}{\sigma_\theta^2} + \frac{\sum_{i=1}^4 (\phi_i - \phi_{i0})^2}{\sigma_\phi^2} + \frac{\sum_{i=1}^4 (v_i - v_{i0})^2}{\sigma_v^2}$$
$$+ 2\lambda_X \Sigma p_x$$
$$+ 2\lambda_Y \Sigma p_y$$
$$+ 2\lambda_Z \Sigma p_z$$
$$+ 2\lambda_E (\Sigma E - \sqrt{s})$$
$$+ 2\lambda_M (M_{dj1} - M_{dj2})$$

# Kinematic Fit - W mass reconstruction (2) - Likelihood

The likelihood is defined as follow :

$$L = \frac{\sum_{i=1}^4 (\alpha_i - \alpha_{i0})^2}{\sigma_\alpha^2} + \frac{\sum_{i=1}^4 (\theta_i - \theta_{i0})^2}{\sigma_\theta^2} + \frac{\sum_{i=1}^4 (\phi_i - \phi_{i0})^2}{\sigma_\phi^2} + \frac{\sum_{i=1}^4 (\nu_i - \nu_{i0})^2}{\sigma_\nu^2}$$

$\Delta y = y_{meas} - y_0$

$$\begin{aligned} &+ 2\lambda_X \Sigma p_x \\ &+ 2\lambda_Y \Sigma p_y \\ &+ 2\lambda_Z \Sigma p_z \\ &+ 2\lambda_E (\Sigma E - \sqrt{s}) \\ &+ 2\lambda_M (M_{dj1} - M_{dj2}) \end{aligned}$$

# Kinematic Fit - W mass reconstruction (2) - Likelihood

The likelihood is defined as follow :

$$L = \frac{\sum_{i=1}^4 (\alpha_i - \alpha_{i0})^2}{\sigma_\alpha^2} + \frac{\sum_{i=1}^4 (\theta_i - \theta_{i0})^2}{\sigma_\theta^2} + \frac{\sum_{i=1}^4 (\phi_i - \phi_{i0})^2}{\sigma_\phi^2} + \frac{\sum_{i=1}^4 (v_i - v_{i0})^2}{\sigma_v^2}$$
$$+ 2\lambda_X \Sigma p_x$$
$$+ 2\lambda_Y \Sigma p_y$$
$$+ 2\lambda_Z \Sigma p_z$$
$$+ 2\lambda_E (\Sigma E - \sqrt{s})$$
$$+ 2\lambda_M (M_{dj1} - M_{dj2})$$
$$V^{-1} = \begin{pmatrix} \sigma_\alpha^2 & 0 & 0 & 0 \\ 0 & \sigma_\theta^2 & 0 & 0 \\ 0 & 0 & \sigma_\phi^2 & 0 \\ 0 & 0 & 0 & \sigma_v^2 \end{pmatrix}$$



# Kinematic Fit - W mass reconstruction (2) - Likelihood

The likelihood is defined as follow :

$$L = \frac{\sum_{i=1}^4 (\alpha_i - \alpha_{i0})^2}{\sigma_\alpha^2} + \frac{\sum_{i=1}^4 (\theta_i - \theta_{i0})^2}{\sigma_\theta^2} + \frac{\sum_{i=1}^4 (\phi_i - \phi_{i0})^2}{\sigma_\phi^2} + \frac{\sum_{i=1}^4 (v_i - v_{i0})^2}{\sigma_v^2}$$

+  $2\lambda_X \Sigma p_x$   
+  $2\lambda_Y \Sigma p_y$   
+  $2\lambda_Z \Sigma p_z$   
+  $2\lambda_E (\Sigma E - \sqrt{s})$   
+  $2\lambda_M (M_{dj1} - M_{dj2})$

