

# Performance of the Unified Monte Carlo Method of Data Evaluation



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# OVERVIEW

- Introduction: Monte Carlo method**
- UMC formulation**
- UMC sampling: Brute Force, Metropolis**
  
- Toy models: Linear**
- UMC convergence**
  
- Toy models: Ratio data**
- Log transformation**
  
- Conclusions and outlook**



# MONTE CARLO METHOD

D.L. Smith, “Covariance Matrices for Nuclear Cross-Sections Derived from Nuclear Model Calculations”.

Report **ANL/NDM-159**, Argonne National Laboratory, 2005

$$\overline{\sigma}_i = \frac{1}{K} \sum_{k=1}^K \sigma_{ik} \quad V_{ij} = \overline{\sigma_i \sigma_j} - \overline{\sigma}_i \times \overline{\sigma}_j \quad i,j$$

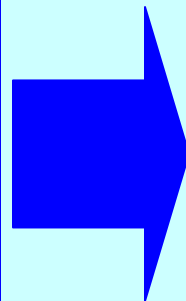
- energy indexes

Monte Carlo calculation of covariance first tested by A. Koning

Monte Carlo prior

+

**GANDR** (GLS)



D.W. Muir, **GANDR** project (IAEA),  
Online at [www-nds.iaea.org/gandr/](http://www-nds.iaea.org/gandr/).

A. Trkov and R. Capote, “Cross-Section Covariance Data”, Th-232 evaluation for ENDF/B-VII.0 (MAT=9040 MF=1 MT=451); Pa-231 and Pa-233 evaluations for ENDF/B-VII.0 (MAT=9133 and 9137 MF=1 MT=451), National Nuclear Data Center, BNL (<http://www.nndc.bnl.gov>), 15 December 2006.



# Merging of Model Calculated and Experimental Results ... More

## (a.k.a. "Auto Repair Shop" Solution)

$\bar{f}$  = collection of functions that related  $\bar{\sigma}$  to the data,  
i.e., given  $\bar{\sigma}$  we can calculate the equivalent to  $\bar{y}$

①

$\bar{\sigma}_E$  = model calculated cross sections       $\bar{V}_E$  = corresponding cov. matrix

$\therefore p(\bar{\sigma} | E, C)$  = probability density function for  $\bar{\sigma}$  given experimental data "E" and calculated model-calculated prior results "C"

$$p(\bar{\sigma} | E, C) = C \exp \left\{ \left(-\frac{1}{2}\right) [\bar{y}_E - \bar{f}(\bar{\sigma})]^T \bar{V}_E^{-1} [\bar{y}_E - \bar{f}(\bar{\sigma})] + \left(-\frac{1}{2}\right) (\bar{\sigma} - \bar{\sigma}_C)^T \bar{V}_C^{-1} (\bar{\sigma} - \bar{\sigma}_C) \right\}$$

$$\bar{\sigma} = \sigma_1, \sigma_2, \dots, \sigma_i, \dots, \sigma_N$$

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# UNIFIED MONTE CARLO (UMC)

D.L. Smith, "A Unified Monte Carlo Approach to Fast Neutron Cross Section Data Evaluation," *Proceedings of the 8th International Topical Meeting on Nuclear Applications and Utilization of Accelerators*, Pocatello, July 29 – August 2, 2007, p. 736.

## BAYES THEOREM & PRINCIPLE OF MAXIMUM ENTROPY

$$p(\boldsymbol{\sigma}) = C \times \mathcal{L}(\mathbf{y}_E, \mathbf{V}_E \mid \boldsymbol{\sigma}) \times p_0(\boldsymbol{\sigma} \mid \boldsymbol{\sigma}_C, \mathbf{V}_C)$$

$$p_0(\boldsymbol{\sigma} \mid \boldsymbol{\sigma}_C, \mathbf{V}_C) \sim \exp\{-(1/2)[(\boldsymbol{\sigma}-\boldsymbol{\sigma}_C)^T \cdot (\mathbf{V}_C)^{-1} \cdot (\boldsymbol{\sigma}-\boldsymbol{\sigma}_C)]\}$$

$$\mathcal{L}(\mathbf{y}_E, \mathbf{V}_E \mid \boldsymbol{\sigma}) \sim \exp\{-(1/2)[(\mathbf{y}-\mathbf{y}_E)^T \cdot (\mathbf{V}_E)^{-1} \cdot (\mathbf{y}-\mathbf{y}_E)]\}, \mathbf{y}=f(\boldsymbol{\sigma})$$

