# Mass Composition

Fabio Convenga & Igor Vaiman, Denise Boncioli, Carmelo Evoli, Sergio Petrera, Francesco Salamida







HISTORY

Caterina, Francesco, Sergio Fraction Fit (extensive study of the frequentist approach)

Fabio, Francesco, Sergio, Denise Fraction Fit SD / (frequentist and bayesian approach, fit with Gumbel/templates) Igor, Carmelo Fraction Fit FD / (bayesian approach, test with new likelihoods with Gumbel/templates, fit with more then five elements)

United efforts to have GAPs and new public code release

# INTRODUCTION

- Frequentist approach compatible with Bayes for **FD**
- Bayes approach used for SD (and for FD) in the next analysis
- The v3r99p3 NN data (hybrids calibrated) are used from https://www.auger.unam.mx/AugerWiki/XmaxMomentsDNN
- **Distributions** built from the released data are **corrected** for the composition bias and the hadronic-interaction model bias, due to the hybrid calibration





- Estimate a resolution of the method in a similar way done for other methods (universality, GAP2019\_035), by using the sample of golden hybrids events, **is not possible.**
- Equivalently, SD-NN distributions turn out to be narrower than Gumbel distributions without detector effects.
- Therefore, we proceeded to explore the behavior of the fraction fit without making any correction for the resolution



# Comparison with FD fractions



- SD and FD fractions overplotted
- Although SD follows the trend of FD, the fit for SD is not optimal:
  - The reduced chi square (as well as the p-value) suggests that the fit does not fit the data well
  - Due to the fact that the SD-NN distributions are tighter then FD ones, the number of masses that can be fit is lower.



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- Introducing a simple broadening of the NN data distributions to see the effects on the fit quality and results
- A Gaussian smearing was introduced for SD-NN X<sub>max</sub> data distributions



### FIT SIGMA TOGETHER WITH FRACTIONS

- Incorporated smearing directly into the fitting process.
- Added sigma as a parameter in the fit for dynamic optimization.
- Gaussian convolution of Xmax distributions.
- The result shows, as expected, better agreement with the FD data
- The sigma appears to have a decreasing trend with energy





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## SIMULATIONS (early studies)







Fabio Convenga (INFN & UNIVAQ)

#### ALTERNATIVE LIKELIHOOD FOR TEMPLATE MASS COMPOSITION ANALYSIS

- Motivation: the Poissonian likelihood does not account for fluctuations in Monte-Carlo templates  $\rightarrow$  it might lead to biased results under some conditions, e.g.
  - Finer binning in *X<sub>max</sub>*
  - Multidimensional analysis (e.g. FD and DNN  $X_{max}$  distributions fit together)
- **Methods**: the problem is known in HE physics, there are several approaches, e.g. Argüelles, Schneider, and Yuan 2019 (ASY)
- Conclusions
  - The standard Poissonian likelihood performs well under a wide variety of conditions
  - The ASY results are harder to interpret
  - For a simple mass composition analysis, the switch is probably not worth the effort, but might be useful for higher-dimensional case

#### ALTERNATIVE LIKELIHOOD FOR TEMPLATE MASS COMPOSITION ANALYSIS

Image: comparison between the standard Poissonian likelihood and ASY likelihood in the context of Bayesian analysis of mass composition



# FRACTION FITS OF THE FD XMAX DISTRIBUTIONS USING 26 NUCLEI

**Motivation**: there are claims that the 4 standard primaries do not represent the whole composition well; do we gain anything by including more primaries?

**Method**: Gumbel parametrization and Bayesian inference scale easily to 26 primaries (standard isotopes or H to Fe); however, the results are trickier to interpret, as almost all individual fractions are consistent with zero.

## **Conclusions**:

- All primaries indeed are not easily represented by a group of just 4 primaries
- Inference with 26 (and possibly more) primaries is possible, although it requires more attention to MCMC convergence
- Proton upper limits might also be affected by the number of primaries in the analysis, but this requires further study

# Cumulative fractions as an alternative representation of the results



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## FRACTION FITS OF THE FD XMAX DISTRIBUTIONS USING 26 NUCLEI

Full 15 groups 10 groups 1.0 0.8 0.6  $f(Z>Z_0)$  $f(Z>Z_0)$  $(Z > Z_0)$ 0.4 0.2 Posterior median Posterior median Posterior median [0.05. 0.95] credible interval [0.05, 0.95] credible interval [0.05, 0.95] credible interval 0.0 Ar Ca Ar Ca Mq Ar Ca Be Mg Mg  $Z_0$ Z<sub>0</sub>  $Z_0$ Posterior median Posterior median 0.35 Posterior median [0.05, 0.95] credible interval [0.05, 0.95] credible interval [0.05, 0.95] credible interval 0.30 0.25 0.20 N N -0.15 0.10 0.05 0.00 Mg Be Be Н Be N F Ar Ca V Fe Н N Mg P Ar Ca V Fe н N F Mg Ρ Ar Ca V Fe F Z Ζ Ζ

Progressive grouping guided by making the groups as uncorrelated as possible in the posterior distribution

lg(E/eV) ∈[19.6, ∞)

# CONCLUSION

- An attempt of using SD-NN  $X_{max}$  distributions for mass fractions fitting has been done
- The SD-NN  $X_{max}$  distributions appear narrower than the FD  $X_{max}$  corrected for acceptance and resolution.
- The SD fit result is **not satisfactory**, nevertheless, the trend follows the FD one.
- It is important to emphasize that, to correctly perform the fit:
  - CORSIKA+Offline simulations should be fed into NN;
  - The single mass distributions in output from NN should be parametrized to produce the appropriate model p.d.f
  - Currently these kinds of simulations are partly available (more information needed) and are being studied
- ASY likelihood could be useful for higher-dimensional case
- Inference with 26 (and possibly more) primaries is possible, although it requires more attention to MCMC convergence