

# Review of Geant4 Goudsmit-Saunderson model

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# Outline

## 1 Motivation, about, not about

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- 2 Theoretical background in a nutshell
  - Goudsmit-Saunderson(GS) theory
  - Combination of GS-theory with screened Rutherford DCS
  - Kawrakow-Bielajew theory

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## Motivation:

- looking for candidate model for multiple elastic scattering of low energy ( $< 100[\text{MeV}]$ ) electrons/positrons that can be used for optimization/vectorization within the Geant-V project <sup>1</sup>
- Kawrakow-Bielajew model is investigated as the first candidate
- one version of this model is currently available in Geant4
- a different version is under implementation in Geant4 only for testing purposes

## What's this presentation about?

- the new version of the model
- the model involves sampling from pre-computed distributions stored in table over a 2D parameter grid
- some advanced sampling techniques are used in the new version that are not frequently used in Geant4 however accurate, fast sampling can be achieved by using them
- these techniques will be discussed as well

## What it's not about?

- this is not a code review !!!
- the currently available Geant4 version of the model won't be discussed or juggled
- the presentation will mainly focus on modelling of angular sampling and other parts like energy loss correction, computation of Lewis's moments are not discussed [but taken into account in the new version in a self consistent way]

Additional remark: detailed discussion of the theory itself would take more than 20 minutes so we will run through that very quickly and will focus on more practical issues. [However, information on the "theory" slides for more detailed study is available]

<sup>1</sup><http://geant.cern.ch/content/about-geant5>



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## Geant4 Goudsmit-Saunderson model is the

- Kawrakow-Bielajew model for elastic scattering

[I.Kawrakow, A.F.Bielajew, NIMB 134(1998)325-336]

- based on Goudsmit-Saunderson theory of multiple elastic scattering

[S.Goudsmit, J.L.Saunderson, PR 57(1940)24-29]

- hybrid model for (no, single) and multiple elastic scattering of  $e^-/e^+$

[A.F.Bielajew, NIMB 111(1996)195-208]

- the screened Rutherford DCS is used for elastic scattering

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Goudsmit-Saunderson angular distribution after travelling a path  $s$ :

$$F(s; \theta)_{GS} = \sum_{\ell=0}^{\infty} \frac{2\ell+1}{4\pi} \exp(-s/\lambda_{\ell}) P_{\ell}(\cos(\theta))$$

- $\frac{d\sigma}{d\Omega}$ -elastic DCS;  $\sigma = \int \frac{d\sigma}{d\Omega} d\Omega$ -elastic cross section;  $\lambda^{-1} = \mathcal{N}\sigma$ -elastic mean free path
- $f_1(\theta) = \frac{1}{\sigma} \frac{d\sigma}{d\Omega}$  is single elastic scattering distribution (note that  $2\pi f_1(\theta) = 2\pi \frac{1}{\sigma} \frac{d\sigma}{d\Omega} = p(\cos(\theta))$ )
- $f_1(\theta)$  is expressed in terms of orthogonal polynomials (Legendre series)  

$$f_1(\theta) = \sum_{\ell=0}^{\infty} \frac{2\ell+1}{4\pi} F_{\ell} P_{\ell}(\cos(\theta))$$
- $F_{\ell} = 2\pi \int_{-1}^1 f_1(\theta) P_{\ell}(\cos(\theta)) d(\cos(\theta)) = \langle P_{\ell}(\cos(\theta)) \rangle$
- $G_{\ell}$  are the  $\ell$ -th transport coefficients  $G_{\ell} \equiv 1 - F_{\ell} = 1 - \langle P_{\ell}(\cos(\theta)) \rangle$
- $\lambda_{\ell}^{-1} \equiv \frac{G_{\ell}}{\lambda} = \frac{1-F_{\ell}}{\lambda} = \frac{1-\langle P_{\ell}(\cos(\theta)) \rangle}{\lambda}$
- then  $F(s; \theta) = \sum_{n=0}^{\infty} f_n(\theta) \mathcal{W}_n(s)$
- $f_n(\theta)$  the angular distribution after  $n$  elastic interactions  $f_n(\theta) = \sum_{\ell=0}^{\infty} \frac{2\ell+1}{4\pi} (F_{\ell})^n P_{\ell}(\cos(\theta))$
- $\mathcal{W}_n(s) = \exp(-s/\lambda) \frac{(s/\lambda)^n}{n!}$  is the probability of having exactly  $n$  elastic interaction along a path  $s$  (i.e. Poisson)

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Using a simple exponentially screened Coulomb potential as the scattering potential in the computation of the scattering amplitudes under the first Born approximation (Wentzel model):

- $\frac{d\sigma}{d\Omega} = |f|^2$  where  $f \equiv f(\theta, \phi)$  is the scattering amplitude
- which  $f_{B1}(\theta, \phi) = -\frac{2m}{4\pi\hbar^2} \int e^{i(\vec{k}_f - \vec{k}_i)\vec{r}'} V(\vec{r}') d^3r'$  in the first Born approximation [where:  $\vec{k}_i$ ,  $\vec{k}_f$  and  $V(\vec{r}')$  are the wave vectors of the incident plane, the outgoing (scattered) spherical wave and the scattering potential respectively. Note that: (i) in case of elastic scattering  $k_i = k_f \equiv k$ ; (ii)  $\hbar\vec{q} = \hbar(\vec{k}_f - \vec{k}_i)$  is the momentum transfer and  $q^2 = |\vec{k}_f - \vec{k}_i|^2 = 2k^2(1 - \cos(\theta)) = 2k^2(2\sin^2(\theta/2))$  where  $\theta \equiv \angle(\vec{k}_i, \vec{k}_f)$  is the scattering angle]
- assuming  $V(\vec{r}) \equiv V(r)$  i.e. spherically symmetric scattering potential, substituting  $\vec{q} = \vec{k}_f - \vec{k}_i$  and choosing the coordinate system for the integration such that  $\vec{q} = q\hat{z}$   

$$f_{B1}(\theta) = -\frac{2m}{q\hbar^2} \int_0^\infty \sin(qr') r' V(r') dr'$$
- then using a simple exponentially screened Coulomb potential as the scattering potential i.e.  

