

GENIE/Professor framework for neutrino data global fit

A first application: global fit of CC 0π datasets

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on behalf of GENIE collaboration



University of Liverpool

19 April 2017
IPPP/NuStec

Outline

- Introduction
- Genie status vs recent datasets
- Tuning mechanism
- Tuning results
- Conclusions

Thanks to

IPPP Associateship award

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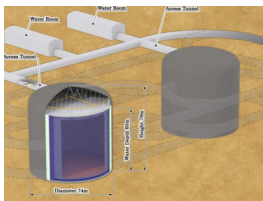
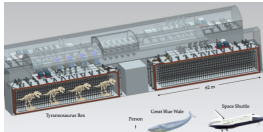
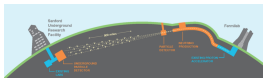
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Why care about 0π ?

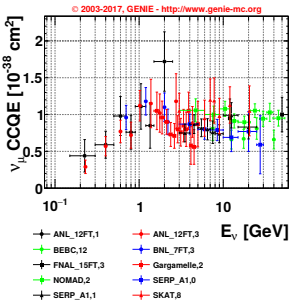
- We want to study neutrinos
 - flavour and mixing
 - Lepton CP violation
- Oscillation experiments
 - T2k, NOvA
 - DUNE, HyperK
 - Beam energy \sim few GeV
- CC 0π is the dominant reaction
- Two body reaction
 - Ideal for ν energy estimation ...
 - ...on free nucleons



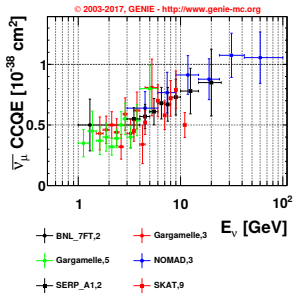
CC Quasi-Elastic - 0π on single nucleons

- Theoretically understood
- Well constrained by experimental information
- Electron scattering
- Neutron β decay
- Experiments on Hydrogen / Deuterium

Neutrinos

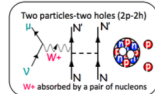
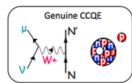


Antineutrinos

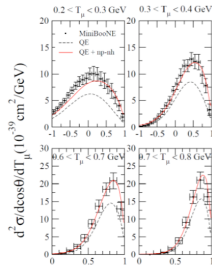


CC Meson Exchange Current - 0π on heavy nuclei

- On higher A nuclei things are complicated
- CCQE is not enough to describe data
 - MiniBooNE
- MEC is required
 - nucleons interactions
 - 2p-2h
 - *np-nh*
 - > 20% effect
 - On carbon



MiniBooNE data

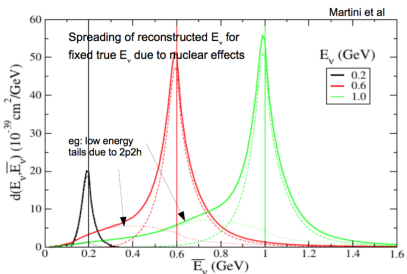


[Martini et al. PRC 84 055502 (2011)]

Effect of MEC on energy reconstruction

- CCQE is a 2-body reaction
 - E_ν depends is just a function of lepton momentum and angle
- MEC is not a 2-body reaction
 - low energy tails in reconstructed energy distributions
- MEC also relevant for CP searches
 - np-nh is different for $\nu/\bar{\nu}$

⇒ MEC is important to achieve precise measurements

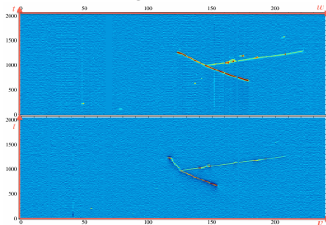


Martini et al.