Lagrange  
Multipliers

# Kinematic Fit - W mass reconstruction (2) - Likelihood

The likelihood is defined as follow :

$$L = \frac{\sum_{i=1}^4 (\alpha_i - \alpha_{i0})^2}{\sigma_\alpha^2} + \frac{\sum_{i=1}^4 (\theta_i - \theta_{i0})^2}{\sigma_\theta^2} + \frac{\sum_{i=1}^4 (\phi_i - \phi_{i0})^2}{\sigma_\phi^2} + \frac{\sum_{i=1}^4 (v_i - v_{i0})^2}{\sigma_v^2}$$
$$+ 2\lambda_X \Sigma p_x$$
$$+ 2\lambda_Y \Sigma p_y$$
$$+ 2\lambda_Z \Sigma p_z$$
$$+ 2\lambda_E (\Sigma E - \sqrt{s})$$
$$+ 2\lambda_M (M_{dj1} - M_{dj2})$$

constraints  $f_i(y)$

Four-vector parametrization as function of the measured parameters :

- $p_x = \alpha E_0 v \sin \theta \cos \phi$
- $p_y = \alpha E_0 v \sin \theta \sin \phi$
- $p_z = \alpha E_0 v \cos \theta$
- $E = \alpha E_0$

**Advantage** = measurements independent (covariance matrix diagonal)

**Disadvantage** = non-linear constraints, derivatives more complicated

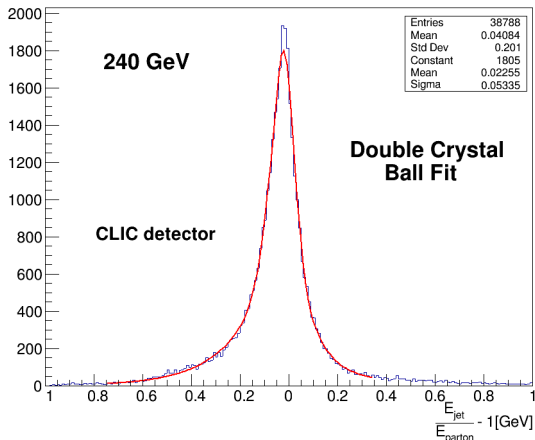
# Kinematic fit - W mass reconstruction (3) - Covariance matrix

No correlation between parameters  $\rightarrow$  diagonal matrix.

$$V^{-1} = \begin{pmatrix} \sigma_{\alpha}^2 & 0 & 0 & 0 \\ 0 & \sigma_{\theta}^2 & 0 & 0 \\ 0 & 0 & \sigma_{\phi}^2 & 0 \\ 0 & 0 & 0 & \sigma_v^2 \end{pmatrix}$$

$\sigma$  determined by fit:

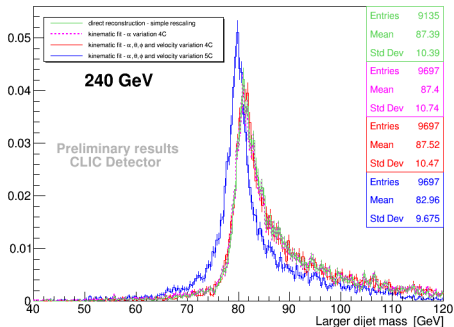
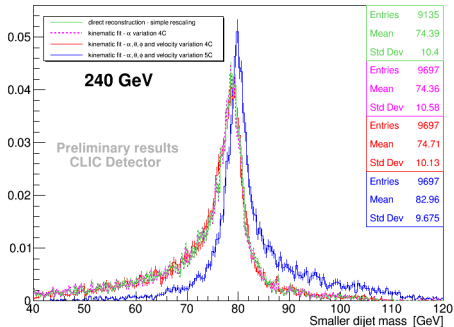
- $\sigma_{\alpha} : \frac{E_{jets}}{E_{partons}} - 1$
- $\sigma_{\theta} : \theta_{genjets} - \theta_{recojets}$
- $\sigma_{\phi} : \phi_{genjets} - \phi_{recojets}$
- $\sigma_v : \frac{p}{E}_{genjets} - \frac{p}{E}_{recojets}$