$$V(r) = \frac{ZZ'e^2}{r} e^{-r/R}$$
[Z target atomic number,  $Z'e$  projectile charge,  $R$  screening radius] we can get  

$$f_{B1}(\theta) = -\frac{2m}{\hbar^2} ZZ'e^2 \left[ \frac{1}{2k^2[1 - \cos(\theta) + R^{-2}/(2k^2)]} \right]$$
- which gives  $\frac{d\sigma}{d\Omega}^{(W)} = \left( \frac{ZZ'e^2}{pc\beta} \right)^2 \frac{1}{(1 - \cos(\theta) + R^{-2}/(2k^2))^2}$
- one can introduce  $A \equiv \frac{1}{4} \left( \frac{\hbar}{p} \right)^2 R^{-2}$  screening parameter [note that  $1/(2k^2R^2) = 2A$ ] that gives the DCS for elastic scattering  

$$\frac{d\sigma}{d\Omega}^{(W)} = \left( \frac{ZZ'e^2}{pc\beta} \right)^2 \frac{1}{(1 - \cos(\theta) + 2A)^2}$$
 and the corresponding

So DCS for elastic scattering within the Wentzel model is

$$\frac{d\sigma}{d\Omega}^{(W)} = \left( \frac{ZZ'e^2}{pc\beta} \right)^2 \frac{1}{(1 - \cos(\theta) + 2A)^2}$$

- $\sigma^{(W)} = \left( \frac{ZZ'e^2}{pc\beta} \right)^2 \frac{\pi}{A(1+A)}$
- $f_1^{(W)}(\theta) = \frac{1}{\pi} \frac{A(1+A)}{(1 - \cos(\theta) + 2A)^2}$
- $G_\ell^{(W)}(A) = 1 - F_\ell = 1 - \ell[Q_{\ell-1}(1 + 2A) - (1 + 2A)Q_\ell(1 + 2A)]$  [ $Q_\ell(x)$  are Legendre functions of the second kind]
- $G_{\ell=1}^{(W)}(A) = 2A \left[ \ln \left( \frac{1+A}{A} \right) (A + 1) - 1 \right]$
- note that  $\frac{1}{\lambda_1} = \frac{G_{\ell=1}^{(W)}(A)}{\lambda}$  gives the possibility set the screening parameter  $A$  such that the corresponding DCS  $\frac{d\sigma}{d\Omega}^{(W)}$  will give back  $\lambda_1$  [therefore e.g.  $\langle \cos(\theta) \rangle = \exp(-s/\lambda_1)$  will be correct]

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First derive Bielajew's hybrid form of the GS distribution i.e. separate the no, single and at least two elastic scattering contributions:



$$\mathcal{W}_{n=0}(s) = \exp(-s/\lambda); \quad \mathcal{W}_{n=1}(s) = \exp(-s/\lambda)(s/\lambda); \quad \mathcal{W}_{n \geq 2}(s) = 1 - \exp(-s/\lambda) - \exp(-s/\lambda)(s/\lambda)$$

- the GS series becomes [note that it is a p.d.f. of  $\theta$  i.e.  $\int_{\Omega} F(s; \theta) d\Omega = 1$ ]

$$F(s; \theta)_{GS} = \sum_{n=0}^{\infty} f_n(\theta) \mathcal{W}_n(s) = f_{n=0}(\theta) \mathcal{W}_{n=0} + f_{n=1}(\theta) \mathcal{W}_{n=1} + \sum_{n=2}^{\infty} f_n(\theta) \mathcal{W}_n(s) = e^{-s/\lambda} \frac{\delta(1 - \cos(\theta))}{2\pi} \\ + (s/\lambda) e^{-s/\lambda} f_{n=1}(\theta) + \sum_{\ell=0}^{\infty} \frac{2\ell + 1}{4\pi} P_{\ell}(\cos(\theta)) \left\{ e^{-(s/\lambda)G_{\ell}} - e^{-(s/\lambda)} [1 + (s/\lambda)(1 - G_{\ell})] \right\}$$

- make the transformation  $\theta \rightarrow \mu \equiv \cos(\theta)$  [which is the p.d.f. of  $\mu$  i.e.  $\int_{-1}^{+1} F(s; \mu) d\mu = 1$ ]

$$F(s; \mu)_{GS} = 2\pi F(s; \theta \rightarrow \mu)_{GS} = e^{-s/\lambda} \delta(1 - \mu) + (s/\lambda) e^{-s/\lambda} 2\pi f_{n=1}(\mu) + \\ \sum_{\ell=0}^{\infty} (\ell + 0.5) P_{\ell}(\mu) \left\{ e^{-(s/\lambda)G_{\ell}} - e^{-(s/\lambda)} [1 + (s/\lambda)(1 - G_{\ell})] \right\}$$

- in order to get all 3 terms in the form of *probability*  $\times$  *p.d.f.*

$$F(s; \mu)_{GS} = e^{-s/\lambda} \delta(1 - \mu) + (s/\lambda) e^{-s/\lambda} 2\pi f_{n=1}(\mu) + (1 - e^{-s/\lambda} - (s/\lambda) e^{-s/\lambda}) F(s; \mu)_{GS}^{2+}$$

where

$$F(s; \mu)_{GS}^{2+} \equiv \sum_{\ell=0}^{\infty} (\ell + 0.5) P_{\ell}(\mu) \frac{e^{-(s/\lambda)G_{\ell}} - e^{-(s/\lambda)} [1 + (s/\lambda)(1 - G_{\ell})]}{1 - e^{-s/\lambda} - (s/\lambda) e^{-s/\lambda}}$$

- no-scattering case: trivial
- single scattering case: using the Wentzel model, the PDF for single scattering  $p(A; \mu) = 2\pi f_{n=1}(\mu) = \frac{2A(1+A)}{(1-\mu+2A)^2}$  the corresponding CDF  $\mathcal{P}(A; \mu) = \frac{(A+1)(1-\mu)}{1-\mu+2A}$  and the sampling  $\mu = \mathcal{P}^{-1}(A; \xi) = 1 - \frac{2A\xi}{1-\xi+A}$  where  $\xi \in \mathcal{U}(0, 1)$
- multiple scattering case: need to sample from  $F(s; \mu)_{GS}^{2+} \rightarrow$  pre-compute

Variable transformation is needed to obtain smooth distributions  $\rightarrow$  reduce memory footprint and improve sampling

