

Predictive Power of Theoretical Modelling of the Nuclear Mean Field: Stochastic Approach

I. Dedes¹⁾ and J. Dudek^{1,2)}

¹⁾IPHC, CNRS/IN₂P₃ and UdS, Strasbourg, France; ²⁾UMCS, Lublin, Poland

SSNET Workshop, Orsay-Paris
November 2016

The Fundamental Method: Inverse Problem Theory of Applied Mathematics

Direct and Inverse Problems in Quantum Theories

Direct and Inverse Problems in Quantum Theories

- Consider an arbitrary, e.g. many-body, theory with its Hamiltonian:

$$\hat{H} = \hat{T} + \hat{V}_{\text{int}}(\dots\{\mathbf{p}\}); \quad \{\mathbf{p}\} \rightarrow \text{Optimal parameters}$$

Direct and Inverse Problems in Quantum Theories

- Consider an arbitrary, e.g. many-body, theory with its Hamiltonian:

$$\hat{H} = \hat{T} + \hat{V}_{\text{int}}(\dots\{\mathbf{p}\}); \quad \{\mathbf{p}\} \rightarrow \text{Optimal parameters}$$

- If we know the parameters, we are able to solve the Direct Problem:

$$\hat{H} \varphi_j(\dots, \{\mathbf{p}\}) = e_j^{\text{th}}(\dots, \{\mathbf{p}\}) \varphi_j(\dots, \{\mathbf{p}\})$$

Direct and Inverse Problems in Quantum Theories

- Consider an arbitrary, e.g. many-body, theory with its Hamiltonian:

$$\hat{H} = \hat{T} + \hat{V}_{\text{int}}(\dots\{\mathbf{p}\}); \quad \{\mathbf{p}\} \rightarrow \text{Optimal parameters}$$

- If we know the parameters, we are able to solve the Direct Problem:

$$\hat{H} \varphi_j(\dots, \{\mathbf{p}\}) = e_j^{\text{th}}(\dots, \{\mathbf{p}\}) \varphi_j(\dots, \{\mathbf{p}\})$$

- However, before any comparison theory-experiment, and even more generally: Before any calculation we must solve the Inverse Problem:

To determine the optimal parameters of the Hamiltonian

Inverse Problem in Quantum Theories

- Given parameters $\{p\} \rightarrow$ Schrödinger equation produces 'data':

$$\hat{H}(p) \rightarrow \{E_p, \psi(p)\} \leftrightarrow \boxed{\hat{O}_H(p) = d^{\text{th}} \leftarrow \text{Direct Problem}}$$

Inverse Problem in Quantum Theories

- Given parameters $\{p\} \rightarrow$ Schrödinger equation produces 'data':

$$\hat{H}(p) \rightarrow \{E_p, \psi(p)\} \leftrightarrow \boxed{\hat{O}_H(p) = d^{\text{th}} \leftarrow \text{Direct Problem}}$$

- To find the optimal parameters we must invert the above relation:

$$\boxed{p^{\text{opt}} = \hat{O}_H^{-1}(d^{\text{exp}}) \leftarrow \text{Inverse Problem}}$$

Inverse Problem in Quantum Theories

- Given parameters $\{p\} \rightarrow$ Schrödinger equation produces 'data':

$$\hat{H}(p) \rightarrow \{E_p, \psi(p)\} \leftrightarrow \boxed{\hat{O}_H(p) = d^{\text{th}} \leftarrow \text{Direct Problem}}$$

- To find the optimal parameters we must invert the above relation:

$$\boxed{p^{\text{opt}} = \hat{O}_H^{-1}(d^{\text{exp}}) \leftarrow \text{Inverse Problem}}$$

- In many-body theories the existence of operator \hat{O}_H^{-1} is doubtful, in fact no mathematical methods of such a construction are known

Inverse Problem in Quantum Theories

- Given parameters $\{p\} \rightarrow$ Schrödinger equation produces 'data':

$$\hat{H}(p) \rightarrow \{E_p, \psi(p)\} \leftrightarrow \boxed{\hat{O}_H(p) = d^{\text{th}} \leftarrow \text{Direct Problem}}$$

- To find the optimal parameters we must invert the above relation:

$$\boxed{p^{\text{opt}} = \hat{O}_H^{-1}(d^{\text{exp}}) \leftarrow \text{Inverse Problem}}$$

- In many-body theories the existence of operator \hat{O}_H^{-1} is doubtful, in fact no mathematical methods of such a construction are known
- If \hat{O}_H has no inverse we say that inverse problem is ill-posed**

Inverse Problem in Quantum Theories

- Given parameters $\{p\} \rightarrow$ Schrödinger equation produces 'data':

$$\hat{H}(p) \rightarrow \{E_p, \psi(p)\} \leftrightarrow \boxed{\hat{O}_H(p) = d^{\text{th}} \leftarrow \text{Direct Problem}}$$

- To find the optimal parameters we must invert the above relation:

$$\boxed{p^{\text{opt}} = \hat{O}_H^{-1}(d^{\text{exp}}) \leftarrow \text{Inverse Problem}}$$

- In many-body theories the existence of operator \hat{O}_H^{-1} is doubtful, in fact no mathematical methods of such a construction are known

- If \hat{O}_H has no inverse we say that inverse problem is ill-posed**

- In physics this issue remains unsolved: Instead of finding optimal parameters by solving the Inverse Problem $\rightarrow \rightarrow$ "one minimises χ^2 "

A Powerful Method: Local Taylor Expansion

A Powerful Method: Local Taylor Expansion

- Parameter adjustment is obtained via the χ^2 -minimisation

$$\chi^2(\mathbf{p}) = \sum_{j=1}^{n_d} [e_j^{\text{exp}} - e_j^{\text{th}}(\mathbf{p})]^2 \rightarrow \frac{\partial \chi^2}{\partial p_k} = 0, \quad k = 1 \dots n_m$$

with n_d - number of data points; n_m - number of model parameters

A Powerful Method: Local Taylor Expansion

- Parameter adjustment is obtained via the χ^2 -minimisation

$$\chi^2(\mathbf{p}) = \sum_{j=1}^{n_d} [e_j^{\text{exp}} - e_j^{\text{th}}(\mathbf{p})]^2 \rightarrow \frac{\partial \chi^2}{\partial p_k} = 0, \quad k = 1 \dots n_m$$

with n_d - number of data points; n_m - number of model parameters

- Usually we iterate this non-linear problem using Taylor linearization

$$e_j^{\text{th}}(\mathbf{p}^{[\text{it}+1]}) \approx e_j^{\text{th}}(\mathbf{p}^{[\text{it}]}) + \sum_{k=1}^{n_m} \left(\frac{\partial e_j^{\text{th}}}{\partial p_k} \right) \Big|_{\mathbf{p}=\mathbf{p}^{[\text{it}]}} (\mathbf{p}_k^{[\text{it}+1]} - \mathbf{p}_k^{[\text{it}]})$$

Short-hand notation: $\mathbf{J}_{jk}^{[\text{it}]} \stackrel{\text{df}}{=} \left(\frac{\partial e_j^{\text{th}}}{\partial p_k} \right) \Big|_{\mathbf{p}=\mathbf{p}^{[\text{it}]}}$ and $\mathbf{b}_j^{[\text{it}]} = [e_j^{\text{exp}} - e_j^{\text{th}}(\mathbf{p}^{[\text{it}]})]$