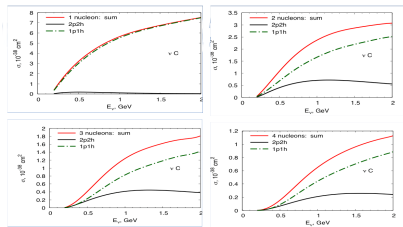
Search for 2p-2h

- Characteristic events
 - 2 back-to-back nucleons
- Nuclear effect can change observed topology
 - migrations in the number of observed protons
- future LarTPCs (or gas TPCs) important role
 - Disentangle FSI from MEC
 - CC 0 π samples proton multiplicity
- Important dataset that will "soon" be available

ArgoNEUT



[Phys.Rev. D90 (2014) 1, 012008]



[Ulrich Mosel]

MC generators

- What can we do as generator people?
- Comparing different data and models
 - Being quantitative
 - ⇒ highlight tensions
 - Call for experiments: we need full covariance matrices
 - feedback for experiments
 - ⇒ drive the format of cross section releases
 - ⇒ hint toward key measurements
- Global fits
 - Model ⇒ Cross sections is not analytic

What is the status of Genie in all of this?

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What is the status of Genie in all of this?



Genie - Models for 0π

- Default - G00_00a
 - No MEC
 - CCQE process is LwlynSmith Model
 - Dipole Axial Form Factor - Depending on $M_A = 0.99 \text{ GeV}$
 - Nuclear model: Fermi Gas Model - Bodek, Ritchie

- Default + MEC - G16_01b
 - with **Empirical MEC**
 - CCQE process is LwlynSmith Model
 - Dipole Axial Form Factor - Depending on $M_A = 0.99 \text{ GeV}$
 - Nuclear model: Fermi Gas Model - Bodek, Ritchie

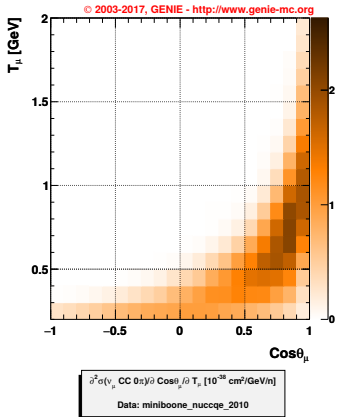
- Nieves, Simo, Vacas Model - G16_02a
 - **Theory motivated MEC**
 - CCQE process is Nieves
 - Dipole Axial Form Factor - Depending on $M_A = 0.99 \text{ GeV}$
 - Nuclear model: Local Fermi Gas Model

- G17_02a (not presented in this talk) - G17_02a
 - with Z-Expansion for Axial form factor
 - Get rid of M_A



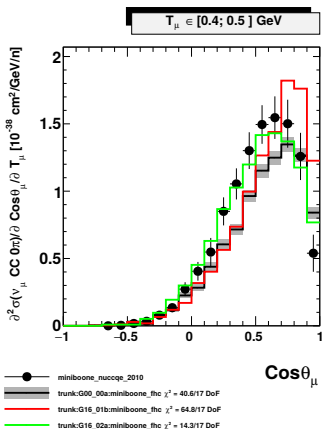
MiniBooNE CCQE

- Both ν and $\bar{\nu}$
- Double differential cross section
- flux integrated
- No correlations
- Preferred model is Nieves Model (G16_02a)
 - excellent agreement for ν
 - $\chi^2 = 101/137$ DoF
- worse for $\bar{\nu}$
 - $\chi^2 = 176/78$ DoF



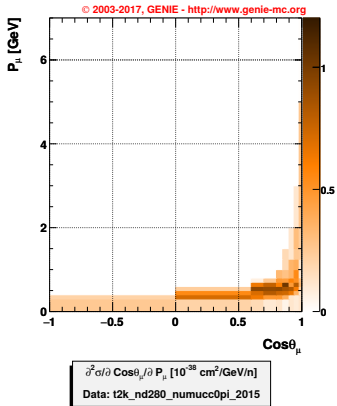
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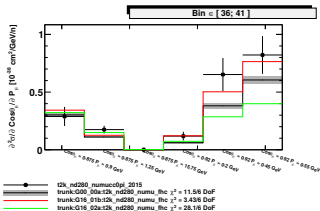
T2K ND280 0 π

- Double differential cross section
- flux integrated
- Fully correlated
- Tensions between datasets
- Preferred model is G16_01b
 - $\chi^2 = 135/67$ DoF
- all models look reasonable "By eye" estimation
 - correlation is complicated
 - We can't ignore it!