- suppose that we apply the transformation  $u = f(a_1, \dots, a_n; \mu)$  [where  $u \in [0, 1]$  the transformed variable  $f$  is the transformation function with  $a_1, \dots, a_n$  parameters that control the shape of the result of the transform]
- let  $q^{2+}(u)$  PDF of  $u$  be the transformed  $F(s; \mu)_{GS}^{2+}$  PDF of  $\mu$  that needs to satisfy the requirement  $q^{2+}(s; u)du = F(s; \mu)_{GS}^{2+}d\mu$  [i.e. the probability of having  $u$  falling into the  $du$  interval around  $u$  according to the transformed PDF  $q^{2+}(u)$  is equal to the probability of having  $\mu$  falling into the  $d\mu$  interval around  $\mu$  according to the original PDF  $F(s; \mu)_{GS}^{2+}$ ]
- which means that  $q^{2+}(s; u) = F(s; \mu)_{GS}^{2+} \frac{d\mu}{du}$  where  $\frac{d\mu}{du} = \left(\frac{du}{d\mu}\right)^{-1} = \left(\frac{\partial f(a_1, \dots, a_n; \mu)}{\partial \mu}\right)^{-1}$
- the parameters  $a_i$   $i = 1, \dots, n$  of the transformation can be determined through the optimization

$$0 = \frac{\partial}{\partial a_i} \left[ \int_0^1 [q^{2+}(s; u) - 1]^2 du \right] = \int_{-1}^{+1} \left[ F(s; \mu)_{GS}^{2+} \left( \frac{\partial f(a_1, \dots, a_n; \mu)}{\partial \mu} \right)^{-1} \right]^2 \left[ \frac{\partial^2 f(a_1, \dots, a_n; \mu)}{\partial \mu \partial a_i} \right] d\mu$$

[we want the transformed  $q^{2+}(s; u)$  PDF to be as close as possible to the uniform distribution (in least-square sense)]

- in the case of using the Wentzel model one can take  $u = f(a; \mu) = \frac{(a+1)(1-\mu)}{1-\mu+2a}$ ; the corresponding inverse transform  $\mu = 1 - \frac{2au}{1-u+a}$  [note that  $f(a; \mu)$  corresponds to the single scattering Wentzel CDF with a scaled  $a = w^2 A$  screening parameter, where the scaling factor  $w$  is arbitrary at the moment; the motivation behind this: if  $\mathcal{P}(\mu)$  would be the exact CDF that corresponds to the original PDF  $F(s; \mu)_{GS}^{2+}$  and one would use  $f(\mu) \equiv \mathcal{P}(\mu)$ , the transformed distribution would be the uniform distribution (in order to see this, just plug  $f(\mu) \equiv \mathcal{P}(\mu)$  into the third item on this page).]

- the optimal parameter of the transformation can be determined by plugging the chosen transformation function  $u = f(a; \mu) = \frac{(a+1)(1-\mu)}{1-\mu+2a}$  into the results of the optimization i.e.

$$0 = \int_{-1}^{+1} \left[ F(s; \mu)_{GS}^{2+} \left( -\frac{[1-\mu+2a]^2}{2a(1+a)} \right) \right]^2 \left[ -2 \frac{1-\mu(1+2a)}{[1-\mu+2a]^3} \right] d\mu \text{ that leads to the optimal solution}$$

$$a = \frac{\alpha}{4\beta} + \sqrt{\left(\frac{\alpha}{4\beta}\right)^2 + \frac{\alpha}{4\beta}}$$

where

$$\alpha = \sum_{\ell=0}^{\infty} \gamma_{\ell}(s, \lambda, A) \left\{ \left( 1.5\ell + \frac{0.065}{\ell+1.5} + \frac{0.065}{\ell-0.5} + 0.75 \right) \gamma_{\ell}(s, \lambda, A) - 2(\ell+1)\gamma_{\ell+1}(s, \lambda, A) + \frac{(\ell+1)(\ell+2)}{(2\ell+3)} \gamma_{\ell+2}(s, \lambda, A) \right\}$$

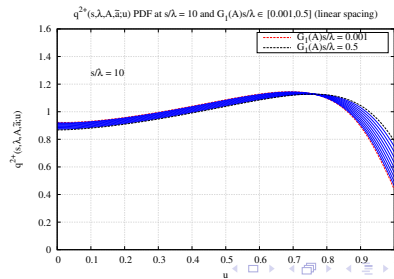
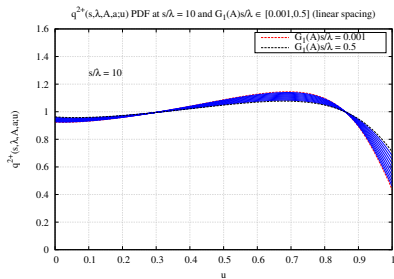
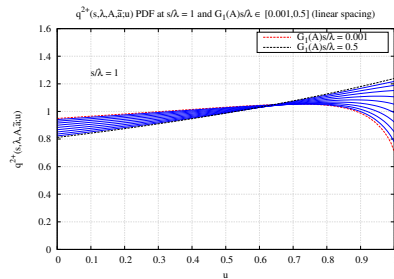
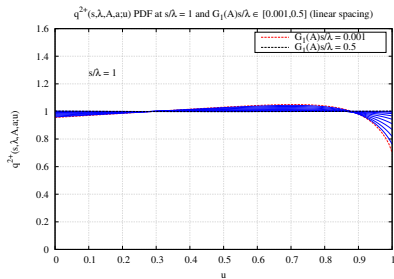
$$\beta = \sum_{\ell=0}^{\infty} (\ell+1) \gamma_{\ell}(s, \lambda, A) \gamma_{\ell+1}(s, \lambda, A) \text{ and } \gamma_i(s, \lambda, A) = \frac{e^{-(s/\lambda)G_i(A)} - e^{-(s/\lambda)}[1+(s/\lambda)(1-G_i(A))]}{1 - e^{-s/\lambda} - (s/\lambda)e^{-s/\lambda}}$$

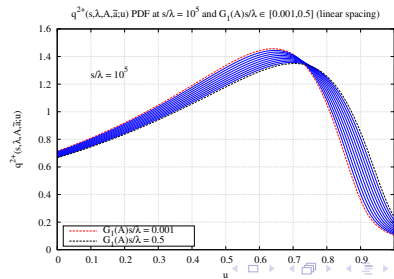
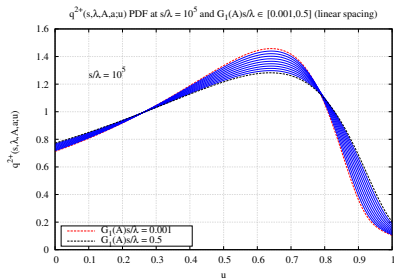
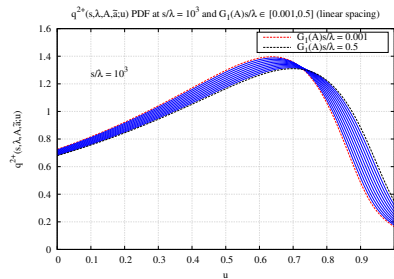
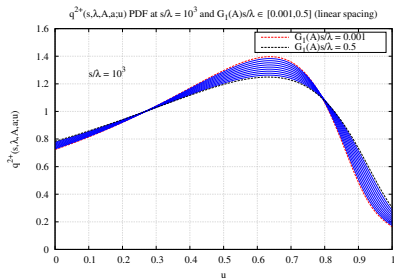
- it would be too expensive to compute these optimal values of  $a$  at runtime (at the back transform) so one can use a polynomial fit to the optimal  $w^2 \approx \tilde{w}^2$  then  $a \approx \tilde{a} = \tilde{w}^2 A$  can be obtained (both at pre-computation and at run time for the back transform). Kawrakow obtained

$$\frac{\tilde{w}^2}{0.5(s/\lambda)+2} = \begin{cases} 1.347 + t(0.209364 - t(0.45525 - t(0.50142 - t0.081234))) & \text{if } s/\lambda < 10 \\ -2.77164 + t(2.94874 - t(0.1535754 - t0.00552888)) & \text{otherwise} \end{cases}$$

where  $t = \ln(s/\lambda)$ .