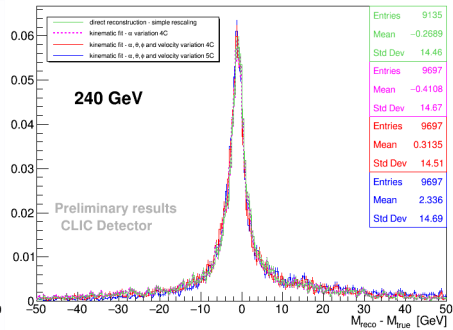
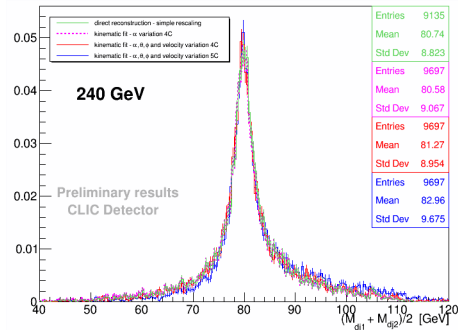
## Resume

- Before fit : jets four-vector
- Kinematic fit : computation of  $\Delta y$ , the correction to apply on parameters in order to fulfil constraints taking into account their uncertainties.
- Fit output :
  - corrected jets four-vector
  - $W$  mass given by the mass equality constraint

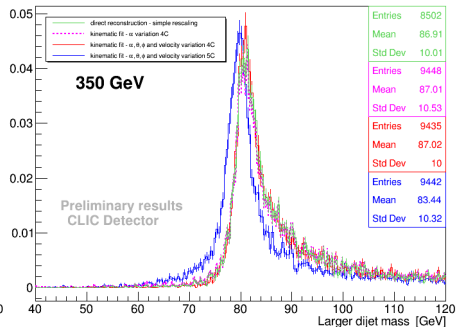
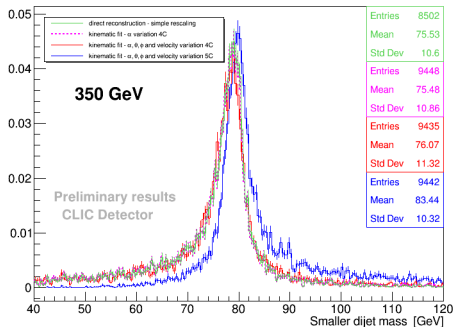
# Kinematic fit - Results 240 GeV (1)



# Kinematic fit - Results 240 GeV (2)

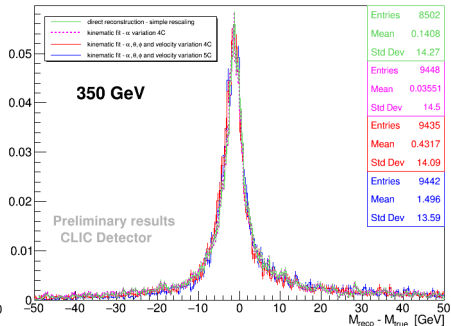
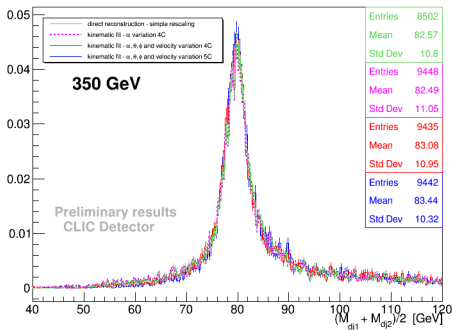


# Kinematic fit - Results 350 GeV (1)

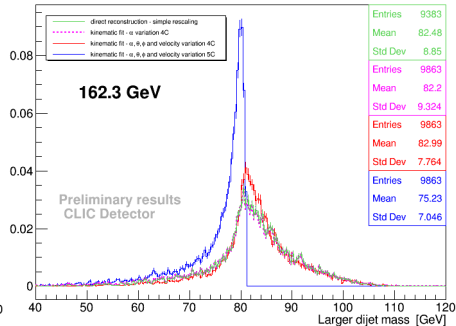
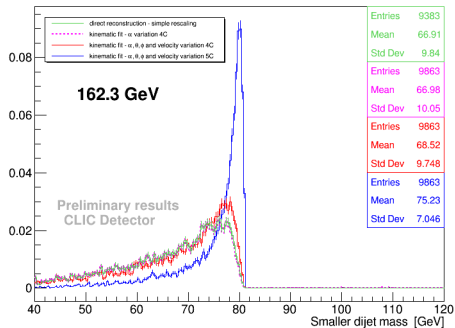