$\mathbf{y}_E, \mathbf{V}_E$ : measured quantities with "n" elements

$\mathbf{y}_C, \mathbf{V}_C$ : calculated using nuclear models with "m" elements

**UMC based on  $p(\boldsymbol{\sigma})$ , GLS on the peak of the distribution**



# UMC sampling schemes

**BF approach:** A set of independent  $\{\boldsymbol{\sigma}\}$

$$\bar{\sigma}_{Ck} - \psi [(\mathbf{V}_C)_{ii}]^{1/2} \leq \sigma_{ik} \leq \bar{\sigma}_{Ck} + \psi [(\mathbf{V}_C)_{ii}]^{1/2}$$

$$\sigma_{ik} = \bar{\sigma}_{Ck} + (2\gamma - 1) \psi [(\mathbf{V}_C)_{ii}]^{1/2}$$

**METROPOLIS approach:** An stochastic Markov chain  $\{\boldsymbol{\sigma}\}$  distributed following  $p(\boldsymbol{\sigma})$

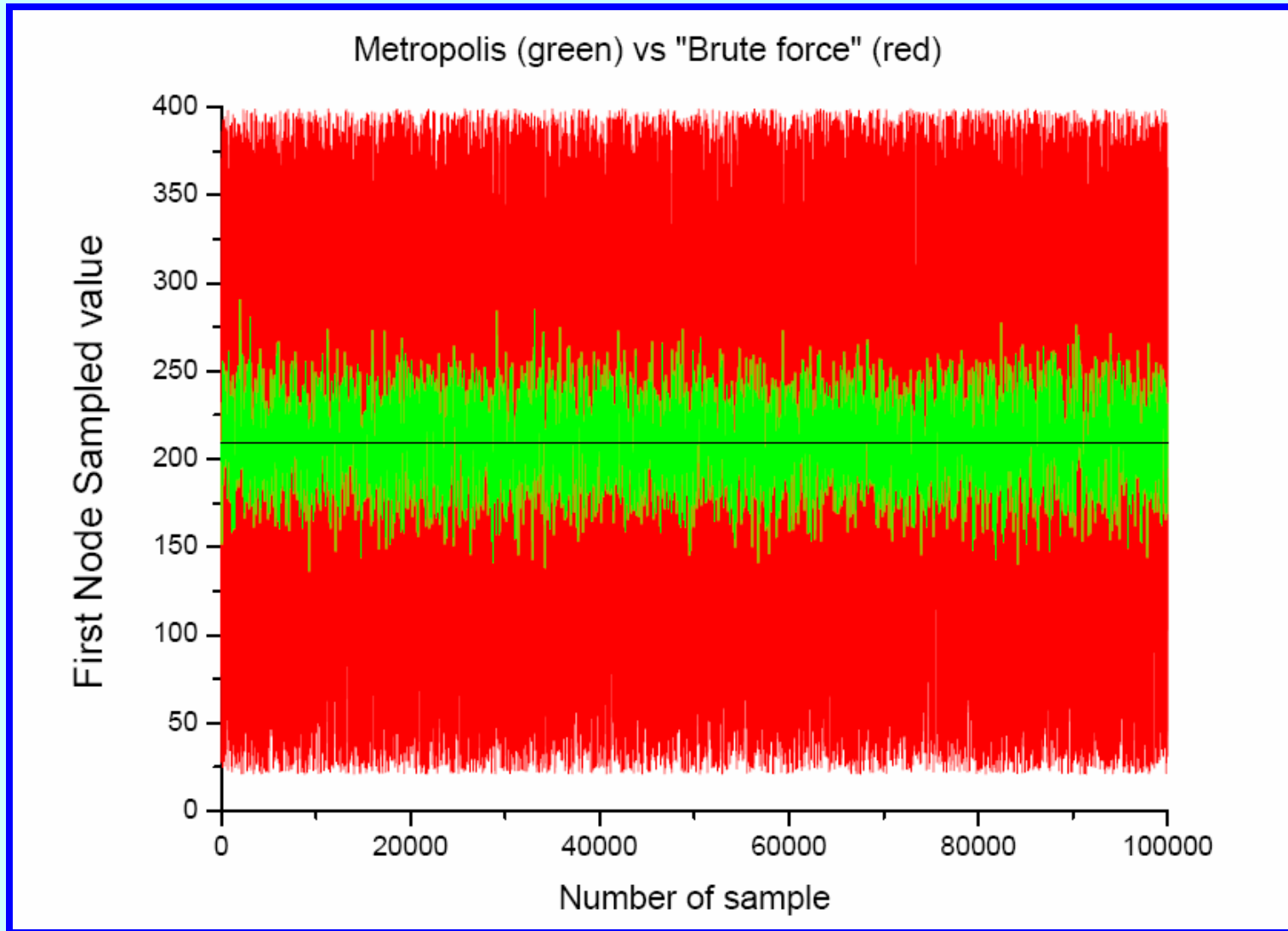
$$\boldsymbol{\sigma}' = \boldsymbol{\sigma}(t) + (2\gamma - 1) \delta [(\mathbf{V}_C)_{ii}]^{1/2}, \text{ being } \boldsymbol{\sigma}(t=0) = \bar{\boldsymbol{\sigma}}_C$$