- the transformed distribution  $q^{2+}(s, \lambda, a, A; u) = \frac{2a(1-a)}{[1-u+a]^2} \sum_{\ell}^{\infty} (\ell+0.5) P_{\ell} \left[ 1 - \frac{2au}{1-u+a} \right] \gamma_{\ell}(s, \lambda, A)$





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We have the  $q^{2+}(s/\lambda, G_1s/\lambda; u)$  PDFs pre-computed over a pre-defined 2D grid of  $\{(s/\lambda)_i\}$  and  $\{(G_1s/\lambda)_j\}$  sets of parameter values carefully chosen such that linear interpolation in  $\log(s/\lambda)$  and  $G_1s/\lambda$  will yield accurate results. If the actual parameter values are  $(s/\lambda)_i \leq s/\lambda < (s/\lambda)_{i+1}$ ,  $(G_1s/\lambda)_j \leq G_1s/\lambda < (G_1s/\lambda)_{j+1}$  and suppose that the final sampling from the PDF gives  $u$  i.e.  $\mathcal{P}^{-1}(\xi) = u$   $\xi \in \mathcal{U}(0, 1)$   $u_k \leq u < u_{k+1}$

- interpolation in the parameters
- identification of grid points  $u_k \leq u < u_{k+1}$  such that  $\mathcal{P}(u_k) \leq \xi < \mathcal{P}(u_{k+1})$
- interpolation of the inverse CDF to obtain  $\mathcal{P}^{-1}(\xi) = u$  i.e. interpolation in the  $\mathcal{P}^{-1}(\xi_k) = u_k \leq \mathcal{P}^{-1}(\xi) = u < \mathcal{P}^{-1}(\xi_{k+1}) = u_{k+1}$  interval where  $\xi_\ell = \mathcal{P}(u_\ell)$



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**Interpolation in the parameters:** suppose that (i) we have  $p(A; x)$  PDF of the stochastic variable  $x$  pre-computed over an  $A$  grid with  $\{a_i\}$  pre-defined values of the parameter; (ii) the  $\{a_i\}$  grid is dense enough for linear interpolation in  $A$

- for a given  $a_i \leq a < a_{i+1}$  value of the parameter, first we should interpolate the the PDF between the  $a_i \leq a < a_{i+1}$  parameter grid points to get  $p(a; x)$ , then we should sample from the interpolated PDF  $p(a; x)$
- however, since the  $\{a_i\}$  grid is dense enough for linear interpolation of the PDF in  $A$ , we can use interpolation by weights(or statistical interpolation) in the form
 
$$p(a; x) = \frac{a_{i+1}-a}{a_{i+1}-a_i} p(a_i; x) + \frac{a-a_i}{a_{i+1}-a_i} p(a_{i+1}; x)$$
- which results in a form of composition(i.e. in general  $p(x) = \sum_k P_k(p_k(x))p_k(x)$ ) since the probability of taking the PDF  $p(a_i; x)$  is  $P(p(a_i; x)) = \frac{a_{i+1}-a}{a_{i+1}-a_i}$  and the  $1 - P(p(a_i; x))$  is the probability of taking the PDF  $p(a_{i+1}; x)$ 
  - first we make the selection between the  $p(a_i; x)$  and  $p(a_{i+1}; x)$  PDFs
  - we take  $p(a_i; x)$  if  $\xi < \frac{a_{i+1}-a}{a_{i+1}-a_i}$ ,  $\xi \in \mathcal{U}(0, 1)$  and  $p(a_{i+1}; x)$  otherwise
  - then we need to sample from the selected, already pre-calculated and stored PDFs
- note, that we can use this method since the  $q^{2+}(s/\lambda, G_1 s/\lambda; u)$  PDFs are smooths and the pre-defined parameter grids are dense enough that linear interpolation in  $\log(s/\lambda)$  and  $G_1 s/\lambda$  will yield accurate results
- the proper pre-computed  $q^{2+}$  PDF can be selected by using two uniform random sample

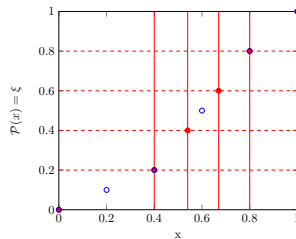
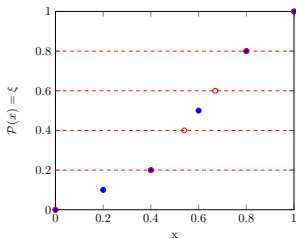
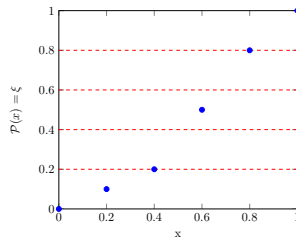
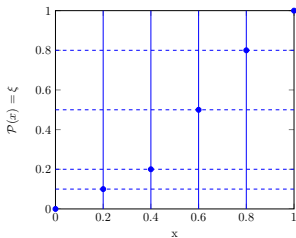
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**Identification of grid points:** when we need to sample from a pre-computed  $p(x)$  PDF table with the corresponding  $\mathcal{P}(x)$  CDF we need to solve the inverse equation  $\mathcal{P}^{-1}(\xi) = x$  where  $\xi \in \mathcal{U}(0, 1)$ .

