## Standardizing a Renewed Fission Product Yield Library and Related Covariances

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## Motivations

- Application to depletion perturbation theory
- Recent extension (ORSEN) to TSURFER module to perform nuclear data adjustment for fixed-source problems ${ }^{1}$
- To establish methodology to generate evaluated fission product yield data with related covariances
- Is a fission product yield covariance matrix, a matrix with prescribed row/column sum?
- To establish HFIR (High Flux Isotope Reactor) as a facility relevant for nuclear data measurements
- To improve the ENDF/B-VIII. 0 fission product yield sub-library
- To consistently perform uncertainty quantification analysis for fuel decay heat, radio toxicity, burn up credit
- Consistency between (cumulative and independent) product yield and decay sub-library
- Experimental database with consistently constrained correlated data

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## Independent Fission Product Yields (IFPY)

## Definitions

Independent fission product yield $y$ from the fission of a nucleus with mass number $A_{\top}$ and atomic number $Z_{f}$

$$
I \equiv I(A, Z, M ; \vec{x}) \quad \text { with } \quad \vec{x} \equiv \vec{x}\left(A_{f}, Z_{f}, E\right)
$$

- For neutron-induced fission, $A_{f}=A_{\top}+1$ (compound nucleus undergoing fission). For spontaneous fission, $A_{f}=A_{\top}$
- For a semi-empirical model, the independent fission yield depends on a set of parameters:

$$
\begin{aligned}
\vec{x} & \equiv\left\{\vec{\mu}\left(A_{f}, Z_{f}, E\right), \vec{\lambda}\left(A_{f}, Z_{f}, E\right)\right\} \\
I & \equiv \underbrace{Y(A ; \vec{\mu})}_{\text {Sum yield }} \times \underset{\text { Fractional yield }}{F(A, Z ; \vec{\lambda})} \times \underbrace{R(A, Z, M)}_{\text {Isomeric ratio }}
\end{aligned}
$$

## Constraints

- $\Sigma_{Z} F(A, Z ; \vec{\lambda})=1 \quad \forall A$
- $\sum_{M} R(A, Z, M)=1 \quad \forall A, Z$
- $Y(A)=\sum_{Z, M} I(A, Z, M ; \vec{x}) \forall A$
- $\sum_{A, Z, M} I(A, Z, M ; \vec{x})=2$
- $\sum_{A, Z, M} A \cdot I(A, Z, M ; \vec{x})=A_{f}-\bar{v}(E)$
- $\sum_{A, Z, M} Z \cdot I(A, Z, M ; \vec{x})=Z_{f}$
- $\sum_{A} Y(A ; \vec{\mu})=2$
- $\sum_{A} A \cdot Y(A ; \vec{\mu})=A_{f}-\bar{v}(E)$
- $\sum_{A, Z, M} Z \cdot F(A, Z, M ; \vec{\lambda}) \cdot Y(A ; \vec{\mu})=Z_{f}$


## IFPY Uncertainties in ENDF/B-VIII. 0

- ENDF/B-VIII. 0 sum yield $Y_{\mathrm{E}}(A)$ calculated from one of the constraints $Y_{\mathrm{E}}(A)=\sum_{Z, M} I_{\mathrm{E}}(A, Z, M)$
- Sum yield uncertainty $\Delta Y_{\mathrm{E}}(A)$ calculated from quadratic summation $\Delta Y_{\mathrm{E}}(A)=\sqrt{\sum_{Z, M}\left[\Delta I_{\mathrm{E}}(A, Z, M)\right]^{2}}$
- ENDF/B-VIII. 0 IFPYs do not have correlations, therefore related covariance matrix is diagonal
- Strategy to generate a constrained fission product yield covariance matrix
- Set of sum yields and related uncertainties, $Y_{\mathrm{E}}(A) \pm \Delta Y_{\mathrm{E}}(A) \forall A$, was used to generate randomly sampled and constrained sets of sum yields, $Y^{k}(A) \forall A(k=1, \ldots, N)$
- Mean values $\langle Y(A)\rangle=\sum_{k=1}^{N} Y^{k}(A) / N \forall A$
- Covariance matrix $\left\langle\Delta Y(A) \Delta Y\left(A^{\prime}\right)\right\rangle=\sum_{k=1}^{N}\left(Y^{k}(A)-\langle Y(A)\rangle\right)\left(Y^{k}\left(A^{\prime}\right)-\left\langle Y\left(A^{\prime}\right)\right\rangle\right) / N \forall A, A^{\prime}$
- Consistency checks
- The set of mean values $\langle Y(A)\rangle \forall A$ is constrained since the set of $Y^{k}(A) \forall A$ is constrained for each sweep $k=1, \ldots, N$
- $\left|\langle Y(A)\rangle-Y_{\mathrm{E}}(A)\right| \ll 1 \forall A$