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GENIE

- New Models
 - MEC models
 - Empirical
 - Nieves Simo Vacas
 - Better CCQE model
 - Nieves
 - ...
 - Nuclear models
- Multiple combinations
 - Need to check the balance between each component



will have a tuning!

- New Models

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will have a tuning!

The Comparisons

The GENIE suite contains a package devoted to comparing GENIE predictions against publicly released datasets.

- Crucial technology for **new GENIE global fit** to neutrino scattering data
- Provides the opportunity to improve and develop GENIE models
- All sorts of data
 - **Modern Neutrino Cross Section measurement**
 - nuclear targets
 - typically flux-integrated differential cross-sections
 - MiniBooNE, T2K, MINERvA
 - **Historical Neutrino Cross Section Measurement**
 - Bubble chamber experiment
 - Measurements of neutrino-induced **hadronic system characteristics**

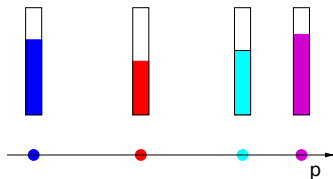
Professor

- <http://professor.hepforge.org>
- Numerical assistant
- Developed for ATLAS experiment
- $I(p)$ used instead of a full MC
 - ① MC runs subset of param space
 - ② sample bin's behaviour
 - ③ Parametrization $I(p)$
 - Polynomial interpolation
 - Repeat for each bin
- a parameterization $I_j(p)$ for each bin
- Minimize according to $\bar{I}(p)$
- ~ 15 parameters
- Special thanks to H. Schulz
 - based here in Durham



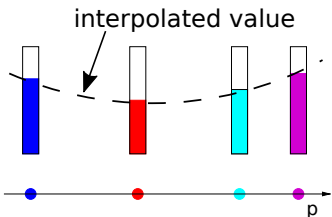
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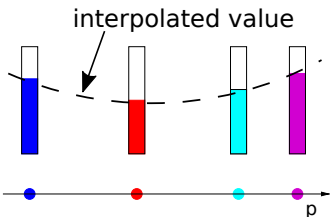
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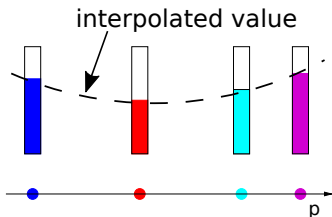
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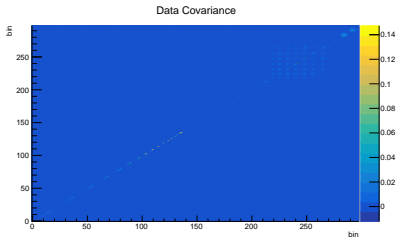
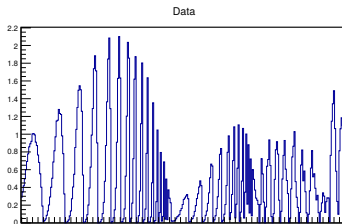


Advantages

- Highly parallelizable
 - independent from the minimization
- All kind of parameters can be tuned
 - Not only reweight-able
- Advanced system
 - Take into account correlations
 - weights specific for each bin and/or dataset
 - Proper treatment while handling multiple datasets
 - Restrict the fit to particular subsets
 - Nuisance parameters can be inserted
 - proper treatment for datasets without correlations (MiniBooNE)
- Reliable minimization algorithm
 - based on Minuit

Datasets - 298 data points

- MiniBooNE ν_μ CCQE
 - 2D histogram
 - 137 points
- MiniBooNE $\bar{\nu}_\mu$ CCQE
 - 2D histogram
 - 78 points
- T2K ND280 0π (2015)
 - irregular 2D histogram
 - 67 points
- MINERvA ν_μ CCQE
 - 1D histogram
 - 8 points
- MINERvA $\bar{\nu}_\mu$ CCQE
 - 1D histogram
 - 8 points