- the first step is to find  $k$  such that  $\mathcal{P}(x_k) = \xi_k \leq \xi < \mathcal{P}(x_{k+1}) = \xi_{k+1}$
- this step can be done quickly if the inverse CDF  $\mathcal{P}^{-1}(\xi)$  is known at equally probably intervals
- it means that  $\text{Dom}[\mathcal{P}^{-1}] = [0, 1]$  is divided up to equal bins  
 $\{\xi_k\}_{k=0}^N$ ,  $\xi_{k+1} - \xi_k = \text{const.} = 1/N \forall k \in 0, \dots, N-1$  and the corresponding  $\mathcal{P}^{-1}(\xi_k) = x_k$  values are known
- however, usually it is the domain of the PDF that we divide up  $\{x_j\}_{j=0}^M$ ,  $x_0 = x_{\min}$ ,  $x_M = x_{\max}$  and we compute the PDF  $p(x_j)$  at the grid points
- in this case we have two possibilities to achieve equally probably intervals:
  - adjust the size of the individual bins of the  $\{x_j\}_{j=0}^M$  grid such that  
 $\int_{x_j}^{x_{j+1}} p(x) dx = \text{const} \forall j = 0, \dots, M-1$ . The easiest way to achieve this is: (i) define the grid  $\{\xi_k\}_{k=0}^N$ ,  $\xi_{k+1} - \xi_k = \text{const.} = 1/N \forall k \in 0, \dots, N-1$ ; (ii) then determine the  $\mathcal{P}^{-1}(\xi_k)$  inverse CDF values by interpolation using the known  $\mathcal{P}^{-1}(\xi_j = x_j)$  values. HOWEVER, special care needs to be taken when one interpolates the (inverse) CDF!!! (see later)

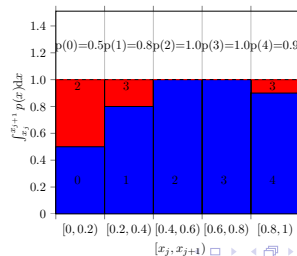
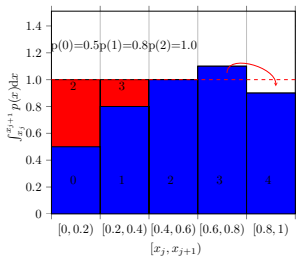
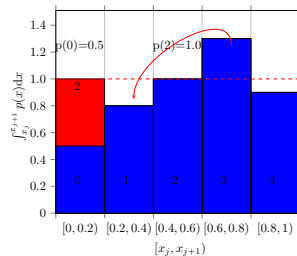
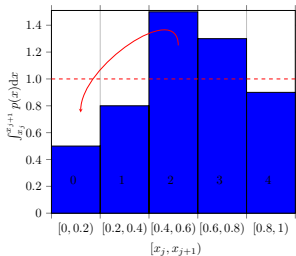
## Sampling of bins in case of pre-computed PDF



**Identification of grid points:** when we need to sample from a pre-computed  $p(x)$  PDF table with the corresponding  $\mathcal{P}(x)$  CDF we need to solve the inverse equation  $\mathcal{P}^{-1}(\xi) = x$  where  $\xi \in \mathcal{U}(0, 1)$ .

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  - adjust the size of the individual bins of the  $\{x_j\}_{j=0}^M$  grid such that  $\int_{x_j}^{x_{j+1}} p(x) dx = \text{const} \forall j = 0, \dots, M-1$ . The easiest way to achieve this is: (i) define the grid  $\{\xi_k\}_{k=0}^N$ ,  $\xi_{k+1} - \xi_k = \text{const.} = 1/N \forall k \in 0, \dots, N-1$ ; (ii) then determine the  $\mathcal{P}^{-1}(\xi_k)$  inverse CDF values by interpolation using the known  $\mathcal{P}^{-1}(\xi_j = x_j)$  values. HOWEVER, special care needs to be taken when one interpolates the inverse CDF!!! (see later)
  - keep the equal size of the individual bins of the  $\{x_j\}_{j=0}^M$  grid and reshuffle the  $p(x_j)$  PDF values such that  $\int_{x_j}^{x_{j+1}} p(x) dx = \text{const} = \text{mean} \forall j = 0, \dots, M-1$  by mixing "probabilities" from different bins i.e. barrow/lend probabilities and record it in a table (Walker's alias sampling)

## Sampling of bins in case of pre-computed PDF



- results in equally probably CDF bins
- if we store:
  - the probability of the lower bars  $p(j) \rightarrow [0.5, 0.8, 1.0, 1.0, 0.9]$
  - and the original bin locations of the moved pieces  $\rightarrow [2, 3, -, -, 3]$
  - in theory the sampling can be done with 2 independent random numbers  $\xi_1, \xi_2$
  - the first will give one of the equally probably bins  $j$
  - then if  $\xi_2 < p(j)$  we will take the bin  $j \rightarrow x_j$  and the corresponding alias bin otherwise
  - however the same sampling can be straightforwardly done even with only one random number
- drawbacks compared to the "simply" equally probably CDF:
  - the monotonic property of the CDF is "lost" i.e.  $\xi_a < \xi_b \not\rightarrow x_a < x_b$  since probabilities are mixed from different bins (cannot be used for sampling in a restricted interval)
  - additional random number is needed to perform the interpolation (within the sampled bin)



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**interpolation of the inverse CDF:** after the determination of bin  $j$  such that  $\mathcal{P}(\xi_j) \leq \xi < \mathcal{P}(\xi_{j+1})$  one needs to solve  $\mathcal{P}^{-1}(\xi) = x$  i.e. interpolation within  $\mathcal{P}^{-1}(\xi_j) = x_j \leq \mathcal{P}^{-1}(\xi) = x < \mathcal{P}^{-1}(\xi_{j+1}) = x_{j+1}$

- using liner interpolation is usually not appropriate because it is equivalent to approximate the PDF between  $x_j$  and  $x_{j+1}$  ( $\mathcal{P}^{-1}(\xi_j) = x_j, \mathcal{P}^{-1}(\xi_{j+1}) = x_{j+1}$ ) with a constant

- the applied interpolation should satisfy  $\frac{d\mathcal{P}^{-1}(\xi)}{d\xi} = \left(\frac{d\mathcal{P}(x)}{dx}\right)^{-1} = \frac{1}{p(x)}$  and  $\mathcal{P}^{-1}(\xi_j) = x_j$ ,  $\mathcal{P}^{-1}(\xi_{j+1}) = x_{j+1}$

- one can approximate the CDF within the bin by using second order Taylor approximation:

- $\mathcal{P}(x) \approx \tilde{\mathcal{P}}(x) = \mathcal{P}(x_j) + \mathcal{P}'(x_j)[x - x_j] + 0.5\mathcal{P}''(x_j)[x - x_j]^2 =$

$$\mathcal{P}(x_j) + p(x_j)[x - x_j] + 0.5p'(x_j)[x - x_j]^2 \approx \mathcal{P}(x_j) + p(x_j)[x - x_j] + 0.5 \frac{p(x_{j+1}) - p(x_j)}{x_{j+1} - x_j} [x - x_j]^2$$