## Sum Yield Uncertainty and Constraints on ${ }^{235} \mathrm{U}$ (thermal)

$$
\sum_{A}\langle Y(A)\rangle=2 \text { (constraint no. 1) } \quad \sum_{A}\langle Y(A)\rangle A=A_{f}-\bar{v} \text { (constraint no. 2) } \quad \sum_{A}\langle Y(A)\rangle(1+A)=2+A_{f}-\bar{v} \text { (constraint no. 1+2) }
$$



- No meaningful differences (<0.5\%) between ENDF/B-VIII. 0 sum yields $Y_{\mathrm{E}}(A)$ and constrained $\langle Y(A)\rangle$ sampled within $Y_{\mathrm{E}}(A) \pm \Delta Y_{\mathrm{E}}(A)$
- Large reduction in the sum yield uncertainty ( $\approx-40 \%$ ) when constraints are applied to the sampled sum yields
- Rare cases where the uncertainty increased


## Sum Yield Covariance/Correlation Matrices



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## Results of the Covariance Analysis

Impact of the Constraints to the Row/Column Sums

- Covariance/correlation matrices very sparse
- Short-range correlations mainly appearing between yields at the peaks of the mass distribution
- Constraint no. 1: the results of the constrain, $\sum_{A}\langle Y(A)\rangle=2$, produces a covariance matrix having zero row/column sum
- Constraint no. 2: the constrain $\sum_{A}\langle Y(A)\rangle A=A_{f}-\bar{v}$ does not generate a prescribed row/column sum
- Constraint no. 1+2: as in constrain no. 2
- Note: A matrix with zero row/column sum is singular


## Model for the Sum Yields

- Five Gaussian model: $Y(A ; \vec{\mu})=\sum_{i=1}^{5} N_{i} \psi_{i}$
- Gaussian curves: $\psi_{i}(A)=\left(\sqrt{2 \pi} \sigma_{i}\right)^{-1} e^{-\left(A-A_{i}\right)^{2} /\left(2 \sigma_{i}^{2}\right)}$
- Symmetry conditions: $A_{1}=\left(A_{f}-\bar{v}\right) / 2, A_{4}=2 A_{1}-A_{2}, A_{5}=2 A_{1}-A_{3}$
- Symmetry conditions: $\sigma_{2}=\sigma_{4}, \sigma_{5}=\sigma_{3}, N_{4}=N_{2}, N_{5}=N_{3}, N_{3}=1-N_{2}-N_{1} / 2$
- Energy-dependent parameters: $\vec{\mu}=\left\{N_{1}, \sigma_{1}, N_{2}, A_{2}, \sigma_{2}, A_{3}, \sigma_{3}\right\}$
- $\sigma_{i}(E)=m_{i}\left(E-E_{f}\right)^{1 / 2}$ being $E=E_{n}+B_{n}$ the excitation energy and $E_{f}$ the fission barrier
- $A_{1}=\left(A_{f}-\bar{v}_{0}\right) / 2-\beta E / 2$ (energy dependence of the center)
$-A_{i>1}(E)=A_{i}\left(E_{f}\right)+\alpha\left(E-E_{f}\right)^{-1 / 2}$
$-N_{1}(E)=\sin ^{2} \theta_{1}$ with $\tan \theta_{1}=2\left(E-E_{1}\right) / \Gamma_{1}$
$-N_{2}(E)=\cos ^{2} \theta_{1} \cos ^{2} \theta_{2}$ with $\tan \theta_{2}=2\left(E-E_{2}\right) / \Gamma_{2}$
$-N_{3}(E)=(1 / 2) \sin ^{2} \theta_{1}+\cos ^{2} \theta_{1} \sin ^{2} \theta_{2}$ (equivalent to $N_{3}$ above)
- Model parameters: $m_{i=1,2,3}, \Gamma_{i=1,2}, A_{i=2,3}{ }^{2}$
- Note: the mass distribution $Y(A ; \vec{\mu})$ is normalized to 2 because of the condition on $N_{3}$

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## Fitting Sum Yield Data with a Gaussian Model (Normalized to 2)