Model and parameters

- Default + Empirical MEC
- G16_01b in the new naming scheme
- Parameters:
 - $QEL-M_A \in [0.7; 1.8]$ GeV - Default value is 0.99 GeV
 - $QEL-CC-XSecScale \in [0.8; 1.2]$ - Default value is 1
 - $RES-CC-XSecScale \in [0.5; 1.5]$ - Default value is 1
 - $MEC-FracCCQE \in [0; 1]$ - Default value is 0.45
 - $FSI-PionMFP-Scale \in [0.6; 1.4]$ - Default value is 1
 - $FSI-PionAbs-Scale \in [0.4; 1.6]$ - Default value is 1
- No priors on the parameters
 - Considering on M_A

Professor Output

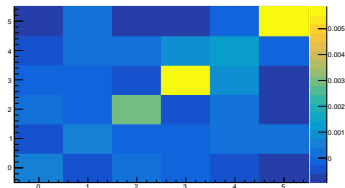
- Parameters best fit

- 0 M_A
- 1 QEL-CC-XSecScale
- 2 RES-CC-XSecScale
- 3 MEC-FracCCQE
- 4 FSI-PionMFP-Scale
- 5 FSI-PionAbs-Scale

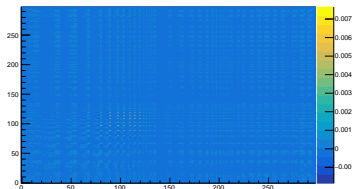
- Prediction covariance

- due to the propagation of the param. covariance
- So far not used
- Tool to propagate systematic parameters

Parameter Covariance



Prediction Covariance



Sheer results

Parameter	Best fit	Nominal
M_A (GeV/ c^2)	1.21 ± 0.02	0.99
QEL-CC-XSecScale	0.95 ± 0.02	1
RES-CC-XSecScale	1.02 ± 0.05	1
MEC-FracCCQE	0.53 ± 0.08	0.45
FSI-PionMFP-Scale	0.75 ± 0.04	1
FSI-PionAbs-Scale	0.87 ± 0.07	1

- M_A is reasonably low
- Scaling factors for single processes are compatible with nominal values
- You can find the complete comparisons plots in the indico page

Single datasets

Datasets were fitted separately

Parameter	Neutrino fit	Anti-neutrino fit	Global fit
M_A (GeV/ c^2)	1.17 ± 0.02	1.26 ± 0.03	1.21 ± 0.02
QEL-CC-XSecScale	0.93 ± 0.01	0.97 ± 0.02	0.95 ± 0.02
RES-CC-XSecScale	0.86 ± 0.05	0.98 ± 0.09	1.02 ± 0.05
MEC-FracCCQE	0.85 ± 0.03	0.7 ± 0.1	0.53 ± 0.08
FSI-PionMFP-Scale	0.87 ± 0.02	1.39 ± 0.03	0.75 ± 0.04
FSI-PionAbs-Scale	1.51 ± 0.03	0.7 ± 0.1	0.87 ± 0.07

Fit Results	Neutrino fit	Anti-neutrino fit	Global fit	Nominal Values
Miniboone $\nu_\mu \chi^2$	152 / 137	171 / 137	138 / 137	441 / 137
MiniBooNE $\bar{\nu}_\mu \chi^2$	60 / 78	32.4 / 78	36.2 / 78	50.4 / 78
T2K χ^2	237 / 67	276 / 67	252 / 67	135 / 67
MINERvA $\nu_\mu \chi^2$	6.11 / 8	8.07 / 8	7.79 / 8	17.5 / 8
MINERvA $\bar{\nu}_\mu \chi^2$	8.19 / 8	11.5 / 8	5.7 / 8	6.23 / 8
Global dataset χ^2	463 / 292	499 / 292	440 / 292	650 / 298

- M_A and cross section scale factors are in good agreement
- FSI parameters are not
- The agreement with data is reasonable
 - Better than original model