A Powerful Method: Local Taylor Expansion

- Parameter adjustment is obtained via the χ^2 -minimisation

$$\chi^2(\mathbf{p}) = \sum_{j=1}^{n_d} [e_j^{\text{exp}} - e_j^{\text{th}}(\mathbf{p})]^2 \rightarrow \frac{\partial \chi^2}{\partial p_k} = 0, \quad k = 1 \dots n_m$$

with n_d - number of data points; n_m - number of model parameters

- Usually we iterate this non-linear problem using Taylor linearization

$$e_j^{\text{th}}(\mathbf{p}^{[\text{it}+1]}) \approx e_j^{\text{th}}(\mathbf{p}^{[\text{it}]}) + \sum_{k=1}^{n_m} \left(\frac{\partial e_j^{\text{th}}}{\partial p_k} \right) \Big|_{\mathbf{p}=\mathbf{p}^{[\text{it}]}} (\mathbf{p}_k^{[\text{it}+1]} - \mathbf{p}_k^{[\text{it}]})$$

Short-hand notation: $\mathbf{J}_{jk}^{[\text{it}]} \stackrel{\text{df}}{=} \left(\frac{\partial e_j^{\text{th}}}{\partial p_k} \right) \Big|_{\mathbf{p}=\mathbf{p}^{[\text{it}]}}$ and $\mathbf{b}_j^{[\text{it}]} = [e_j^{\text{exp}} - e_j^{\text{th}}(\mathbf{p}^{[\text{it}]})]$

- Inserting into $\chi^2(\mathbf{p})$ gives the linearised iterative representation

$$\chi^2(\mathbf{p}^{[\text{it}+1]}) = \sum_{j=1}^{n_d} \left[\sum_{k=1}^{n_m} \mathbf{J}_{jk}^{[\text{it}]} \cdot (\mathbf{p}_k^{[\text{it}+1]} - \mathbf{p}_k^{[\text{it}]}) - \mathbf{b}_j^{[\text{it}]} \right]^2$$

Inverse Problem in Linearised Representation

- One may easily show that within the new, linearised representation

$$\frac{\partial \chi^2}{\partial \mathbf{p}_i} = 0 \rightarrow (\mathbf{J}^T \mathbf{J}) \cdot \mathbf{p} = \mathbf{J}^T \mathbf{b} \leftrightarrow \mathbf{J}^T \mathbf{J} \stackrel{\text{df}}{=} \mathcal{A}$$

Inverse Problem in Linearised Representation

- One may easily show that within the new, linearised representation

$$\frac{\partial \chi^2}{\partial \mathbf{p}_i} = 0 \rightarrow (\mathbf{J}^T \mathbf{J}) \cdot \mathbf{p} = \mathbf{J}^T \mathbf{b} \leftrightarrow \mathbf{J}^T \mathbf{J} \stackrel{\text{df}}{=} \mathcal{A}$$

- In *Applied Mathematics* we slightly change wording and notation:

$$\{\mathbf{p}\} \rightarrow \mathcal{P} : \text{'Causes'} \text{ and } \{\mathbf{J}^T \mathbf{b}\} \rightarrow \mathcal{D} : \text{'Effects'} \Rightarrow \mathcal{A} \cdot \mathcal{P} = \mathcal{D}$$

Inverse Problem in Linearised Representation

- One may easily show that within the new, linearised representation

$$\frac{\partial \chi^2}{\partial p_i} = 0 \rightarrow (J^T J) \cdot \mathbf{p} = J^T \mathbf{b} \leftrightarrow J^T J \stackrel{\text{df}}{=} \mathcal{A}$$

- In *Applied Mathematics* we slightly change wording and notation:

$$\{\mathbf{p}\} \rightarrow \mathcal{P} : \text{'Causes'} \text{ and } \{J^T \mathbf{b}\} \rightarrow \mathcal{D} : \text{'Effects'} \Rightarrow \mathcal{A} \cdot \mathcal{P} = \mathcal{D}$$

- From the measured 'Effects', called Data, represented by \mathcal{D} , we extract information about the optimal parameters, \mathcal{P} , by inverting the matrix \mathcal{A} :

$$\underbrace{\mathcal{A} \cdot \mathcal{P} = \mathcal{D}}_{\text{Direct Problem}} \rightarrow \underbrace{\mathcal{P} = \mathcal{A}^{-1} \cdot \mathcal{D}}_{\text{Inverse Problem}}$$

Stability of Solutions of Nuclear Inverse Problem

- We consider linear equations: $\mathcal{P} = \mathcal{A}^{-1} \cdot \mathcal{D}$

$$\begin{bmatrix} \mathcal{P}_1 \\ \mathcal{P}_2 \\ \dots \\ \mathcal{P}_m \end{bmatrix} = \underbrace{\begin{bmatrix} \mathcal{A}_{11} & \mathcal{A}_{12} & \dots & \mathcal{A}_{1d} \\ \mathcal{A}_{21} & \mathcal{A}_{22} & \dots & \mathcal{A}_{2d} \\ \dots & \dots & \dots & \dots \\ \mathcal{A}_{m1} & \mathcal{A}_{m2} & \dots & \mathcal{A}_{md} \end{bmatrix}^{-1}}_{\mathcal{A}^{-1}: m \times d \text{ rectangular matrix}} \begin{bmatrix} \mathcal{D}_1 \\ \mathcal{D}_2 \\ \dots \\ \mathcal{D}_d \end{bmatrix}$$

Stability of Solutions of Nuclear Inverse Problem

- We consider linear equations: $\mathcal{P} = \mathcal{A}^{-1} \cdot \mathcal{D}$

$$\begin{bmatrix} \mathcal{P}_1 \\ \mathcal{P}_2 \\ \dots \\ \mathcal{P}_m \end{bmatrix} = \underbrace{\begin{bmatrix} \mathcal{A}_{11} & \mathcal{A}_{12} & \dots & \mathcal{A}_{1d} \\ \mathcal{A}_{21} & \mathcal{A}_{22} & \dots & \mathcal{A}_{2d} \\ \dots & \dots & \dots & \dots \\ \mathcal{A}_{m1} & \mathcal{A}_{m2} & \dots & \mathcal{A}_{md} \end{bmatrix}^{-1}}_{\mathcal{A}^{-1}: m \times d \text{ rectangular matrix}} \begin{bmatrix} \mathcal{D}_1 \\ \mathcal{D}_2 \\ \dots \\ \mathcal{D}_d \end{bmatrix}$$

- $[\mathcal{A}_{ik}]$ depend on: 1) Hamiltonian, and 2) Selection of data points

Stability of Solutions of Nuclear Inverse Problem

- We consider linear equations: $\mathcal{P} = \mathcal{A}^{-1} \cdot \mathcal{D}$

$$\begin{bmatrix} \mathcal{P}_1 \\ \mathcal{P}_2 \\ \dots \\ \mathcal{P}_m \end{bmatrix} = \underbrace{\begin{bmatrix} \mathcal{A}_{11} & \mathcal{A}_{12} & \dots & \mathcal{A}_{1d} \\ \mathcal{A}_{21} & \mathcal{A}_{22} & \dots & \mathcal{A}_{2d} \\ \dots & \dots & \dots & \dots \\ \mathcal{A}_{m1} & \mathcal{A}_{m2} & \dots & \mathcal{A}_{md} \end{bmatrix}^{-1}}_{\mathcal{A}^{-1}: m \times d \text{ rectangular matrix}} \begin{bmatrix} \mathcal{D}_1 \\ \mathcal{D}_2 \\ \dots \\ \mathcal{D}_d \end{bmatrix}$$

- $[\mathcal{A}_{ik}]$ depend on: 1) Hamiltonian, and 2) Selection of data points
- If one of the parameters is a function of another, say, $p_k = f(p_{k'})$ then one may show, that two columns of \mathcal{A} are linearly dependent

Stability of Solutions of Nuclear Inverse Problem

- We consider linear equations: $\mathcal{P} = \mathcal{A}^{-1} \cdot \mathcal{D}$

$$\begin{bmatrix} \mathcal{P}_1 \\ \mathcal{P}_2 \\ \dots \\ \mathcal{P}_m \end{bmatrix} = \underbrace{\begin{bmatrix} \mathcal{A}_{11} & \mathcal{A}_{12} & \dots & \mathcal{A}_{1d} \\ \mathcal{A}_{21} & \mathcal{A}_{22} & \dots & \mathcal{A}_{2d} \\ \dots & \dots & \dots & \dots \\ \mathcal{A}_{m1} & \mathcal{A}_{m2} & \dots & \mathcal{A}_{md} \end{bmatrix}^{-1}}_{\mathcal{A}^{-1}: m \times d \text{ rectangular matrix}} \begin{bmatrix} \mathcal{D}_1 \\ \mathcal{D}_2 \\ \dots \\ \mathcal{D}_d \end{bmatrix}$$

- $[\mathcal{A}_{ik}]$ depend on: 1) Hamiltonian, and 2) Selection of data points
- If one of the parameters is a function of another, say, $p_k = f(p_{k'})$ then one may show, that two columns of \mathcal{A} are linearly dependent
- If this happens $\rightarrow \mathcal{A}$ -matrix becomes singular [Ill-Posed Problem]

Ill-Posed: Correlation between parameters and the data is lost!