## 

| Nonlinear least-squares (NLLS) Marquardt-Levenberg algorithm |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $m_{1}$ | $=7.89369$ |  | 0.1047 |  | (1.326 |  |
| $m_{2}$ | $=3.40107$ |  | 0.03528 |  | (1.037 |  |
| $m_{3}$ | $=2.25366$ |  | 0.05165 |  | (2.292 |  |
| $a_{2}$ | $=141.489$ | +/- | 0.1379 |  | (0.097 |  |
| $a_{3}$ | $=134.352$ |  | 0.1298 |  | (0.096 |  |
| $\Gamma_{1}$ | $=102.018$ |  | 8.371 |  | (8.205 |  |
| $\Gamma_{2}$ | $=25.2895$ |  | 0.8446 |  | (3.34\%) |  |
| Correlation matrix of the fit parameters |  |  |  |  |  | $\Gamma_{2}$ |
| $m_{1}$ | 1.000 |  |  |  |  |  |
| $m_{2}$ | -0.061 1.000 |  |  |  |  |  |
| $m_{3}$ | 0.057-0.564 | 1.000 |  |  |  |  |
| $a_{2}$ | $0.047-0.879$ | 0.685 | 1.000 |  |  |  |
| $a_{3}$ | $0.033-0.656$ | 0.760 | 0.787 | 1.000 |  |  |
| $\Gamma_{1}$ | $0.328-0.020$ | 0.106 | 0.034 | 0.024 | 1.000 |  |
| $\Gamma_{2}$ | -0.057 0.829 | -0.732 | -0.910 | -0.848 | -0.060 | 1.000 |

- Small differences in the fitted model parameters when data sets with different uncertainty are used in the fit
- The theoretical sum yield uncertainties (obtained by the correlation matrix for the fitted parameters) are smaller than the fitted data


## Fitting Sum Yield Data with Gaussian Model (Normalized to 2)



Correlation matrix


- Strong positive/negative correlations of the yields within the peaks and between the peaks
- Correlation matrix shows strong correlations for very small yields (valley and wings of the mass distribution)
- Covariance matrix has row/column with sum rule zero ${ }^{3}$
- Constraint of the sum yield produced a covariance matrix with prescribed row/column

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## Conclusions

- Numerical simulations to generate covariance matrices of constrained sum yield distributions were performed
- Monte Carlo simulations showed covariance matrices generated with sum yield distribution normalized to 2 , have zero row/column sum
- The correlations generated by applying the constraints to the sampled yields induced a reduction in the sum yield uncertainties
- When the constraints to the yield distribution are not a linear function of the distribution, the covariance matrices do not have zero row/column sum value
- The 5 Gaussian model implicitly defined to satisfy one of the constraints (normalized to 2 ) was used in a leastsquare procedure
- Calculated from the covariance matrix of 7 fitted parameters and related partial derivatives, the covariance matrix of the yield distribution obeyed the row-column sum zero rule (within numerical precision and except for very small yields)


## Appendix: TSURFER Standard Methodology

The GLLS method in TSURFER is based on minimizing

$$
\begin{equation*}
\chi^{2}=\Delta \alpha^{\top} C^{-1} \Delta \alpha+\Delta m^{\top} V^{-1} \Delta m \tag{1}
\end{equation*}
$$

Indices : $\alpha \equiv$ nuclear data, $m \equiv$ measured integral quantities, $k \equiv k(\alpha)$ calculated integral quantities

- $\Delta \alpha=\frac{\alpha^{\prime}-\alpha}{\alpha}:(n \times 1)$ vector of adjusted nuclear data with $(n \times n)$ relative covariance matrix $C$ with elements $C_{i j}=\frac{\left\langle\delta \alpha_{i} \delta \alpha_{j}\right\rangle}{\alpha_{i} \alpha_{j}}$
- $\Delta m=\frac{m^{\prime}-m}{m}:(s \times 1)$ vector of adjusted measured responses with $(s \times s)$ relative covariance matrix $V$ with elements $V_{i j}=\frac{\left\langle\delta m_{i} \delta m_{j}\right\rangle}{m_{i} m_{j}}$