T2K effect on the fit

- T2K ND280 data are complicated
 - Tensions
 - Correlations \Rightarrow anti-intuitive
- T2K ND280 data can not even be fitted by their own with the current model

$$\Rightarrow \chi^2 = 127/61$$

- T2K fit results are not compatible with other dataset

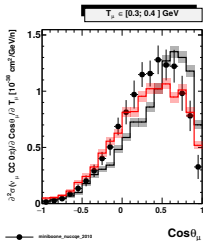
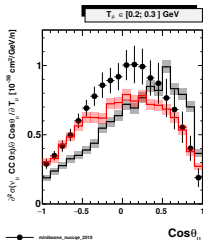
$$\Rightarrow \chi^2 = 1023/137 \text{ vs MiniBooNE } \nu_\mu \text{ CCQE}$$

$$\Rightarrow \chi^2 = 1567/292 \text{ vs whole fitted dataset}$$

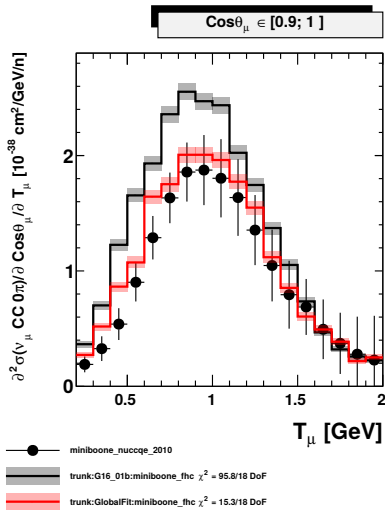
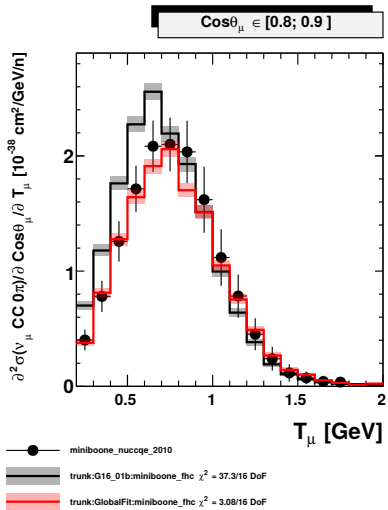
- global fit can suffer from this
- Effect is clear
 - discrepancy in low momentum muons
 - $T_\mu < 400 \text{ MeV}$
- No reason to remove this dataset from the fit
 - Their effort on the error estimation should be praised

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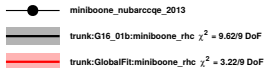
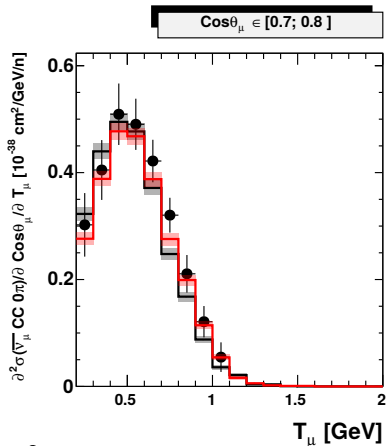
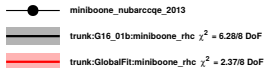
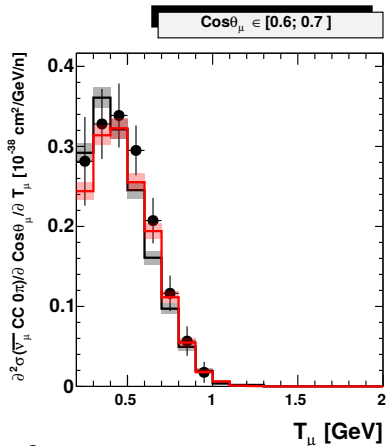