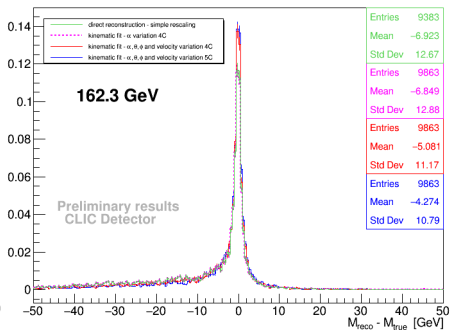
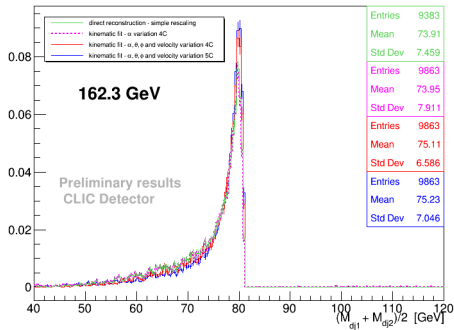
# Kinematic fit - Results 350 GeV (2)



# Kinematic fit - Results 162.3 GeV (1)



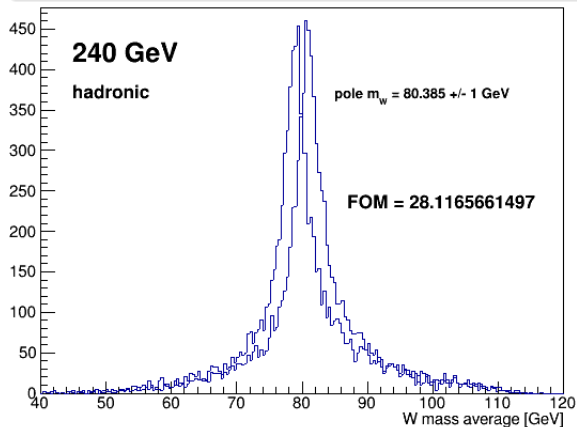
# Kinematic fit - Results 162.3 GeV (2)



# W mass measurement - Figure Of Merit (1)

## The W mass...

... is determined by comparison of the distribution with templates generated for  $M_W \pm 1 \text{ GeV}$ . The figure of merit (FOM) is used to estimate the statistical uncertainty of  $M_W$ .

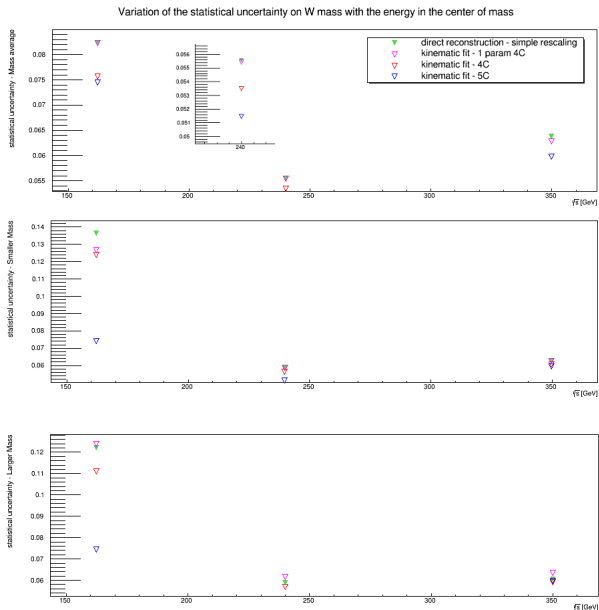


FOM computed like  
binned max. likelihood

$$FOM = \Delta M_W \frac{\sum (b_{79} + b_{81})}{\sum \frac{(b_{79} - b_{81})^2}{b_{79} + b_{81}}}$$

$$\sigma_{m_W, stat} = \frac{\sqrt{FOM}}{\sqrt{N_{event}}}$$

# W mass measurement - Figure Of Merit (2)



10 000  
events

# Conclusion and Outlook

- Kinematic fit for the hadronic channel study is fully developed (4C and 5C fit)
- Improvement of  $W$  mass reconstruction for 240 and 350 GeV.
- The 5C fit at 162.3 GeV shows better  $W$  mass reconstruction but only the off-shell mass is well reconstructed. At this energy only the 4C fit will be used.