If  $p(\boldsymbol{\sigma}') > \gamma p(\boldsymbol{\sigma}(t))$  then  $\boldsymbol{\sigma}(t+1) = \boldsymbol{\sigma}'$ ; else  $\boldsymbol{\sigma}(t+1) = \boldsymbol{\sigma}(t)$

$$p_0(\boldsymbol{\sigma} | \boldsymbol{\sigma}_C, \mathbf{V}_C) \sim \exp\{-(1/2)[(\boldsymbol{\sigma} - \boldsymbol{\sigma}_C)^T \cdot (\mathbf{V}_C)^{-1} \cdot (\boldsymbol{\sigma} - \boldsymbol{\sigma}_C)]\}$$



# SPREAD OF SAMPLED VALUES



# LINEAR MODEL: $y = \sigma$

<u>Node</u>	<u>Model</u>	<u>Expt</u>	$\sigma_E(\%)$	<u>Expt / Model</u>	<u>Comments</u>
1	210	205.6	30.0%	0.979	within error
2	40	39.3	2.0%	0.983	within error
3	20	26	30.0%	1.300	marginal
4	10	14	5.0%	1.400	discrepant
5	7	6.7	3.0%	0.957	marginal
6	6	8.5	50.0%	1.417	within BIG error
7	6				No exp.data

$\text{covexp}(3,1) = \text{covexp}(1,3) = 0.2 \sigma_E(1) \sigma_E(3)$  - weak correlation  
 $\text{covexp}(5,2) = \text{covexp}(2,5) = 0.8 \sigma_E(2) \sigma_E(5)$  - strong correlation





# MODEL DATA & CORRELATION

```
***** MODEL DATA
Pmod( 1) = 210.0000 +/- 63.0000 ( 30.0% )      Ymod( 1) = 210.0000
Pmod( 2) =  40.0000 +/- 12.0000 ( 30.0% )      Ymod( 2) =  40.0000
Pmod( 3) =  20.0000 +/-  6.0000 ( 30.0% )      Ymod( 3) =  20.0000
Pmod( 4) =  10.0000 +/-  3.0000 ( 30.0% )      Ymod( 4) =  10.0000
Pmod( 5) =   7.0000 +/-  2.1000 ( 30.0% )      Ymod( 5) =   7.0000
Pmod( 6) =   6.0000 +/-  1.8000 ( 30.0% )      Ymod( 6) =   6.0000
Pmod( 7) =   6.0000 +/-  1.8000 ( 30.0% )      Ymod( 7) =   6.0000
```

```
MODEL CORRELATION MATRIX (PRIOR):
0.1000000E+01
0.9500000E+00 0.1000000E+01
0.9000000E+00 0.9500000E+00 0.1000000E+01
0.8500000E+00 0.9000000E+00 0.9500000E+00 0.1000000E+01
0.8000000E+00 0.8500000E+00 0.9000000E+00 0.9500000E+00 0.1000000E+01
0.7500000E+00 0.8000000E+00 0.8500000E+00 0.9000000E+00 0.9500000E+00 0.1000000E+01
0.7000000E+00 0.7500000E+00 0.8000000E+00 0.8500000E+00 0.9000000E+00 0.9500000E+00 0.1000000E+01
```