- that results in  $x = \mathcal{P}^{-1}(\xi) \approx \tilde{\mathcal{P}}^{-1}(\xi) = x_j - \left[ p(x_j) - \sqrt{p^2(x_j) + 2c[\xi - \xi_j]} \right] / c$ ;  $c = \frac{p(x_{j+1}) - p(x_j)}{x_{j+1} - x_j}$

- $\frac{d\tilde{\mathcal{P}}^{-1}(\xi)}{d\xi} = \frac{1}{\sqrt{2c(\xi - \xi_j) + p^2(x_j)}}$

- $\frac{d\tilde{\mathcal{P}}^{-1}(\xi)}{d\xi} \Big|_{\xi=\xi_j} = \frac{1}{p(x_j)}$  and  $\tilde{\mathcal{P}}^{-1}(\xi_j) = x_j$

- $\frac{d\tilde{\mathcal{P}}^{-1}(\xi)}{d\xi} \Big|_{\xi=\xi_{j+1}} = \frac{1}{p(x_{j+1})}$  and  $\tilde{\mathcal{P}}^{-1}(\xi_{j+1}) = x_{j+1}$  only if  $p(x)$  is linear between  $x_j, x_{j+1}$

- then the sampled value  $x \approx \tilde{x} = \tilde{\mathcal{P}}^{-1}(\xi) = x_j - \left[ p(x_j) - \sqrt{p^2(x_j) + 2c[\xi - \xi_j]} \right] / c$ , where

$$c = \frac{p(x_{j+1}) - p(x_j)}{x_{j+1} - x_j}$$

**interpolation of the inverse CDF:** after the determination of bin  $j$  such that  $\mathcal{P}(\xi_j) \leq \xi < \mathcal{P}(\xi_{j+1})$  one needs to solve  $\mathcal{P}^{-1}(\xi) = x$  i.e. interpolation within  $\mathcal{P}^{-1}(\xi_j) = x_j \leq \mathcal{P}^{-1}(\xi) = x < \mathcal{P}^{-1}(\xi_{j+1}) = x_{j+1}$

- using liner interpolation is usually not appropriate because it is equivalent to approximate the PDF between  $x_j$  and  $x_{j+1}$  ( $\mathcal{P}^{-1}(\xi_j) = x_j, \mathcal{P}^{-1}(\xi_{j+1}) = x_{j+1}$ ) with a constant
- the applied interpolation should satisfy  $\frac{d\mathcal{P}^{-1}(\xi)}{d\xi} = \left(\frac{d\mathcal{P}(x)}{dx}\right)^{-1} = \frac{1}{p(x)}$  and  $\mathcal{P}^{-1}(\xi_j) = x_j$ ,  $\mathcal{P}^{-1}(\xi_{j+1}) = x_{j+1}$
- a better solution is to use rational function approximation in the form of

- $x = \mathcal{P}^{-1}(\xi) \approx \tilde{\mathcal{P}}^{-1}(\xi) = x_j + \frac{(1+a_j+b_j)\alpha}{1+a_j\alpha+b_j\alpha^2} [x_{j+1} - x_j]$ , where  $\alpha = \frac{\xi - \xi_j}{\xi_{j+1} - \xi_j}$
- $\tilde{\mathcal{P}}^{-1}(\xi_j) = x_j$  and  $\tilde{\mathcal{P}}^{-1}(\xi_{j+1}) = x_{j+1}$  independently form the values  $a_j, b_j$
- $\frac{d\tilde{\mathcal{P}}^{-1}(\xi)}{d\xi} = \frac{(1+a_j+b_j)(1-b_j\alpha^2)}{[1+a_j\alpha+b_j\alpha^2]^2} \frac{x_{j+1}-x_j}{\xi_{j+1}-\xi_j}$  and the parameters  $a_j, b_j$  can be determined from the requirements

$$\left. \frac{d\tilde{\mathcal{P}}^{-1}(\xi)}{d\xi} \right|_{\xi=\xi_j} = \frac{1}{p(x_j)}$$

$$\left. \frac{d\tilde{\mathcal{P}}^{-1}(\xi)}{d\xi} \right|_{\xi=\xi_{j+1}} = \frac{1}{p(x_{j+1})}$$

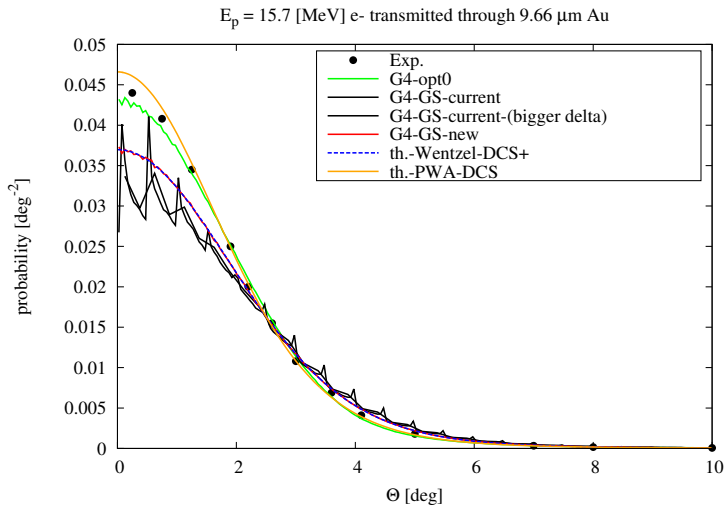
- that yields  $b_j = 1 - \left[ \frac{\xi_{j+1} - \xi_j}{x_{j+1} - x_j} \right]^2 \frac{1}{p(x_j)p(x_{j+1})}$  and  $a_j = \frac{\xi_{j+1} - \xi_j}{x_{j+1} - x_j} \frac{1}{p(x_j)} - 1 - b_j$
- then the sampled value  $x \approx \tilde{x} = \tilde{\mathcal{P}}^{-1}(\xi) = x_j + \frac{(1+a_j+b_j)\alpha}{1+a_j\alpha+b_j\alpha^2} [x_{j+1} - x_j]$ , with  $\alpha = \frac{\xi - \xi_j}{\xi_{j+1} - \xi_j}$