Next step : 2C fit for the semi-leptonic channel. The neutrino introduces unmeasured parameters to the fit.

Thanks for your attention

# BACK-UP

# Kinematic fit - Mathematics development (1)

Taylor development at first order :

$$f(y') \sim f_i(y^*) + \sum_{i=1}^4 \frac{\partial f_i}{\partial y_i} (\Delta y_i - \Delta y_i^*) \sim 0 \quad (1)$$

With vector notation and  $B = \frac{\partial f}{\partial \vec{y}}$ , this equation can be written

$$\vec{f}^* + B(\Delta \vec{y} - \Delta \vec{y}^*) \sim 0 \quad (2)$$

or

$$B\Delta \vec{y} - \vec{c} = 0 \quad \text{with} \quad \vec{c} = B\Delta \vec{y}^* - \vec{f}^* \quad (3)$$

Finally, the equation (1) becomes :

$$L = \Delta \vec{y}^T V^{-1} \Delta \vec{y} + 2\lambda^T (B\Delta \vec{y} - \vec{c}) \quad (4)$$

which is minimal if  $\frac{\partial L}{\partial \vec{y}} = 0$  and  $\frac{\partial L}{\partial \lambda} = 0$ .



## Kinematic fit - Mathematics development (2)

According to the equation (4), the equations to solve are :

$$\frac{\partial L}{\partial y} = V^{-1} \Delta y + B^T \lambda = 0 \quad (5)$$

$$\frac{\partial L}{\partial \lambda} = B \Delta y - \vec{c} = 0 \quad (6)$$

With matrix notation this system becomes :

$$\begin{pmatrix} V^{-1} & B^T \\ B & 0 \end{pmatrix} \begin{pmatrix} \Delta y \\ \lambda \end{pmatrix} = \begin{pmatrix} 0 \\ \vec{c} \end{pmatrix} \quad (7)$$

then,

$$\begin{pmatrix} \Delta y \\ \lambda \end{pmatrix} = \begin{pmatrix} V^{-1} & B^T \\ B & 0 \end{pmatrix}^{-1} \begin{pmatrix} 0 \\ \vec{c} \end{pmatrix} \quad (8)$$

The tuned parameters  $\alpha$ ,  $\theta$ ,  $\phi$  and  $v$  which are used to determined the fitted four-vector of each jets, can be computed with the  $\Delta y$  from equation (8)

## Kinematic fit - Mathematics development (3)

$$B = \frac{\partial f}{\partial y} = \begin{pmatrix} \frac{\partial \Sigma p_x}{\partial \alpha} & \frac{\partial \Sigma p_x}{\partial v} & \frac{\partial \Sigma p_x}{\partial \phi} & \frac{\partial p_x}{\partial \theta} \\ \frac{\partial \Sigma p_y}{\partial \alpha} & \frac{\partial \Sigma p_y}{\partial v} & \frac{\partial \Sigma p_y}{\partial \phi} & \frac{\partial p_y}{\partial \theta} \\ \frac{\partial \Sigma p_z}{\partial \alpha} & \frac{\partial \Sigma p_z}{\partial v} & \frac{\partial \Sigma p_z}{\partial \phi} & \frac{\partial p_z}{\partial \theta} \\ \frac{\partial(\Sigma E - \sqrt{s})}{\partial \alpha} & \frac{\partial(\Sigma E - \sqrt{s})}{\partial v} & \frac{\partial(\Sigma E - \sqrt{s})}{\partial \phi} & \frac{\partial(\Sigma E - \sqrt{s})}{\partial \theta} \end{pmatrix} \quad (9)$$

As the constraints depend directly on the four-vector components  $P = (\vec{p}, E)$ , each matrix term can be simplified with a derivative chain :

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial P} \frac{\partial P}{\partial y} \quad \text{with} \quad f = \Sigma p_i \quad (10)$$