**Here we detected our dangerous enemy:
Parametric Correlations
and their negative impact on the theory predictions**

Here we detected our dangerous enemy: Parametric Correlations and their negative impact on the theory predictions

- Strictly speaking: The exactly ill-posed inverse problem (\mathcal{A}^{-1} does not exist) has no solutions since modelling does not constrain parameters:

“Changing data does not change parameters”

Here we detected our dangerous enemy: Parametric Correlations and their negative impact on the theory predictions

- Strictly speaking: The exactly ill-posed inverse problem (\mathcal{A}^{-1} does not exist) has no solutions since modelling does not constrain parameters:

“Changing data does not change parameters”

... and yet physicists often keep minimising χ^2 !!

Here we detected our dangerous enemy: Parametric Correlations and their negative impact on the theory predictions

- Strictly speaking: The exactly ill-posed inverse problem (\mathcal{A}^{-1} does not exist) has no solutions since modelling does not constrain parameters:
 - “Changing data does not change parameters”
 - ... and yet physicists often keep minimising χ^2 !!
- Unfortunately, the χ^2 usually “works perfectly well” → results may even go through experimental data... [“good r.m.s.”]

Here we detected our dangerous enemy: Parametric Correlations and their negative impact on the theory predictions

- Strictly speaking: The exactly ill-posed inverse problem (\mathcal{A}^{-1} does not exist) has no solutions since modelling does not constrain parameters:
 - “Changing data does not change parameters”
 - ... and yet physicists often keep minimising χ^2 !!
- Unfortunately, the χ^2 usually “works perfectly well” \rightarrow results may even go through experimental data... [“good r.m.s.”]
 - ... but these results have neither mathematical nor not much of the physical significance

Here we detected our dangerous enemy: Parametric Correlations and their negative impact on the theory predictions

- Strictly speaking: The exactly ill-posed inverse problem (\mathcal{A}^{-1} does not exist) has no solutions since modelling does not constrain parameters:
 - “Changing data does not change parameters”
 - ... and yet physicists often keep minimising χ^2 !!
- Unfortunately, the χ^2 usually “works perfectly well” → results may even go through experimental data... [“good r.m.s.”]
 - ... but these results have neither mathematical nor not much of the physical significance
 - ... and even less of prediction capacities!

Here we detected our dangerous enemy: Parametric Correlations and their negative impact on the theory predictions

- Strictly speaking: The exactly ill-posed inverse problem (\mathcal{A}^{-1} does not exist) has no solutions since modelling does not constrain parameters:

“Changing data does not change parameters”

... and yet physicists often keep minimising χ^2 !!

- Unfortunately, the χ^2 usually “works perfectly well” → results may even go through experimental data... [“good r.m.s.”]
 - ... but these results have neither mathematical nor not much of the physical significance
 - ... and even less of prediction capacities!
- ... especially if the inverse problem is ‘just about’ ill posed!

Parametric Correlations within the Inverse Problem:

- a. How to determine their presence?**
- b. How to counteract their consequences
which are likely to ruin the predictive power?**

One can demonstrate that parametric correlations of this kind can conveniently be studied using Monte Carlo methods

One can demonstrate that parametric correlations of this kind can conveniently be studied using Monte Carlo methods

- Given space of data $\{d_1, d_2, \dots d_n\}$ with uncertainties $\{\sigma_1, \sigma_2, \dots \sigma_n\}$

One can demonstrate that parametric correlations of this kind can conveniently be studied using Monte Carlo methods

- Given space of data $\{d_1, d_2, \dots d_n\}$ with uncertainties $\{\sigma_1, \sigma_2, \dots \sigma_n\}$
- With a random-number generator we define what is called ‘Gaussian noise distribution’ around each d_i

One can demonstrate that parametric correlations of this kind can conveniently be studied using Monte Carlo methods

- Given space of data $\{d_1, d_2, \dots, d_n\}$ with uncertainties $\{\sigma_1, \sigma_2, \dots, \sigma_n\}$
- With a random-number generator we define what is called ‘Gaussian noise distribution’ around each d_i
 - We fit the parameter sets $\{p_1, p_2, \dots, p_m\}_j$ great number of times, \mathcal{N} , i.e. for $j = 1, 2, \dots, \mathcal{N}$

One can demonstrate that parametric correlations of this kind can conveniently be studied using Monte Carlo methods

- Given space of data $\{d_1, d_2, \dots d_n\}$ with uncertainties $\{\sigma_1, \sigma_2, \dots \sigma_n\}$
- With a random-number generator we define what is called ‘Gaussian noise distribution’ around each d_i
 - We fit the parameter sets $\{p_1, p_2, \dots p_m\}_j$ great number of times, \mathcal{N} , i.e. for $j = 1, 2, \dots \mathcal{N}$
- From m-tuplets of obtained parameters, $\{p_1, p_2, \dots p_m\}$, we construct the tables and projection plots like the ones which follow

Parametric Correlations

[Illustrations for Skyrme Hartree-Fock Hamiltonian]

To follow the discussion it will be sufficient to know that the Skyrme Hamiltonian depends on the adjustable constants:

$$C_0^\rho, C_1^\rho, C_o^{\rho\alpha}, C_0^\tau, C_1^\tau, C_0^{\nabla J}$$

Parameter-Correlations in Skyrme-HF

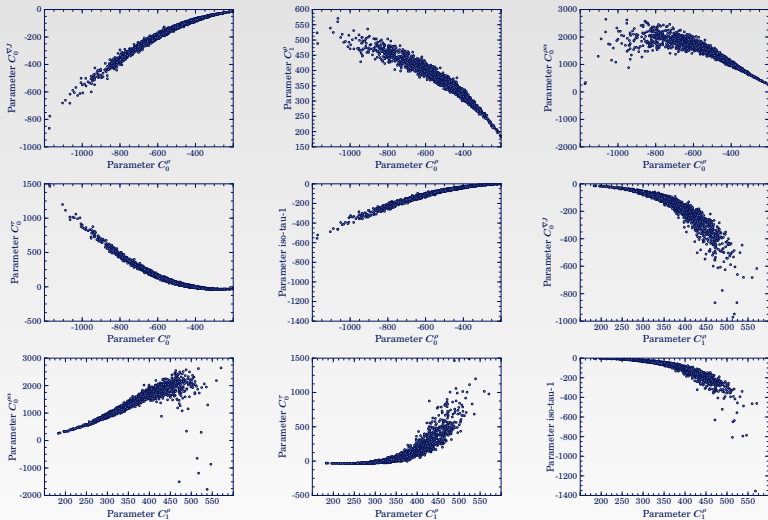


Illustration shows that **majority of these parameters are strongly correlated** excluding the prediction capacities of the model [B. Szpak, PhD thesis]

Parametric Correlations:

Strongly Present the Skyrme-Hartree-Fock Mean Fields

Parametric Correlations:

Strongly Present the Skyrme-Hartree-Fock Mean Fields

**The presence of parametric correlations implies that
no stable extraneous predictive power
can be obtained with this type of the Hamiltonians**

Parametric Correlations:

Strongly Present the Skyrme-Hartree-Fock Mean Fields

**The presence of parametric correlations implies that
no stable extraneous predictive power
can be obtained with this type of the Hamiltonians**

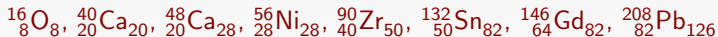
**In other words: This type of the Hamiltonian
may very well allow to fit the data:
Stable extraneous predictions is another issue^{*)}**

^{*)}J. Rikovska-Stone, J. Phys. G31 (2005) R211-R230: Cites over 100 distinct, non-equivalent parameterisations of the Skyrme Hartree-Fock Hamiltonian so far published in the literature

Selection of the Model Mean-Field Hamiltonian for the Project

'WS Universal': among Popular Realistic [Toy?] Models

- Here we decided to use the Woods-Saxon Universal Hamiltonian since our preliminary tests have shown much fewer parametric correlations
- This Hamiltonian is among the Popular Realistic Models, and it is used for calculations of deformed nuclei structure
- We examine the predictive power capacities of the nuclear mean-field theory and its fundamental degrees of freedom: nucleon levels
- To simplify the task without losing conceptual generality we limit ourselves to 'experimentally known' doubly-magic spherical-nuclei:



Woods-Saxon Hamiltonian: Central Potential

- We present here only the spherical variant of the Woods-Saxon potential

$$V_{\text{cent}}^{\text{WS}} = \frac{V_c}{1 + \exp [(r - R_c) / a_c]} ; \quad R_c = r_c A^{1/3}.$$

It has unique features among most of the mean field potentials, namely, each parameter is related to an independent class of experiments:

- V_c - depth parameter; specific transfer reactions
- r_c - radius parameter; electron scattering
- a_c - diffuseness parameter; hadron scattering
- In principle each of these parameters can be determined separately thus helping to counteract certain parametric correlations
- The importance – This potential is broadly used for deformed nuclei:

$$V_{\text{cent}}^{\text{WS}} = \frac{V_c}{1 + \exp [\text{dist}_{\Sigma}(\vec{r}; R_0) / a_c]}$$

with a fixed parameter set for thousands of nuclei \Rightarrow Thus **‘universal’**

Woods-Saxon Hamiltonian: Spin-Orbit Potential

The spherical Woods-Saxon spin-orbit potential has the form

$$V_{so}^{ws} = \frac{\lambda_{so}}{r} \frac{d}{dr} \left[\frac{1}{1 + \exp[(r - R_{so})/a_{so}]} \right] \hat{\ell} \cdot \hat{s}; \quad R_{so} = r_{so} A^{1/3}$$

- λ_{so} - strength parameter
- r_{so} - radius parameter
- a_{so} - diffuseness parameter

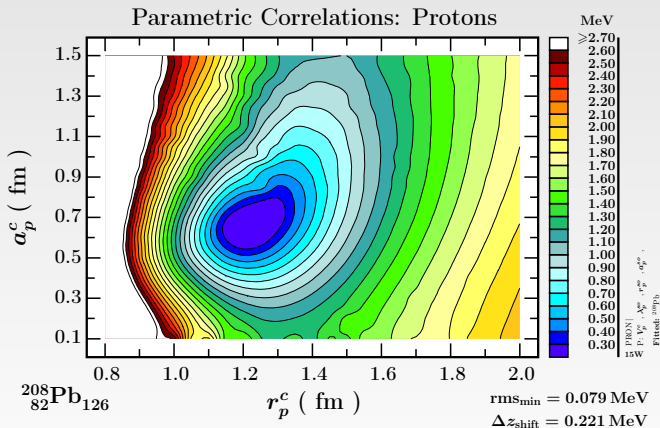
In total two sets of six parameters $\{\mathbf{V}_c, r_c, a_c; \lambda_{so}, r_{so}, a_{so}\}_{\pi, \nu}$

Back to the Parametric Correlation Problem

- One can show that the parametric correlations can be detected through projecting the $\chi^2(\mathbf{p})$ onto a $(\mathbf{p}_j, \mathbf{p}_k)$ -plane: $\min_{i \neq j, k} \chi^2(\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_m)$

Back to the Parametric Correlation Problem

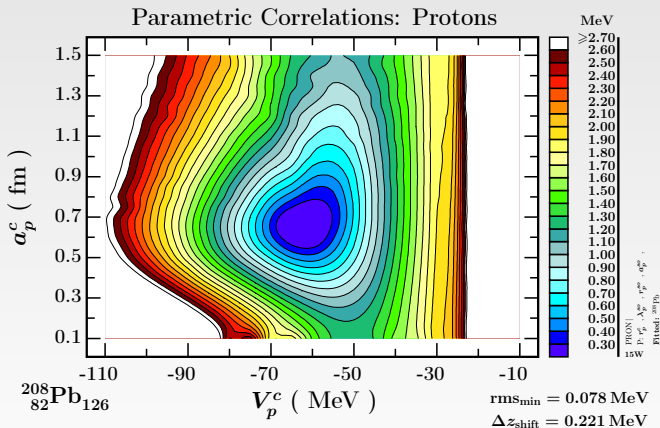
- One can show that the parametric correlations can be detected through projecting the $\chi^2(\mathbf{p})$ onto a $(\mathbf{p}_j, \mathbf{p}_k)$ -plane: $\min_{i \neq j, k} \chi^2(\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_m)$



- As the approximate circular symmetry of this diagram, shows that the central potential **radius** and central potential **diffuseness** are not correlated - thus no danger to the predictive power

Back to the Parametric Correlation Problem

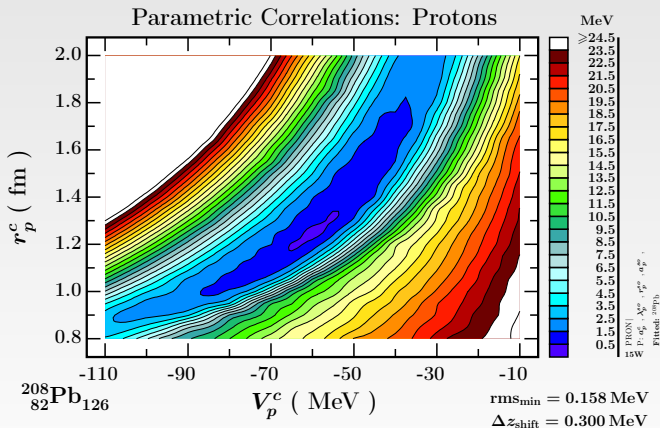
- One can show that the parametric correlations can be detected through projecting the $\chi^2(\mathbf{p})$ onto a (p_j, p_k) -plane: $\min_{i \neq j, k} \chi^2(\mathbf{p}_1, \mathbf{p}_2, \dots, \mathbf{p}_m)$



- These results show that the central potential **depth** and central potential **diffuseness** are not correlated - therefore no danger to the predictive power!