**~ 95% correlation**



# LINEAR MODEL: RESULTS

## BF Calculations

$$0.5 \sigma_C < \psi < 3.5 \sigma_C$$

## Mean Values

### 30% Strong Correlations

#### Maximum Deviations from GLS For All Nodes (%)

30% Strong Correl	0.50/GLS	0.75/GLS	1.00/GLS	1.50/GLS	1.75/GLS	2.00/GLS	2.50/GLS	3.00/GLS	3.50/GLS
BF Mean Values	<7.7%	<3.2%	<0.55%	<0.45%	<1.1%	<0.77%	<1.5%	<8.5%	<7.9%

### 30% Zero Correlations

#### Maximum Deviations from GLS for All Nodes (%)

30% Zero Correl	0.50/GLS	0.75/GLS	1.00/GLS	1.50/GLS	1.75/GLS	2.00/GLS	2.50/GLS	3.00/GLS	3.50/GLS
BF Mean Values	<18%	<13%	<8.2%	<2.8%	<2.0%	<1.2%	<1.6%	<1.7%	<2.6%

### 5% Strong Correlations

#### Maximum Deviations from GLS for All Nodes (%)

5% Strong Correl	0.50/GLS	0.75/GLS	1.00/GLS	1.50/GLS	1.75/GLS	2.00/GLS	2.50/GLS	3.00/GLS	3.50/GLS
BF Mean Values	<1.7%	<1.2%	<0.68%	<0.21%	<0.07%	<0.05%	<0.10%	<0.37%	<0.34%

## METR Calculations

$$0.02 \sigma_C < \delta < 1.25 \sigma_C$$

## Mean Values

### 30% Strong Correlations

#### Maximum Deviations from GLS For All Nodes (%)

30% Strong Correl	0.02/GLS	0.05/GLS	0.10/GLS	0.15/GLS	0.25/GLS	0.50/GLS	0.75/GLS	1.00/GLS	1.25/GLS
MET Mean Values	<0.28%	<0.07%	<0.39%	<0.15%	<0.22%	<1.3%	<0.14%	<1.2%	<3.7%

### 30% Zero Correlations

#### Maximum Deviations from GLS for All Nodes (%)

30% Zero Correl	0.02/GLS	0.05/GLS	0.10/GLS	0.15/GLS	0.25/GLS	0.50/GLS	0.75/GLS	1.00/GLS	1.25/GLS
MET Mean Values	<1.5%	<3.6%	<1.5%	<2.0%	<0.75%	<1.4%	<0.42%	<0.86%	<1.5%