Best fit plots

Best fit - MiniBooNE ν_μ CCQE

Fit has a big impact

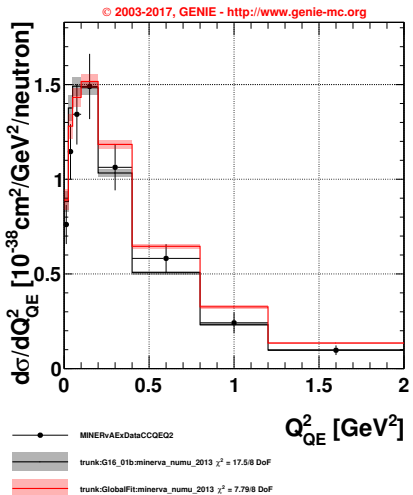
Best fit plots

Best fit - MiniBooNE $\bar{\nu}_\mu$ CCQE

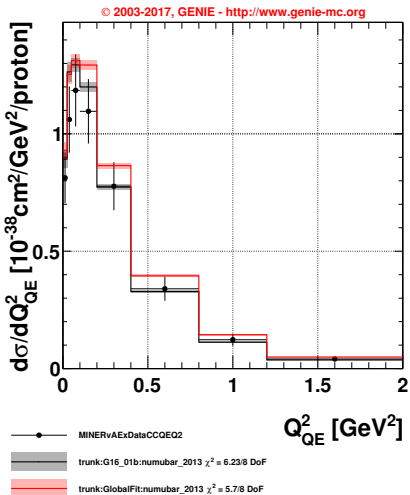
Improvement not really necessary in this case

Best fit - MINERvA

Neutrinos



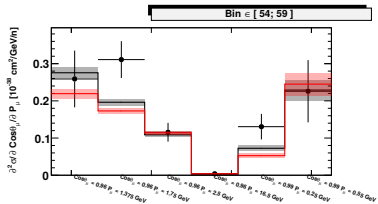
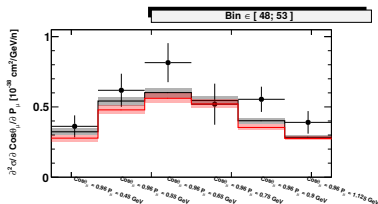
Antineutrinos



⇒ "Eye evaluation" would prefer default model

Best fit - T2K ND280

- agreement with t2k has worsened
 - not surprising
- ⇒ it happened also with models
- χ^2 : 135 → 252 / 67 DoF



Next steps

- More datasets:
 - Bubble chamber CCQE data
 - Why not fitting M_A all together?
 - Data are in our database (see introduction)
 - inclusive cross sections
 - avoid fit results to go in not physical regions
- Fit of new models
 - Full Nieves Model - G16_02b
 - ...
- Find a way to estimate correlations for MiniBooNE
 - Nuisance parameters

Conclusion

- We are renewing Genie
 - new models
 - Easy comparisons with Cross section Data
 - ⇒ Quantitative
 - Deployed in Genie v3 and v4
- We have a very powerful fitting machinery
 - Proved to work
 - This is not an exercise
- We hope that these tools will improve theory / experiments collaboration



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LIV.DAT

Liverpool Big Data Science Centre for Doctoral Training

Open Positions in LIV.DAT

Managing, analysing and interpreting large, complex datasets and high rates of data flow is a growing challenge for many areas of science and industry. However, very little targeted training is provided internationally, and in particular in the UK to address a growing skills gap in this area.

The University of Liverpool with Liverpool John Moores University and international partners are offering 25 fully funded 4-year PhD studentships in Big Data Science starting from 1 October 2017. This projects will address R&D challenges in astrophysics, nuclear particle and accelerator physics and Inverse Monte Carlo studies, Deep Learning and HPC, as well as Data Analysis.

Each Student will benefit from a wide ranging training offered by the CDIT. Studentships to industry partners of a minimum 6 months' duration will form an important element of this unique training program.

Application deadline: 30th April 2017

Contact and further detail:
Prof Dr Carsten P. Muech
Head of Department
Department of Physics
University of Liverpool
L69 7ZJ Liverpool, UK
C.P.Muech@liverpool.ac.uk

www.livdat.org

UNIVERSITY OF LIVERPOOL

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Science & Technology Facilities Council

- New Position in Liverpool
 - Join a big neutrino group
- Position has to be filled in 10 days
- Big data science
 - SBND
 - Argon Tune for GENIE