Back to the Parametric Correlation Problem

- One can show that the parametric correlations can be detected through projecting the $\chi^2(p)$ onto a (p_j, p_k) -plane: $\min_{i \neq j, k} \chi^2(p_1, p_2, \dots, p_m)$



- These results show that the central potential **depth** and central potential **radius** are correlated: $V_c \times r_c^2 \approx \text{const.}$ An ad hoc choice: $r_c \rightarrow r_c^{\text{exp.}}$

Conclusion:

The Central Potential is virtually free from correlations

Conclusion:

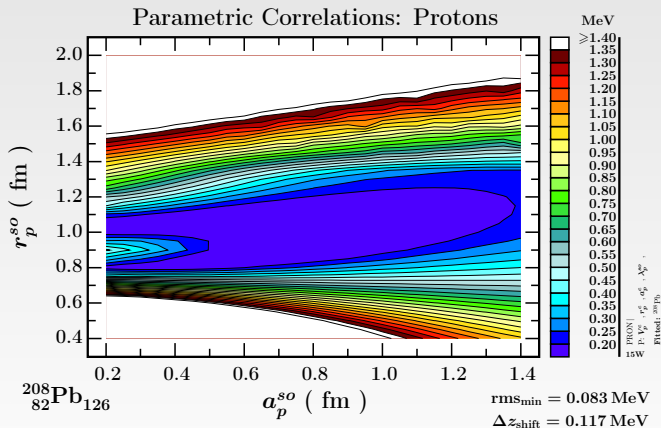
The Central Potential is virtually free from correlations

Next:

Checking the Spin-Orbit Potential

The Spin-Orbit Situation is More Complex

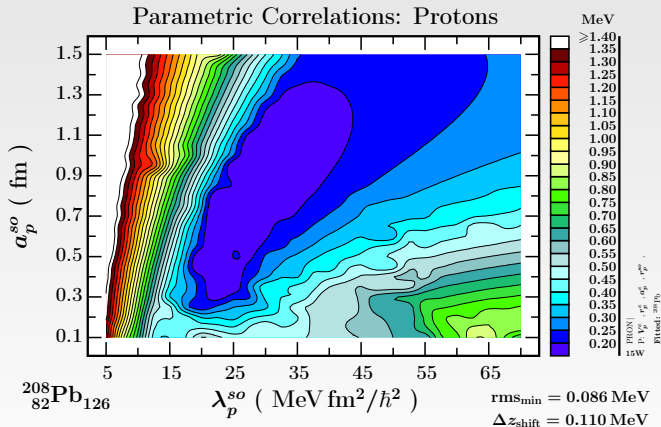
- One can show that the parametric correlations can be detected through projecting the $\chi^2(p)$ onto a (p_j, p_k) -plane: $\min_{i \neq j, k} \chi^2(p_1, p_2, \dots, p_m)$



- These results show that the spin-orbit **diffuseness** and spin-orbit **radius** are weakly correlated

The Spin-Orbit Situation is More Complex

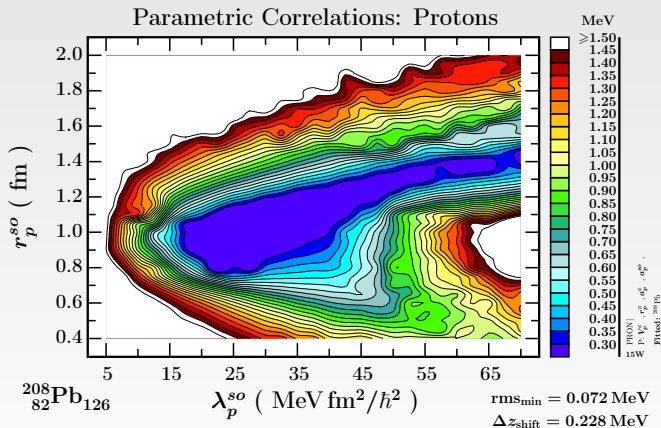
- One can show that the parametric correlations can be detected through projecting the $\chi^2(p)$ onto a (p_j, p_k) -plane: $\min_{i \neq j, k} \chi^2(p_1, p_2, \dots, p_m)$



- These results show that the spin-orbit **diffuseness** and spin-orbit **strength** are **weakly correlated**. Graphical instabilities under control - can be ignored

The Spin-Orbit Situation is More Complex

- One can show that the parametric correlations can be detected through projecting the $\chi^2(p)$ onto a (p_j, p_k) -plane: $\min_{i \neq j, k} \chi^2(p_1, p_2, \dots, p_m)$



- These results show that the spin-orbit **radius** and spin-orbit **strength** are **correlated**. Graphical instabilities under control - can be ignored

Conclusion:

**The Spin-Orbit Potential contains weak
but complex correlations**

Conclusion:

**The Spin-Orbit Potential contains weak
but complex correlations**

Our solution:

Seek physics arguments eliminating correlations

Conclusion:

**The Spin-Orbit Potential contains weak
but complex correlations**

Our solution:

Seek physics arguments eliminating correlations

A possible alternative:

**Using Applied–Mathematics regularisation–methods, e.g.:
‘Truncated Singular Value Decomposition Theorem’**

Conclusion:

**The Spin-Orbit Potential contains weak
but complex correlations**

Our solution:

Seek physics arguments eliminating correlations

A possible alternative:

**Using Applied–Mathematics regularisation–methods, e.g.:
‘Truncated Singular Value Decomposition Theorem’**

However, here we follow the first approach $\rightarrow\rightarrow\rightarrow$

Physics-Guided Improvements of the WS Universal

- It is well known that the microscopic structure of the mean field, $\hat{\mathbf{V}}_{\text{mf}}$, is based on the 2-body interactions, $\hat{\mathbf{v}}_2$:

$$\hat{\mathbf{v}}_2 \leftrightarrow \hat{\mathbf{v}}_{\text{two-body}}(\vec{r}_i - \vec{r}_j) \rightarrow \mathbf{V}_{\text{mean-field}}(\vec{r}_i) \leftrightarrow \hat{\mathbf{V}}_{\text{mf}}(\vec{r}_i)$$

$$\hat{\mathbf{V}}_{\text{mf}}(\vec{r}_i) \propto \sum_{j \neq i} \int \psi_j^*(\vec{r}_j) \hat{\mathbf{v}}_2(\vec{r}_i - \vec{r}_j) \psi_j(\vec{r}_j) d^3\vec{r}_j, \quad \sum_j \psi_j^*(\vec{r}_j) \psi_j(\vec{r}_j) \equiv \rho(\vec{r})$$

- Here we follow the ‘microscopic generalisation of the WS-universal’ in:

Realistic Nuclear Mean Field Approach with the Density-Dependent Spin-Orbit Term;

B. Belgoumène, J. Dudek and T. Werner, *Phys. Lett. B* **267** (4) (1991) 431-437 \Rightarrow

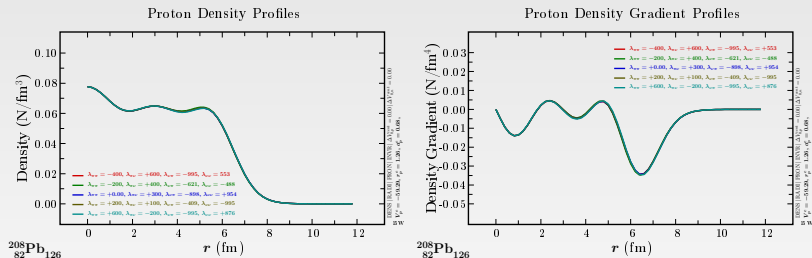
$$\hat{\mathbf{V}}_{\text{so}}^{\pi} = \lambda_{\pi\pi} \frac{1}{r} \frac{d\rho_{\pi}}{dr} + \lambda_{\pi\nu} \frac{1}{r} \frac{d\rho_{\nu}}{dr} \quad \text{Eq.(A)}$$

$$\hat{\mathbf{V}}_{\text{so}}^{\nu} = \lambda_{\nu\pi} \frac{1}{r} \frac{d\rho_{\pi}}{dr} + \lambda_{\nu\nu} \frac{1}{r} \frac{d\rho_{\nu}}{dr} \quad \text{Eq.(B)}$$

Advantages: The new expression includes the iterative self-consistency condition like in the microscopic HF approach rather than pure phenomenology and contains 4 parameters rather than 6. **What are their correlations?**

Density-Dependent Profiles

- The first preliminary tests show that the selfconsistent density and the density gradient do not depend much on the choice of the λ parameters