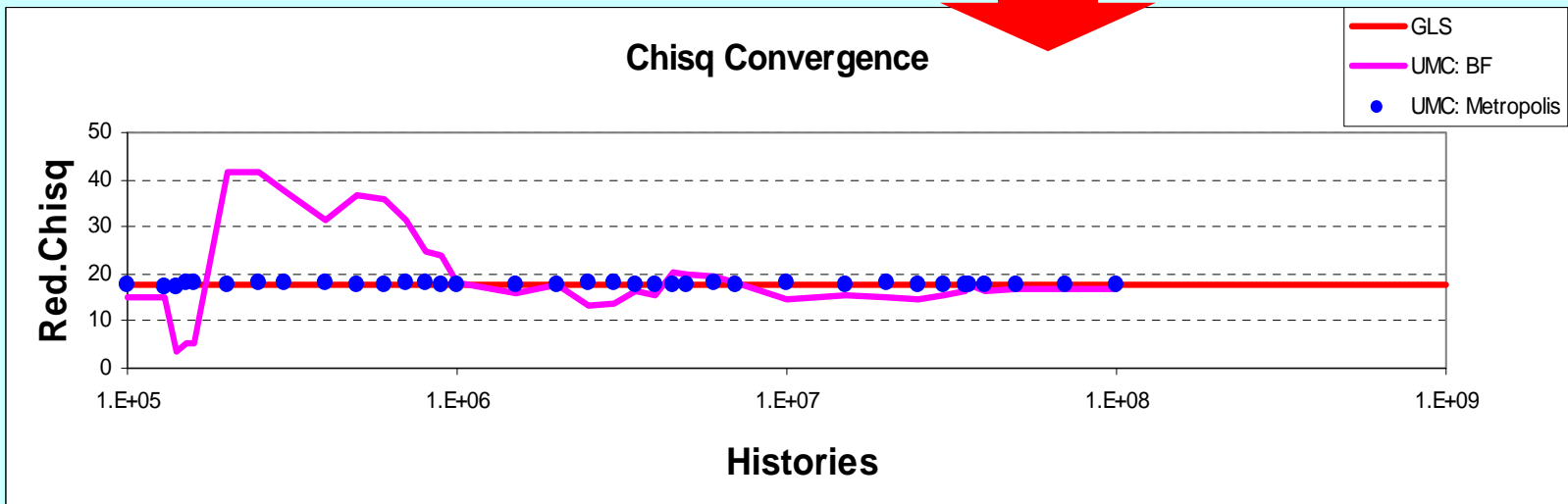
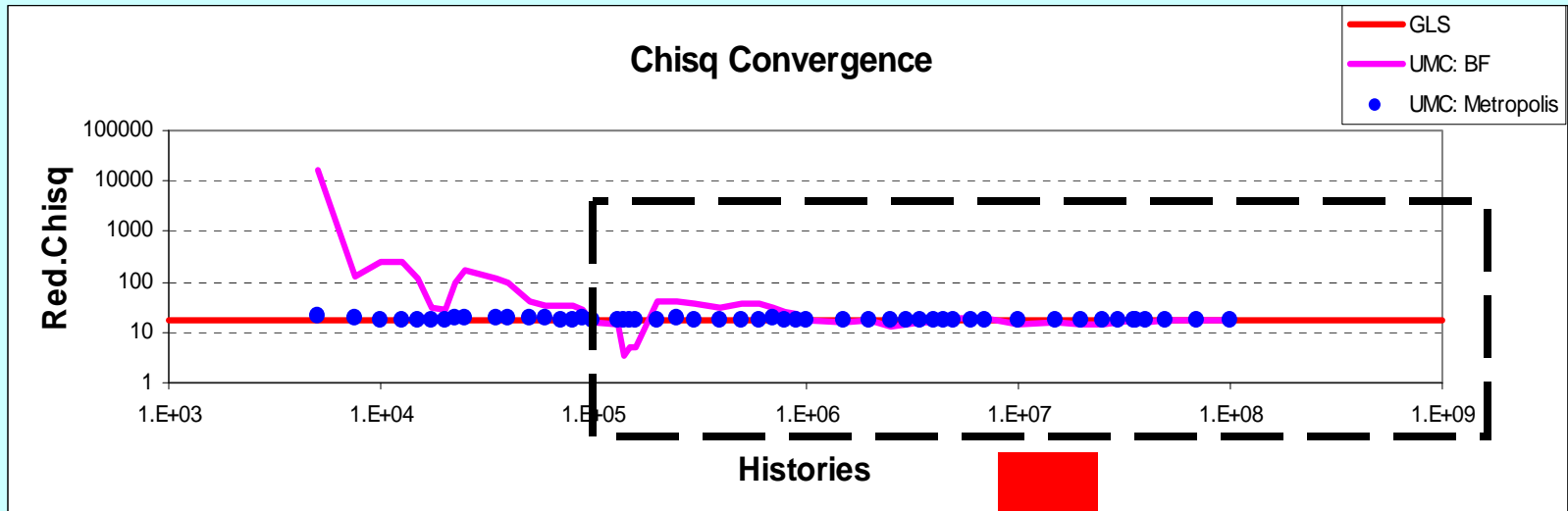
### 5% Strong Correlations

#### Maximum Deviations from GLS for All Nodes (%)

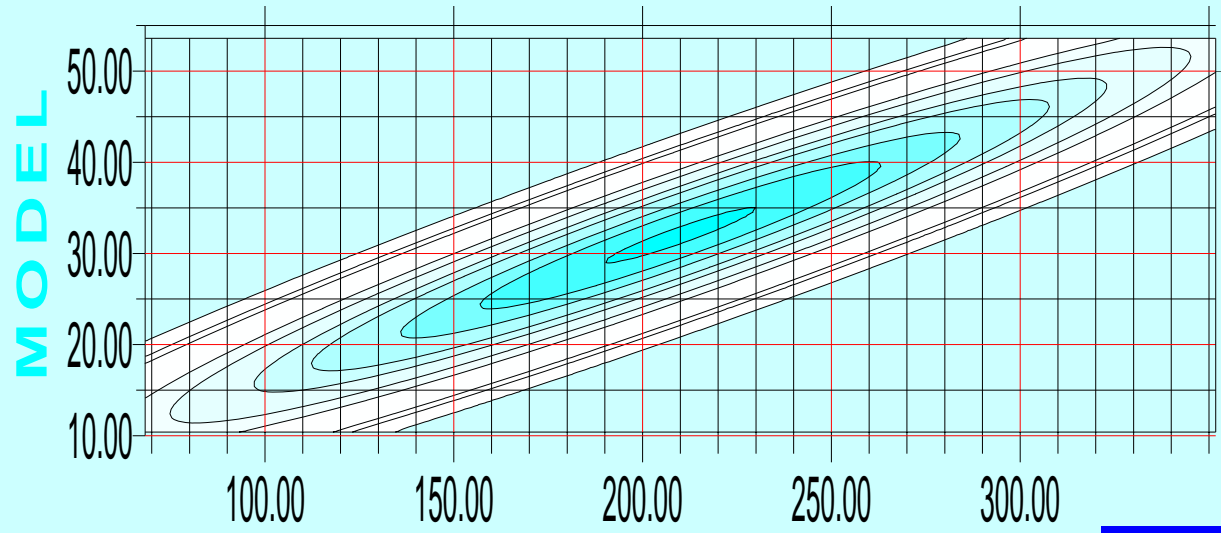
5% Strong Correl	0.02/GLS	0.05/GLS	0.10/GLS	0.15/GLS	0.25/GLS	0.50/GLS	0.75/GLS	1.00/GLS	1.25/GLS
MET Mean Values	<0.16%	<0.11%	<0.04%	<0.08%	<0.03%	<0.02%	<0.04%	<0.11%	<0.11%