## The new version of Kawrakow-Bielajew Goudsmit-Saunderson model:

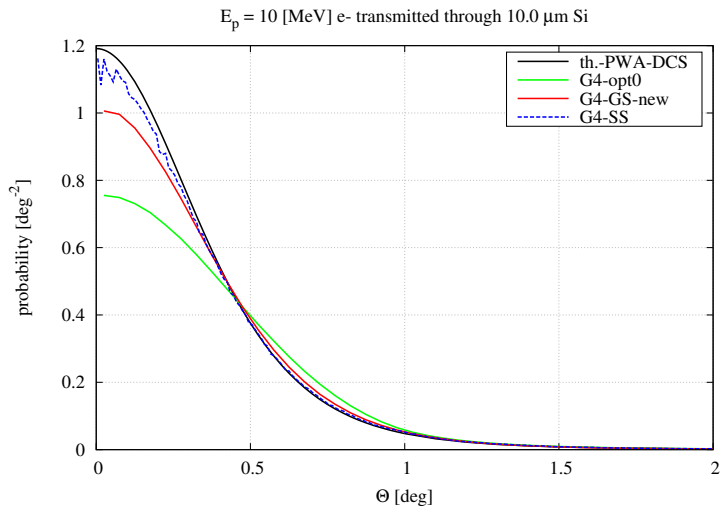
- $q^{2+}(s/\lambda, G_1 s/\lambda; u)$  PDFs are pre-computed over a 2D  $s/\lambda, G_1 s/\lambda$  grid using an  $\ell_{\max} = 10^4$  limit in the GS series
- the previously discussed variable transformation is used to achieve smooth PDFs
- statistical interpolation in  $\log(s/\lambda)$  and  $G_1 s/\lambda$  is used that gives accurate results (no loop, no search, no conditions, 2 random numbers)
- pre-computed data are stored over the 2D parameter grid in form of inverse CDFs with equally probably bins achieved by using rational interpolation :
  - bin identification i.e. find  $k$  such that  $\xi_k \leq \xi < \xi_{k+1}$  can be done in one step (no loop, no search, no conditions)
  - then rational interpolation is used to solve  $\mathcal{P}^{-1}(\xi) = x$ ,  $\xi_k \leq \xi < \xi_{k+1}$  (proper derivatives, no loop, no search, no conditions)
  - only 1 random number is needed to perform the sampling
- results in:
  - accurate, robust sampling
  - significant speed-up: TestEm5 with the new version is about 10% faster than the current version (reached or even faster than opt0)

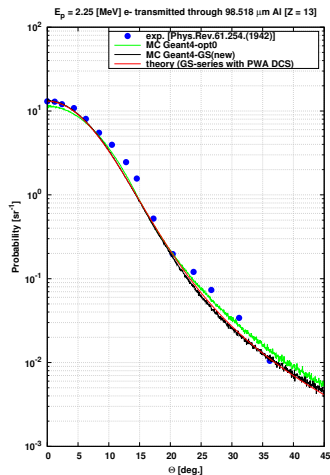
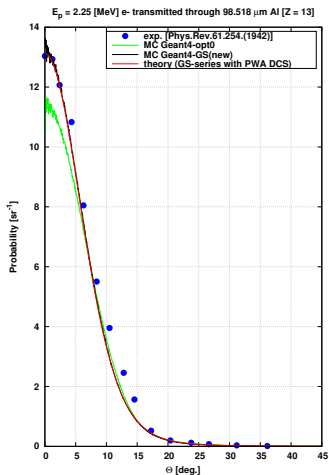
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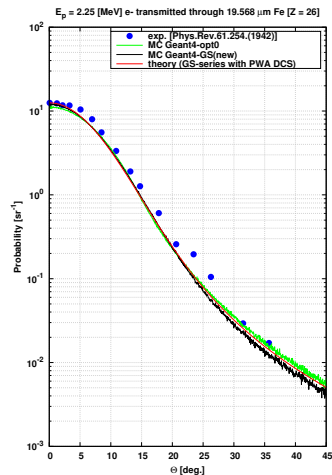
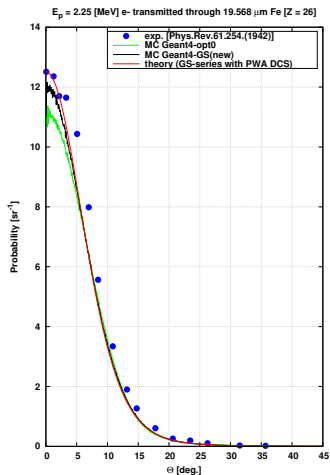
exp.: [A.O.Hanson et al., Phys.Rev.84(1951)634]



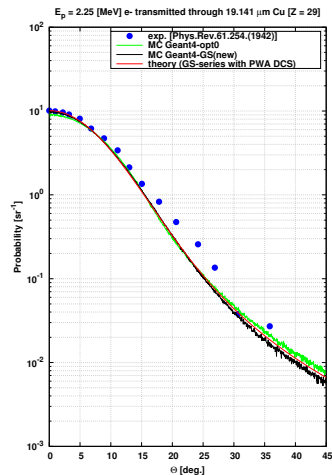
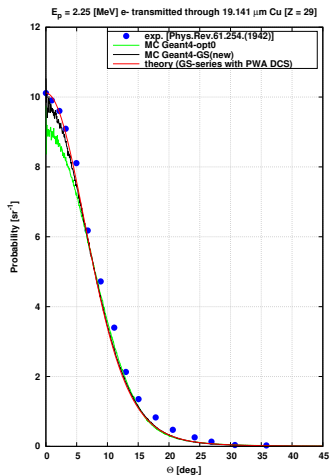


exp.: [L.Kulchitsky, Phys.Rev.61(1941)254]; normalized to theory at  $\theta = 0$

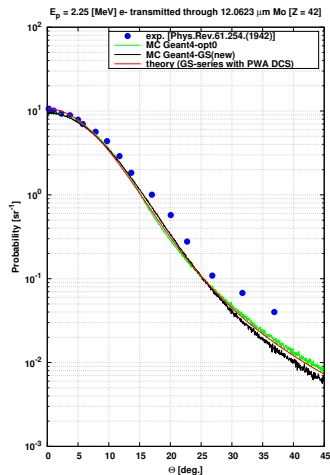
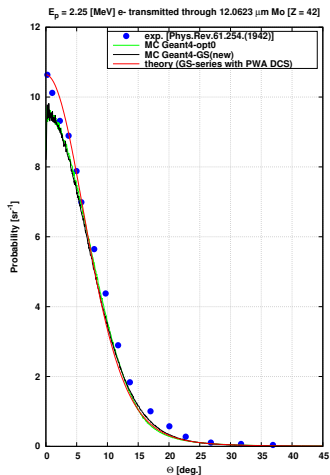