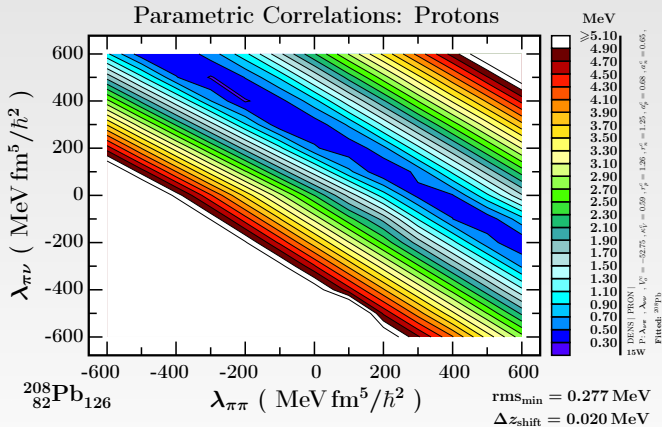


- This means that after the minimisation, parameters compensate mutually their impact... But this must imply the linear parametric $\lambda - \lambda$ correlations!

$$\hat{V}_{\text{so}}^{\pi} = \lambda_{\pi\pi} \frac{1}{r} \frac{d\rho_{\pi}}{dr} + \lambda_{\pi\nu} \frac{1}{r} \frac{d\rho_{\nu}}{dr}$$

Density-Dependent Spin-Orbit: Linear Correlations

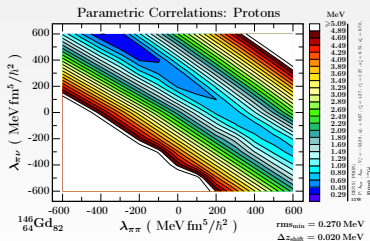
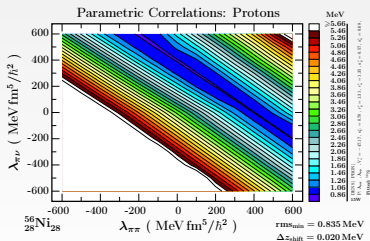
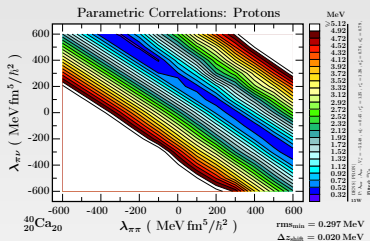
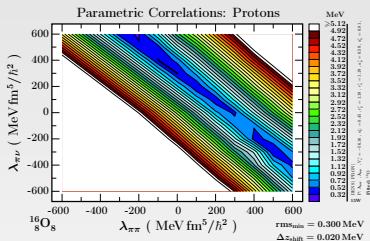
- Correlation between $\lambda_{\pi\pi}$ and $\lambda_{\pi\nu}$ for ^{208}Pb



- Realistic calculations indicate that the density-dependent spin-orbit potential parameters are correlated – but the **correlations are perfectly linear**

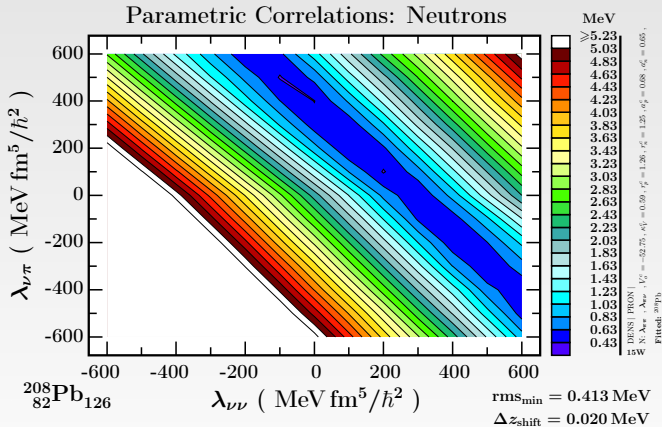
Linear-Correlations in Density-Dependent Spin-Orbit

- The same as before but for ^{16}O , ^{40}Ca , ^{56}Ni and ^{146}Gd



Density-Dependent Spin-Orbit: Linear Correlations

- Correlation between $\lambda_{\nu\nu}$ and $\lambda_{\nu\pi}$ for ^{208}Pb



- Calculations show that the density-dependent spin-orbit potential parameters are correlated – but the $\lambda_{\nu\nu} - \lambda_{\nu\pi}$ correlations are perfectly linear

A Working Conclusion

- A more detailed analysis shows that the valleys on the planes

$$(\lambda_{\pi\pi}, \lambda_{\pi\nu}) \text{ and } (\lambda_{\nu\nu}, \lambda_{\nu\pi})$$

cross at the common point for all the nuclei analysed where:

$$\lambda_{\pi\pi} \approx \lambda_{\pi\nu} \approx \lambda_{\nu\nu} \approx \lambda_{\nu\pi}$$

A Working Conclusion

- A more detailed analysis shows that the valleys on the planes

$$(\lambda_{\pi\pi}, \lambda_{\pi\nu}) \text{ and } (\lambda_{\nu\nu}, \lambda_{\nu\pi})$$

cross at the common point for all the nuclei analysed where:

$$\lambda_{\pi\pi} \approx \lambda_{\pi\nu} \approx \lambda_{\nu\nu} \approx \lambda_{\nu\pi}$$

- **Conclusion:** We may significantly decrease the number of spin-orbit potential parameters thus eliminating correlations.

A Working Conclusion

- A more detailed analysis shows that the valleys on the planes

$$(\lambda_{\pi\pi}, \lambda_{\pi\nu}) \text{ and } (\lambda_{\nu\nu}, \lambda_{\nu\pi})$$

cross at the common point for all the nuclei analysed where:

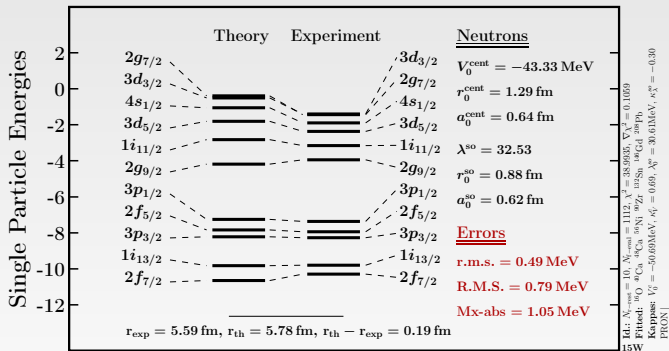
$$\lambda_{\pi\pi} \approx \lambda_{\pi\nu} \approx \lambda_{\nu\nu} \approx \lambda_{\nu\pi}$$

- **Conclusion:** We may significantly decrease the number of spin-orbit potential parameters thus eliminating correlations. **But: Do we loose something? What?**

How Many Degrees of Freedom Does the V_{so} Have?

- We fit all the traditional WS potential parameters to **eight nuclei** (60 neutron levels plus 45 proton levels)

Comparison Theory-Experiment



$^{208}_{82}\text{Pb}_{126}$

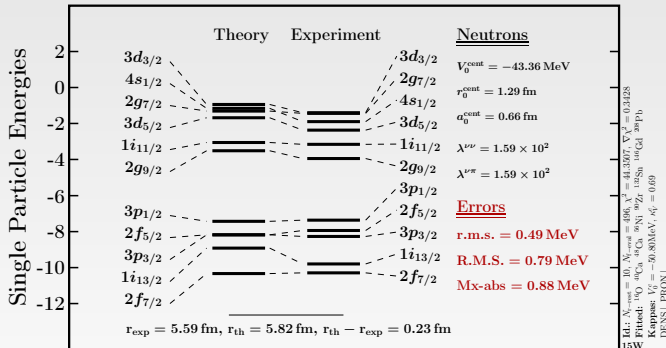
Spherical Woods-Saxon Hamiltonian

- We illustrate the results for ^{208}Pb -neutrons → **Solution r.m.s.=0.49 MeV**
- The answer: 6 - $\{\lambda^{\text{so}}, r_0^{\text{so}}, a_0^{\text{so}}\}$ for protons and $\{\lambda^{\text{so}}, r_0^{\text{so}}, a_0^{\text{so}}\}$ for neutrons

How Many Degrees of Freedom Does the V_{so} Have?