# UMC convergence

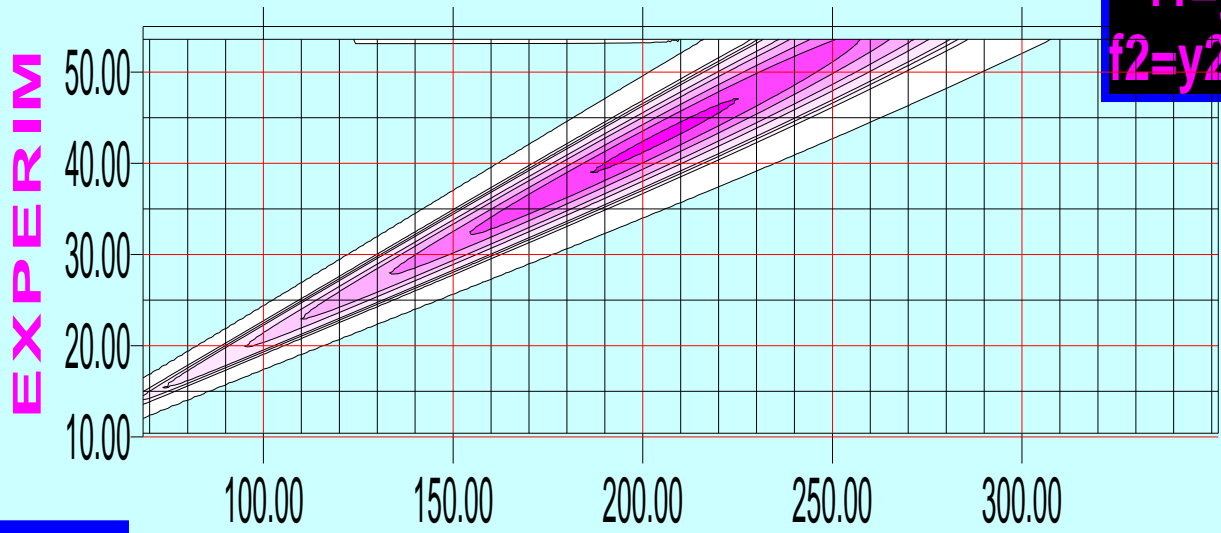


# RATIO CASE



**MODEL**  
 $y1=210 \pm 63$  (30%)  
 $y2=32 \pm 9.6$  (30%)

$Cov(1,2) = 0.95$



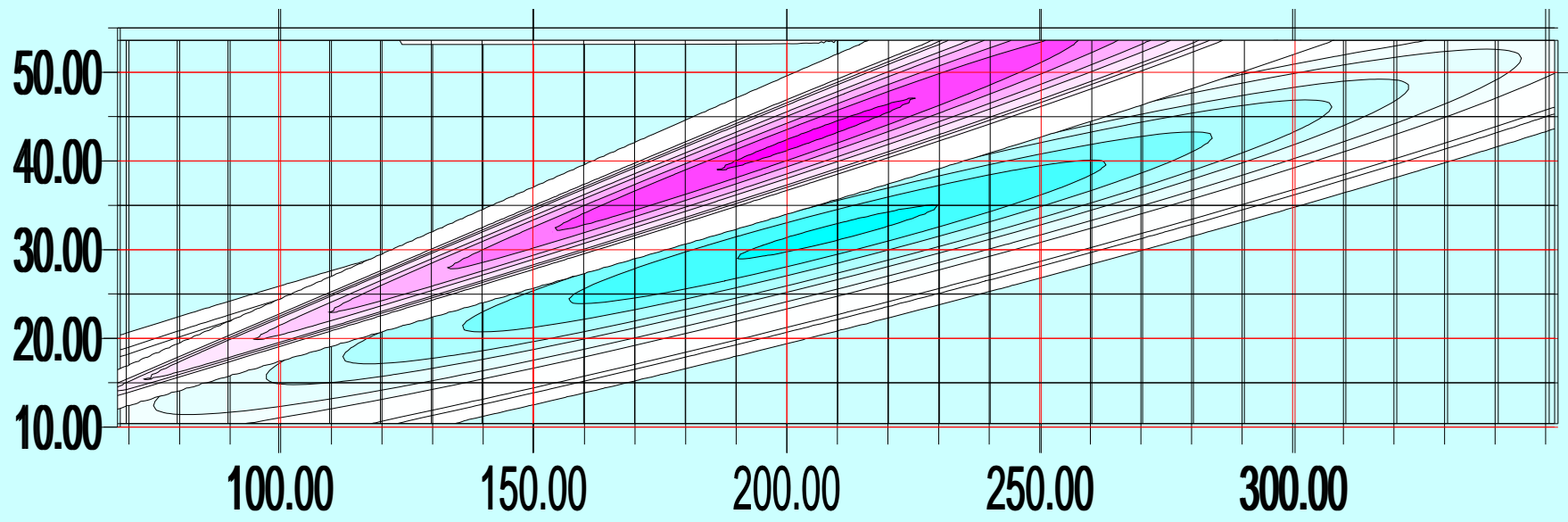
**EXPERIM**  
 $f1=y1=205.6 \pm 61.7$  (30%)  
 $f2=y2/y1=0.209 \pm 0.010$  (5%) ~ 43

