## Benchmarking Status and Goals

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## Full MC Detector Simulation and Event Reconstruction

### Full MC Detector Simulation and Event Reconstruction of $e^+e^- \rightarrow ZH \rightarrow \mu^+\mu^- X$ by Norm Graf

 $\sqrt{s} = 350 \ GeV \qquad L = 500 \ fb^{-1} \qquad \text{Backgrounds:} \qquad e^+e^- \to ZZ^* \to \mu^+\mu^-X, \quad |\cos\theta_{\mu}| < 0.8$  $\gamma\gamma \to e^+e^- \qquad \text{(overlay)}$  $\gamma\gamma \to \mu^+\mu^- \qquad \text{(overlay)}$  $\gamma\gamma \to \text{hadrons} \qquad \text{(overlay)}$ 

Detector response of latest baseline SiD is simulated with GEANT4

Digitization simulated using GEANT4 hits as input (level of detail varies from one subsystem to the next: ccd, si  $\mu$ -strip, calorimeters)

Digitized hits are fed to clustering algorithms which create tracker hits or calorimeter clusters

Isolated MIP clusters in EM, Had, &  $\mu$  calorimeters identify muons and seed track finding in si  $\mu$ -strip.

Full MC Detector Simulation and Event Reconstruction of

 $e^+e^- \rightarrow ZH \rightarrow \mu^+\mu^- X$ by Norm Graf

 $\sqrt{s} = 350 \, GeV$   $L = 500 \, fb^{-1}$ 



#### Old FASTMC study:



## **Tracker Performance Studies**

### SPS1a Selectron Mass Measurement at 1 TeV B. Schumm et al. SDMAR01: $a = 2.1 \times 10^{-5}$ $\frac{\delta p_t}{p_t^2} = a \oplus \frac{b}{p_t \sin \theta}$



Instead of using a fixed detector model, one use simple parameterization of tracker momentum resolution to rapidly vary momentum resolution:













# $M_{\mu\mu}$ Distributions for NN>0.95 for signal and background summed



 $a = 2 \times 10^{-5} \qquad \frac{\delta p_t}{p_t^2} = a \oplus \frac{b}{p_t \sin \theta}$  $b = 1 \times 10^{-3} \qquad p_t^2 = a \oplus \frac{b}{p_t \sin \theta}$ 







## **Calorimeter Performance Studies**

New simple study of  $\Delta M_{W,Z}$  versus  $E_{W,Z}$  &  $\Delta E_{jet}$  using FASTMC  $e^-\gamma \rightarrow v_e W^- \rightarrow v_e \overline{u} d$  $v_e H \rightarrow v_e Z \rightarrow v_e u \overline{u}$ 

No resolution loss from jet-finding, neutrinos, or particles outside fid. vol.

Assume energy dependence 
$$\frac{\Delta E_{jet}}{E_{jet}} = \frac{\alpha}{\sqrt{E_{jet}}} \oplus \beta$$





Use rms of central 90% core to define  $\alpha_{_{90}}$  :

$$\frac{(\Delta E_{jet})_{90}}{E_{jet}} = \frac{\alpha_{90}}{\sqrt{E_{jet}}}$$



Error on  $BR(H \rightarrow WW^*)$  from measurement of  $e^+e^- \rightarrow ZH \rightarrow q\bar{q}WW^* \rightarrow q\bar{q}q\bar{q}l\nu$  at  $\sqrt{s} = 360$  GeV, L=500 fb<sup>-1</sup> J.-C. Brient, LC-PHSM-2004-001





 $e^+e^- \rightarrow \tilde{\chi}_1^+ \tilde{\chi}_1^- \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^0 W^+ W^- \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^0 qqqq$ 



 $e^+e^- \rightarrow \tilde{\chi}_1^+ \tilde{\chi}_1^- \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^0 W^+ W^- \rightarrow \tilde{\chi}_1^0 \tilde{\chi}_1^0 qqqq$ 



Latest Results on  $e^+e^- \rightarrow ZHH \rightarrow q\overline{q}b\overline{b}b\overline{b}$ 



## OLD Neural Net NN<sub>ZHH</sub>

- Use signal and background events that pass preselection to train  $NN_{ZHH}$
- Use the following variables in the ZHH neural net:

## Old definition $\chi^2_{ZHH}$

- Force charged and neutral objects into 6 jets
- Loop over 45 jet-pair combinations & minimize  $\chi^2_{ZHH}$

$$\chi^{2}_{ZHH} = \chi^{2}_{ZHH\_ZHHmass} + \sum_{j=3}^{6} \frac{(NNbtag_{j} - 1)^{2}}{\sigma^{2}_{NNbtag}}$$
$$\chi^{2}_{ZHH\_ZHHmass} = \chi^{2}_{ZHH\_HHmass} + \frac{(M_{12} - M_{Z})^{2}}{\sigma^{2}_{M_{Z}}}$$
$$\chi^{2}_{ZHH\_HHmass} = \frac{(M_{34} - M_{H})^{2}}{\sigma^{2}_{M_{H}}} + \frac{(M_{56} - M_{H})^{2}}{\sigma^{2}_{M_{H}}}$$

 $M_{ij}$  = Mass for jet-pair combination *ij NNbtag*<sub>i</sub> = btag neural net variable for jet j New approach: Instead of variables such as  $\chi^2_{ZHH}$ , which contain kinematic info for 1 of 45 combinations, feed neural net all jet pair masses where jets are ordered according to jet btag neural net value (jet 1 is the most b-like, jet 2 is 2nd most b-like, etc. )



#### Require

$$\sum_{j=1}^{6} NN_{btag}(j) > 3.5$$



Jet pair masses where jets are ordered according to jet btag neural net value (jet 1 is the most b-like, jet 2 is 2nd most b-like, etc.) Require  $\sum_{j=1}^{6} NN_{btag}(j) > 3.5$ ZHH



Jet pair masses where jets are ordered according to jet btag neural net value

(jet 1 is the most b-like, jet 2 is 2nd most b-like, etc.) Require  $\sum_{j=1}^{6} NN_{btag}(j) > 3.5$  $t\overline{t}$ 







w/o gluon rad





with gluon rad



Final state QCD problem may be solved with a more sophisticated jet algorithm and better b/c tagging. Note that we currently force recon particles into 6 jets, which may not be best approach in presence of hard gluon radiation. Better b/c tagging, including flavor tagging, can reduce combinatorics and provide b/c weighted jet energy corrections.



## Benchmarking Goals

1) To go beyond  $e^+e^- \rightarrow ZH \rightarrow \mu^+\mu^-X$  with full MC simulation and reconstruction we need to output PFA results in Reconstructed Particle LCIO format. Haiwen Zhao is working on this.

2) Once we have a PFA algorithm intefaced to Reconstructed Particle LCIO we will do simple analyses with full MC simulation and reconstruction that require jet reconstruction such as the Higgs mass measurement in the 4 jet channel  $e^+e^- \rightarrow ZH \rightarrow qqbb$ 

3) Begin detector optimization studies

4) Compare full and fast MC and improve fast MC

5) Continue fast MC physics studies