- We fit the density-dependent spin-orbit: $\lambda_{nn} = \lambda_{np} = \lambda_{pn} = \lambda_{pp} \equiv \lambda$, to **eight nuclei**

Comparison Theory-Experiment



$^{208}_{82}\text{Pb}_{126}$

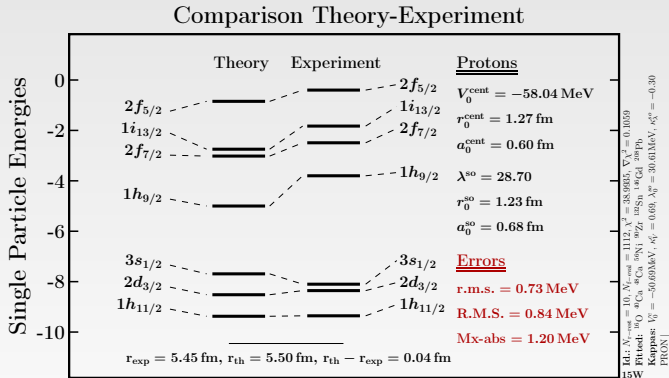
Spherical Woods-Saxon Hamiltonian

- The results for ^{208}Pb -neutrons – **Solution r.m.s.=0.49 MeV is unchanged**
- The answer: **1** parameter - common for the protons and for the neutrons

We repeat the test for the protons

How Many Degrees of Freedom Does the V_{so} Have?

- We fit all the traditional WS potential parameters to **eight nuclei** (60 neutron levels plus 45 proton levels)

 $^{208}_{82}\text{Pb}_{126}$

Spherical Woods-Saxon Hamiltonian

- We illustrate the results for ^{208}Pb -protons – Solution r.m.s.=0.73 MeV

Conclusions & Summary

Conclusions & Summary

- We need to take into account both the theory uncertainties and the experimental errors in order to determine the uncertainties of the model predictions

Conclusions & Summary

- We need to take into account both the theory uncertainties and the experimental errors in order to determine the uncertainties of the model predictions
- The model needs to be verified for the presence/absence of parametric correlations

Conclusions & Summary

- We need to take into account both the theory uncertainties and the experimental errors in order to determine the uncertainties of the model predictions
- The model needs to be verified for the presence/absence of parametric correlations
- The model predictions need to be verified for their stability

Conclusions & Summary

- We need to take into account both the theory uncertainties and the experimental errors in order to determine the uncertainties of the model predictions
- The model needs to be verified for the presence/absence of parametric correlations
- The model predictions need to be verified for their stability
- In the case of presence of parametric correlations, we need to eliminate them.

Conclusions & Summary

- We need to take into account both the theory uncertainties and the experimental errors in order to determine the uncertainties of the model predictions
- The model needs to be verified for the presence/absence of parametric correlations
- The model predictions need to be verified for their stability
- In the case of presence of parametric correlations, we need to eliminate them.
- We have shown that eliminating the spin-orbit parametric correlations, we obtained better or equal quality result.

How Many Degrees of Freedom Does the V_{so} Have?

Conclusions:

The self-consistent density-dependent, and thus ‘more microscopic’ spin-orbit potential, depends effectively on **one** parameter rather than **six**

- We obtain better or equal quality of comparison with experiment
- We arrive at the eliminating of all parametric correlation problems

With this strategy in mind:

**What are the actualised research directions
for the project?**

With this strategy in mind:

**What are the actualised research directions
for the project?**

We have two strategical goals:

- Eliminate parametric correlations and model over-parametrisation in order not to “kill” the predictive power at the start [as presented]

With this strategy in mind:

**What are the actualised research directions
for the project?**

We have two strategical goals:

- Eliminate parametric correlations and model over-parametrisation in order not to “kill” the predictive power at the start [as presented]
- Determine quantitative limitations from the today’s constraints such as experimental and theory errors which we cannot bypass today

In other words:

In other words:

**We can neither increase the number of data points
(volume of sampling) nor the quality of the sampling.**

In other words:

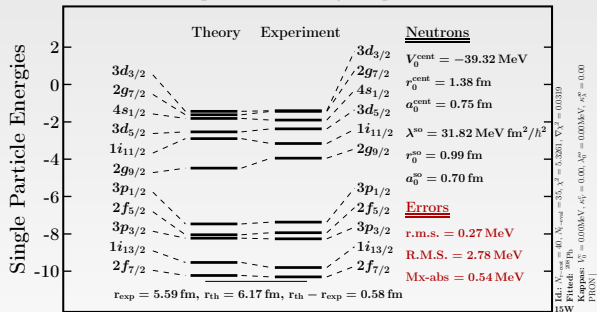
We can neither increase the number of data points (volume of sampling) nor the quality of the sampling.

Under these objective constraints we wish to know how (un)certain is what we calculate with our rather complex computer programs?

Uncertainties of Calculated Nucleon Energies

- The concept of pseudo-experimental levels: Optimise Hamiltonian under some plausible conditions → Replace experimental levels by the model energies → Construct in this way an exact model → Now we can modify the ‘sampling’

Comparison Theory-Experiment



$^{208}_{82}\text{Pb}_{126}$

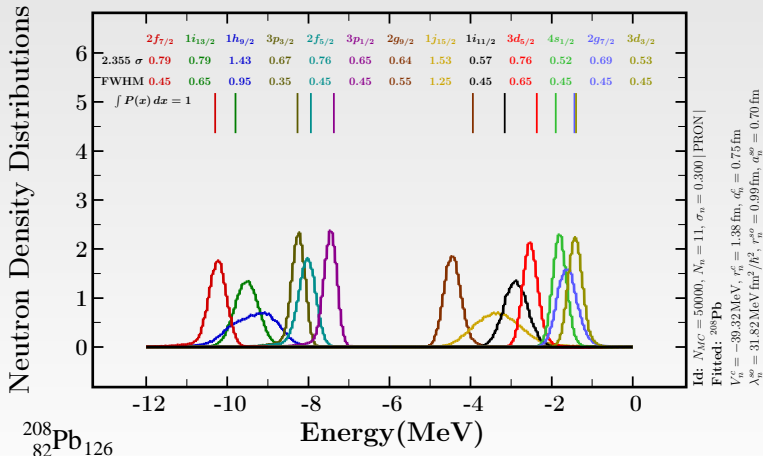
Spherical Woods-Saxon Hamiltonian

- LEFT: ^{208}Pb levels after a fit which will be treated as pseudo-experimental

Uncertainties of Calculated Nucleon Energies

- The pseudo-experimental levels: Now we can modify/increase the 'sampling'

Uncertainty Distributions for $N_n = 11$



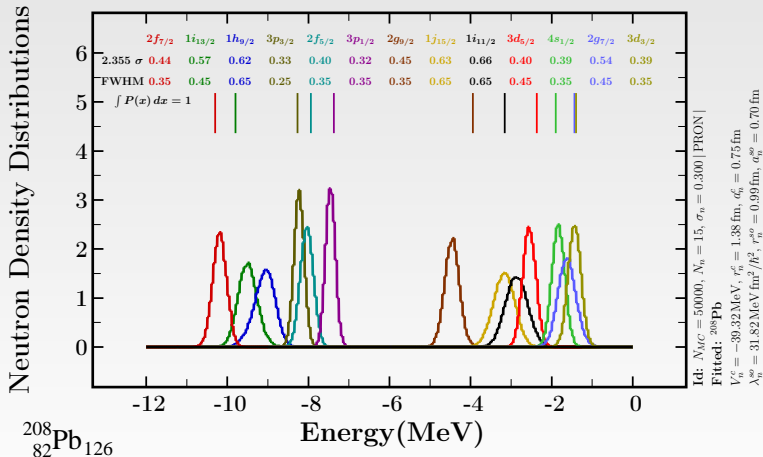
- Definitions: $\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i - \bar{\mathbf{e}})^2}$

$$\bar{\mathbf{e}} = \frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i)$$