Backup slides

Single datasets - MiniBooNE

Parameter	Miniboone ν_μ fit	MiniBooNE $\bar{\nu}_\mu$	MiniBooNE Global fit
M_A (GeV/ c^2)	1.10 ± 0.03	1.25 ± 0.03	1.17 ± 0.02
QEL-CC-XSecScale	1.12 ± 0.02	0.99 ± 0.03	1.05 ± 0.02
RES-CC-XSecScale	0.69 ± 0.06	0.9 ± 0.1	0.68 ± 0.06
MEC-FracCCQE	0.43 ± 0.07	0.63 ± 0.03	0.33 ± 0.08
FSI-PionMFP-Scale	0.95 ± 0.03	1.39 ± 0.04	0.99 ± 0.06
FSI-PionAbs-Scale	1.17 ± 0.07	0.8 ± 0.2	1.08 ± 0.09

Fit Results	Miniboone ν_μ fit	MiniBooNE $\bar{\nu}_\mu$ fit	MiniBooNE Global fit	Global χ^2
Miniboone ν_μ χ^2	121 / 131	153 / 137	124 / 137	
MiniBooNE $\bar{\nu}_\mu$ χ^2	60.4 / 78	29 / 72	40.3 / 78	
T2K χ^2	298 / 67	279 / 67	271 / 67	
MINERvA ν_μ χ^2	11.4 / 8	10.6 / 8	9.17 / 8	
MINERvA $\bar{\nu}_\mu$ χ^2	16.3 / 8	11.7 / 8	10.4 / 8	
Global dataset χ^2	507 / 292	483 / 292	455 / 292	

Single datasets - T2K ND280 ν_μ 0π

Parameter	T2K fit	T2K fit - no corr	T2K fit with priors
M_A (GeV/ c^2)	0.75 ± 0.04	1.03 ± 0.13	
QEL-CC-XSecScale	0.90 ± 0.02	1.11 ± 0.04	
RES-CC-XSecScale	1.2 ± 0.1	1.500 ± 0.001	
MEC-FracCCQE	0.36 ± 0.09	0.3 ± 0.1	
FSI-PionMFP-Scale	0.81 ± 0.05	1.1 ± 0.1	
FSI-PionAbs-Scale	1.1 ± 0.1	1.54 ± 0.08	

Fit Results	T2K fit	T2K fit - no corr
Miniboone ν_μ χ^2	1023 / 137	/ 137
MiniBooNE $\bar{\nu}_\mu$ χ^2	367 / 78	/ 72
T2K χ^2	127 / 61	/ 61
MINERvA ν_μ χ^2	26.1 / 8	/ 8
MINERvA $\bar{\nu}_\mu$ χ^2	23.5 / 8	/ 8
Global dataset χ^2	1567 / 292	/ 292

Single datasets - MINERvA

Parameter	MINERvA ν_μ fit	MINERvA $\bar{\nu}_\mu$	MINERvA Global fit
M_A (GeV/ c^2)	1.16 ± 0.10	1.2 ± 0.1	1.20 ± 0.08
QEL-CC-XSecScale	0.81 ± 0.04	0.83 ± 0.03	0.84 ± 0.04
RES-CC-XSecScale	1.2 ± 0.2	0.7 ± 0.3	1.1 ± 0.1
MEC-FracCCQE	0.7 ± 0.2	0.07 ± 0.08	0.6 ± 0.1
FSI-PionMFP-Scale	1.3 ± 0.1	0.9 ± 0.3	1.2 ± 0.2
FSI-PionAbs-Scale	0.8 ± 0.2	1.2 ± 0.3	0.8 ± 0.3

Fit Results	MINERvA ν_μ fit	MINERvA $\bar{\nu}_\mu$ fit	MINERvA Global fit
Miniboone ν_μ χ^2	/ 131	/ 137	220 / 137
MiniBooNE $\bar{\nu}_\mu$ χ^2	/ 78	/ 72	97.2 / 78
T2K χ^2	/ 67	/ 67	184 / 67
MINERvA ν_μ χ^2	/ 2	/ 8	6.49 / 8
MINERvA $\bar{\nu}_\mu$ χ^2	/ 8	/ 2	3.26 / 8
Global dataset χ^2	/ 292	/ 292	511 / 292