Eq. (1) is minimized subject to the linearity constraint $S \Delta \alpha-\Delta k=0$ (with $S=(\partial k(\alpha) / \partial \alpha /(k / \alpha)) \equiv S(\alpha))$. To do this, one defines the Lagrangian function

$$
\begin{equation*}
\chi^{2}=\Delta \alpha^{\top} C^{-1} \Delta \alpha+\Delta m^{\top} V^{-1} \Delta m+\lambda(S \Delta \alpha-\Delta k) \tag{2}
\end{equation*}
$$

that, subject to the further constraint that adjusted responses must agree ${ }^{4}$, i.e. $k\left(\alpha^{\prime}\right)=m^{\prime}$, can be written as

$$
\begin{equation*}
\chi^{2}=\Delta \alpha^{\top} C^{-1} \Delta \alpha+\Delta m^{\top} V^{-1} \Delta m+\lambda(S \Delta \alpha-F \Delta m+d) . \tag{3}
\end{equation*}
$$

Here the diagonal matrix $F$ has matrix elements $F_{i i}=m_{i} / k_{i}$ of the ratio between measured and calculated responses and $d=\frac{k-m}{m}$ is the discrepancy vector. From the conditions $\partial \chi^{2} / \partial \Delta \alpha=0$ and $\partial \chi^{2} / \partial \Delta m=0$, one has

$$
\begin{equation*}
\Delta \alpha=-\lambda C S^{\top} \text { and } \Delta m=\lambda V F \tag{4}
\end{equation*}
$$

with $\lambda=W^{-1} d$ obtained from the uncertainty of the discrepancy vector obtained by standard error propagation

$$
\begin{equation*}
W=S C S^{\top}+F V F^{\top} \tag{5}
\end{equation*}
$$

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## Appendix : TSURFER Enhanced Methodology

For the adjustment of nuclear data (such as fission product yields) subject to certain physical constraints (slide 3), the Lagrangian function is now defined by an additional term

$$
\begin{equation*}
\chi^{2}=\Delta \alpha^{\top} C^{-1} \Delta \alpha+\Delta m^{\top} V^{-1} \Delta m+\lambda(S \Delta \alpha-F \Delta m+d)+\tilde{\lambda} h^{\top} \Delta \alpha . \tag{6}
\end{equation*}
$$

From the constraint $h^{\top} \Delta \alpha=0$ together with the conditions on the $\chi^{2}$, the adjusted nuclear data vector is

$$
\begin{equation*}
\Delta \alpha=-C\left(\lambda S^{\top}+\tilde{\lambda} h\right) \tag{7}
\end{equation*}
$$

and the adjusted measured responses vector $\Delta m$ is as defined as in Eq. (4). Inserting $\Delta \alpha, \Delta m$ in Eq. (5), the first Lagrangian multiplier $\lambda$ is

$$
\begin{equation*}
\lambda=W^{-1}(d-S h \tilde{\lambda}) \tag{8}
\end{equation*}
$$

From $h^{\top} \Delta \alpha=0$, the condition on the second Lagrangian multiplier is

$$
\begin{equation*}
h^{\top} C\left(-S^{\top} W^{-1} d+S^{\top} W^{-1} S h \tilde{\lambda}-h \tilde{\lambda}\right)=0, \tag{9}
\end{equation*}
$$

where, if $h^{\top} C=\underset{\sim}{0}$ (meaning the zero row/column sum rule is satisfied), the TSURFER algorithm follows the standard methodology (slide 12) and, if $h^{\top} C \neq 0, \tilde{\lambda}$ is

$$
\begin{equation*}
\tilde{\lambda}=\left[\left(S^{\top} W^{-1} S-1\right) h\right]^{-1} S^{\top} W^{-1} d \tag{10}
\end{equation*}
$$

where $h$ is a vector with zero and one elements.

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[^0]:    ${ }^{1}$ Previously, TSURFER was only applicable to criticality problems
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[^1]:    ${ }^{2}$ In this work $E_{f}=6.1 \mathrm{MeV}, \bar{v}=2.4, \alpha=\beta=0$, and the resonance energies $E_{1}=4.6 \mathrm{MeV}, E_{2}=17.3 \mathrm{MeV}$.
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[^2]:    ${ }^{3}$ Deviations from zero can be seen for a few rows/columns related to very small yields of magnitude $\approx 10^{-11}$.
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[^3]:    ${ }^{4}$ In TSURFER the integral quantity $k\left(\alpha^{\prime}\right)$ is calculated by first order approximation as $k\left(\alpha^{\prime}\right)=k(\alpha)+S(\alpha)\left(\alpha^{\prime}-\alpha\right)=m^{\prime}$ assuming $S(\alpha) \approx S\left(\alpha^{\prime}\right)$.
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