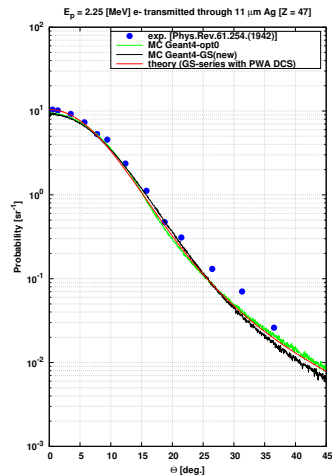
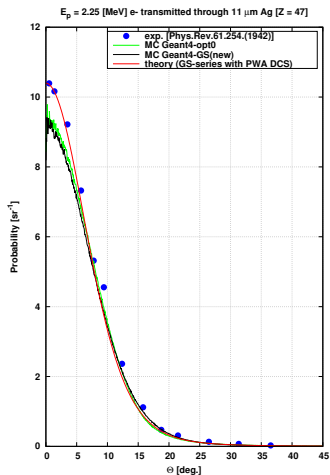
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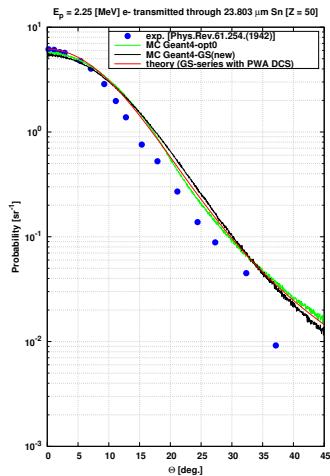
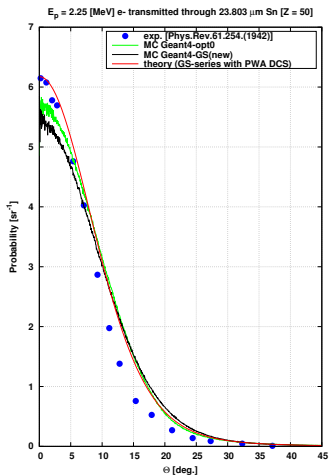
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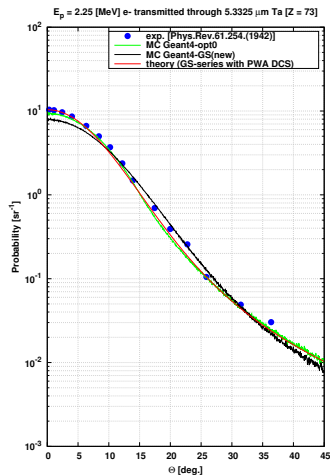
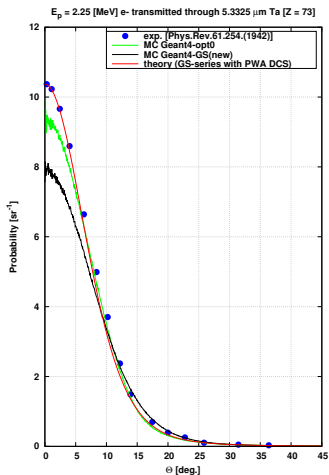
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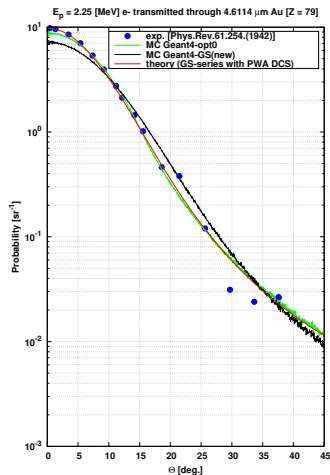
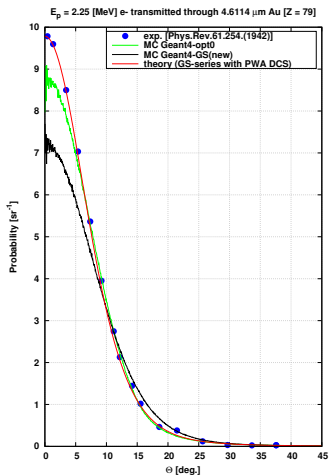
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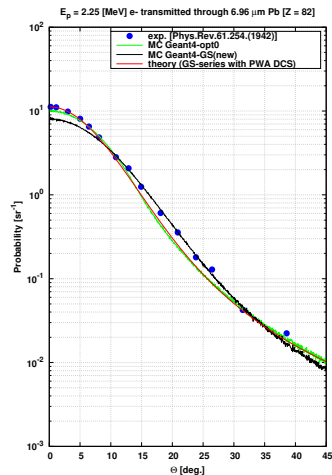
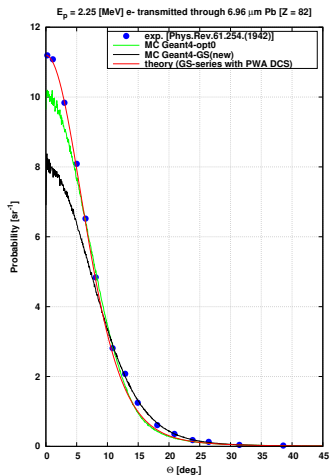
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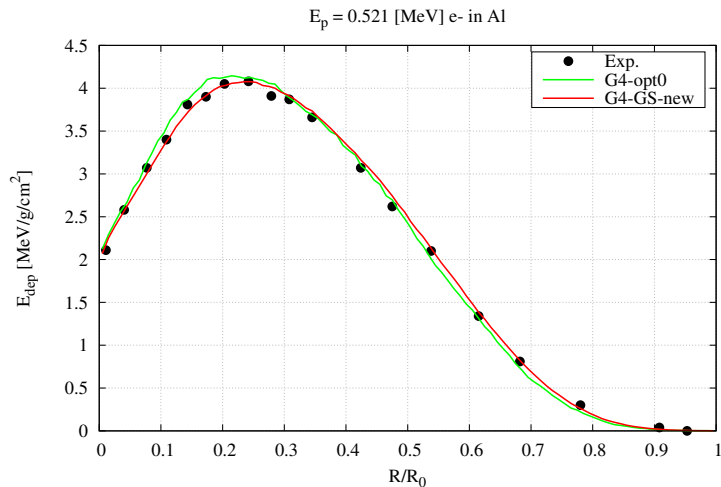


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exp.: [G.J.Lockwood et al., Sandia report SAND79-0414.UC-34a, February 1987; O.Kadri et al., NIMB 258(2007)381]

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- the model in the form of the new implementation can be used as a relatively fast option with the advantages (compared to opt0):
  - the model is free from tuning parameters
  - with limitations that can be well understood ( $\rightarrow$  no more surprise)
- the source of limitations is the simple form of the DCS for elastic scattering
- note, that it is this simple analytical form that makes possible to obtain a material independent, pre-computed table of angular distributions
- any correction would lead material dependency
- instead of introducing corrections based on more accurate numerical PWA-DCS for elastic scattering one should investigate the possibly of using a separate model that based on these PWA-DCS

Thank you for your attention!