$Cov(1,2) = 0.$

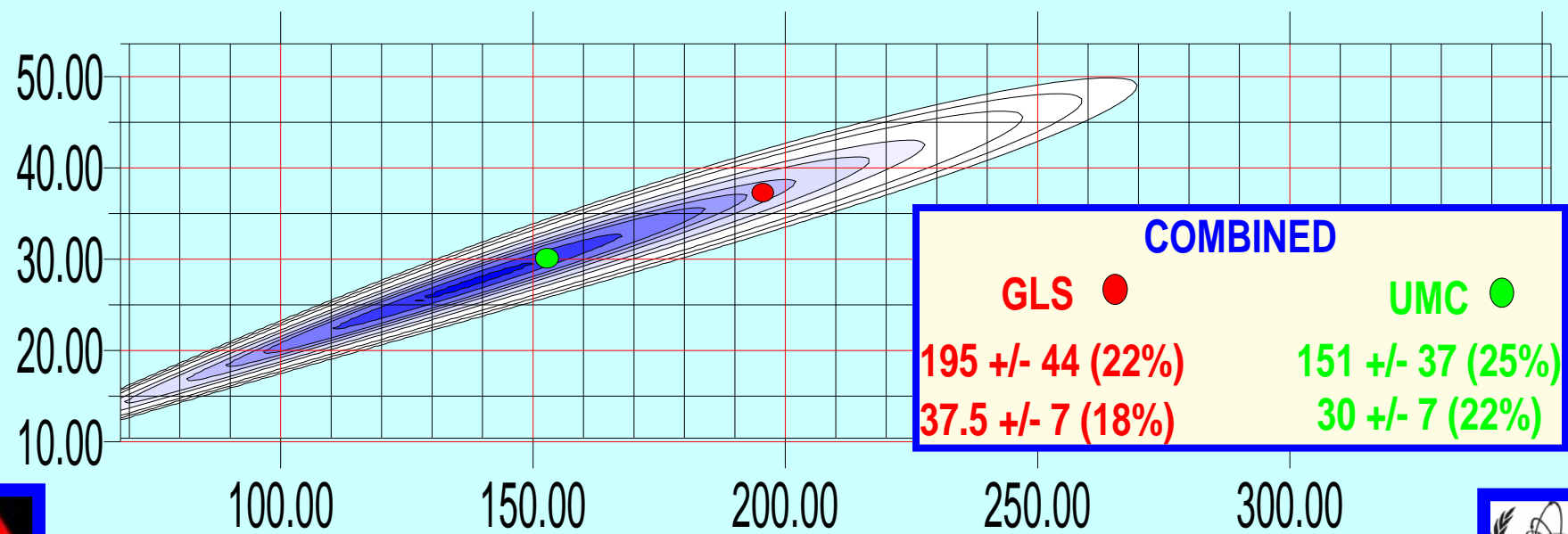


# 5% exp. ratio unc., 95% model correl.

EXPERIM



COMBINED



# GLS FAILURE: ANALYSIS

**5% exp. ratio unc.  
95% model correlation**

<u>Quantity</u>	<u>Node 1</u>	<u>Node 2</u>	<u>Ratio</u>
BF/GLS	0.7767	0.7929	1.0209
METR/GLS	0.7728	0.7891	1.0210
METR/BF	0.9950	0.9951	1.0001

**5% exp. ratio unc.  
no model correlation**

<u>Quantity</u>	<u>Node 1</u>	<u>Node 2</u>	<u>Ratio</u>
BF/GLS	1.0180	0.9795	0.9622
METR/GLS	1.0232	0.9850	0.9626
METR/BF	1.0051	1.0056	1.0004

**30% exp. ratio unc.  
95% model correlation**

<u>Quantity</u>	<u>Node 1</u>	<u>Node 2</u>	<u>Ratio</u>
BF/GLS	1.0002	1.0007	1.0005
METR/GLS	0.9995	0.9998	1.0004
METR/BF	0.9992	0.9991	0.9999



# LOG TRANSFORMATION

```
***** LOG(MODEL DATA)
Pmod( 1)= 5.3471 +/- .6000 ( 11.2% )
Pmod( 2)= 3.4657 +/- .6000 ( 17.3% )
```

```
***** LOG(MODEL FUNCTION)
Ymod( 1)= 5.3471
Ymod( 2)= -1.8814
```

```
MODEL CORRELATION MATRIX (PRIOR):
.1000000E+01
.9500000E+00 .1000000E+01
```

```
***** LOG(EXPERIMENTAL DATA)
Yexp( 1)= 5.3259 +/- .3000 ( 5.6% )
Yexp( 2)= -1.5654 +/- .0100 ( -.6% )
```

```
***** ORIGINAL MODEL DATA
Pmod( 1)= 210.0000 +/- 126.0000 ( 60.0% )
Pmod( 2)= 32.0000 +/- 19.2000 ( 60.0% )
```

```
***** ORIGINAL MODEL FUNCTION
Ymod( 1)= 210.0000
Ymod( 2)= .1524
```

```
EXPERIMENTAL CORRELATION MATRIX:
.1000000E+01
.0000000E+00 .1000000E+01
```

```
***** ORIGINAL EXPERIMENTAL DATA
Yexp( 1)= 205.6000 +/- 61.6800 ( 30.0% )
Yexp( 2)= .2090 +/- .0021 ( 1.0% )
```

## RESULTS FOR GLS METHOD (LOG TRANSFORMATION):

Mean	Sigma[%]	Red.Chisq
1.999575E+02	2.676447E+01	-1.261845E-02
4.175392E+01	2.677929E+01	1.020535E+02

## RESULTS FOR UMC Metropolis (model + exp)

Mean	Sigma[%]	Red.Chisq
1.999971E+02	2.665413E+01	-1.266861E-02
4.176194E+01	2.666949E+01	1.029021E+02

## RESULTS FOR GLS METHOD (DIRECT):

Mean	Sigma[%]	Red.Chisq
1.988118E+02	2.779634E+01	2.383451E+03
4.212220E+01	2.001335E+01	-1.662790E+01

## RESULTS FOR UMC Metropolis (DIRECT):

Mean	Sigma[%]	Red.Chisq
1.859502E+02	2.391304E+01	5.271764E+01
3.881475E+01	2.387615E+01	-3.378792E-03



# SUMMARY

- ❑ UMC is a viable tool for cross-section data evaluation
- ❑ Metropolis sampling scheme is recommended for UMC calculations
- ❑ When data values are cross sections or cross sections and integral (spectrum-averaged) cross sections, GLS and UMC are equivalent so GLS is recommended
- ❑ If ratio or other explicitly non-linear data are introduced UMC may be preferable to GLS