Uncertainties of Calculated Nucleon Energies

- The pseudo-experimental levels: Now we can modify/increase the 'sampling'

Uncertainty Distributions for $N_n = 15$



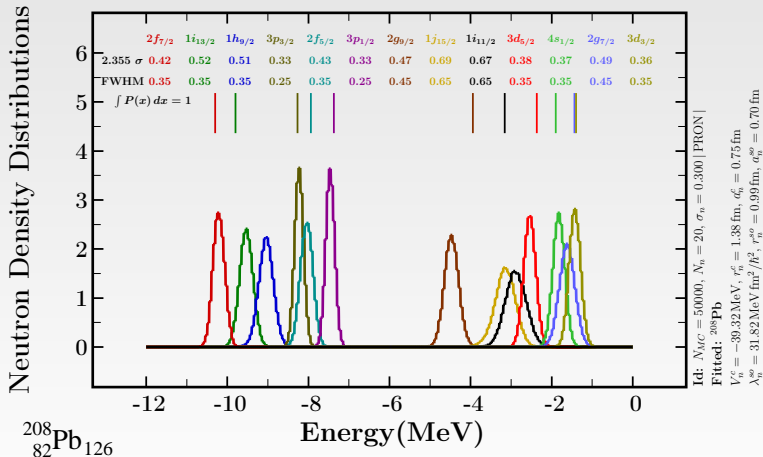
- Definitions: $\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i - \bar{\mathbf{e}})^2}$

$$\bar{\mathbf{e}} = \frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i)$$

Uncertainties of Calculated Nucleon Energies

- The pseudo-experimental levels: Now we can modify/increase the 'sampling'

Uncertainty Distributions for $N_n = 20$



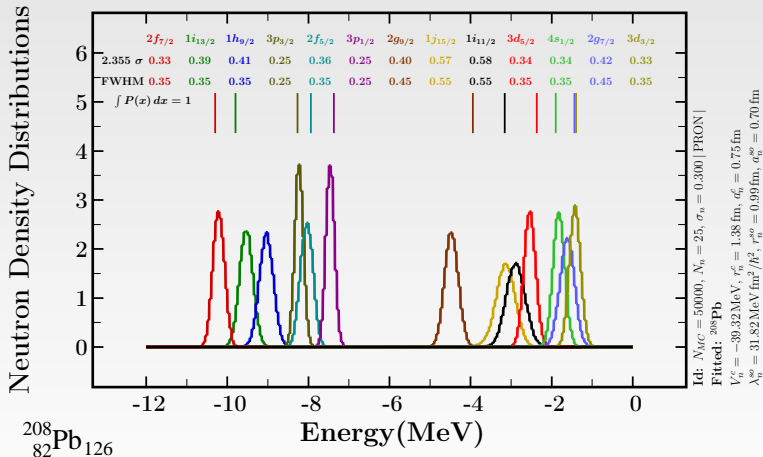
- Definitions: $\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i - \bar{\mathbf{e}})^2}$

$$\bar{\mathbf{e}} = \frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i)$$

Uncertainties of Calculated Nucleon Energies

- The pseudo-experimental levels: Now we can modify/increase the 'sampling'

Uncertainty Distributions for $N_n = 25$



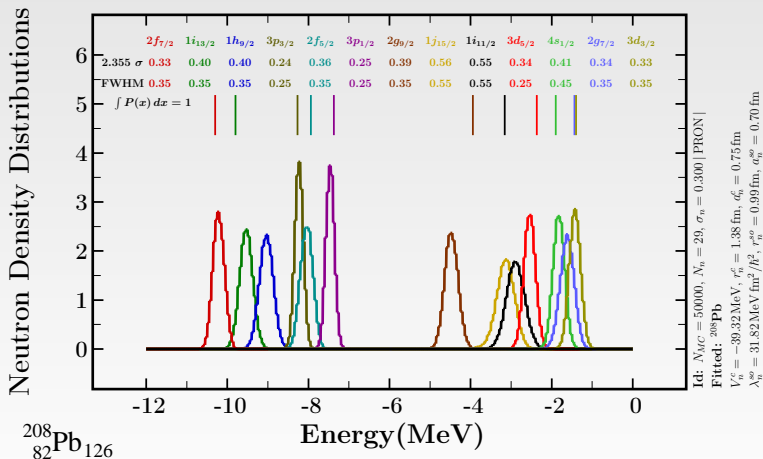
- Definitions: $\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i - \bar{\mathbf{e}})^2}$

$$\bar{\mathbf{e}} = \frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i)$$

Uncertainties of Calculated Nucleon Energies

- The pseudo-experimental levels: Now we can modify/increase the 'sampling'

Uncertainty Distributions for $N_n = 29$



- Definitions: $\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i - \bar{\mathbf{e}})^2}$

$$\bar{\mathbf{e}} = \frac{1}{n} \sum_{i=1}^n (\mathbf{e}_i)$$

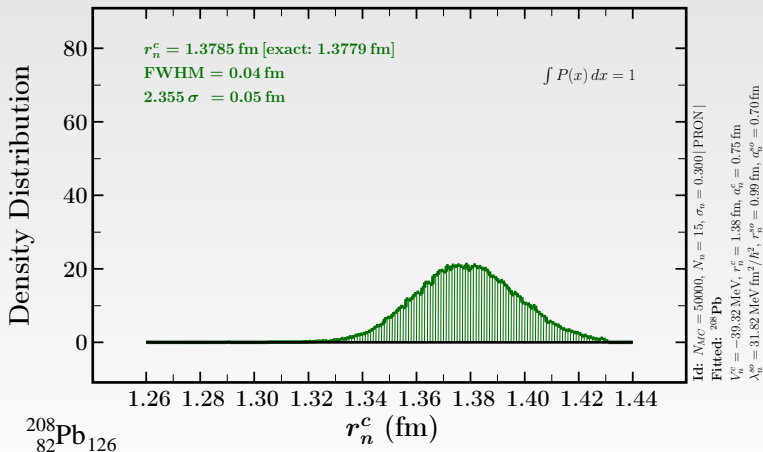
Thank you!

Central Radius Uncertainties

Uncertainties of the Optimal Parameters: r_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

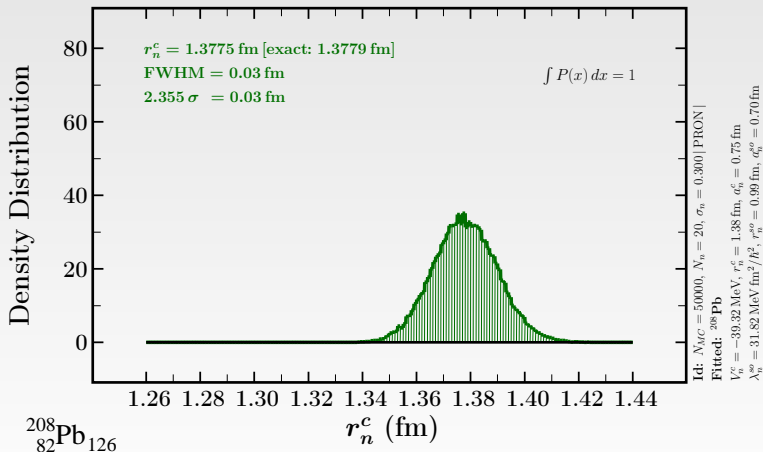


- Here: Sampling composed of 15 levels around the Fermi level

Uncertainties of the Optimal Parameters: r_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

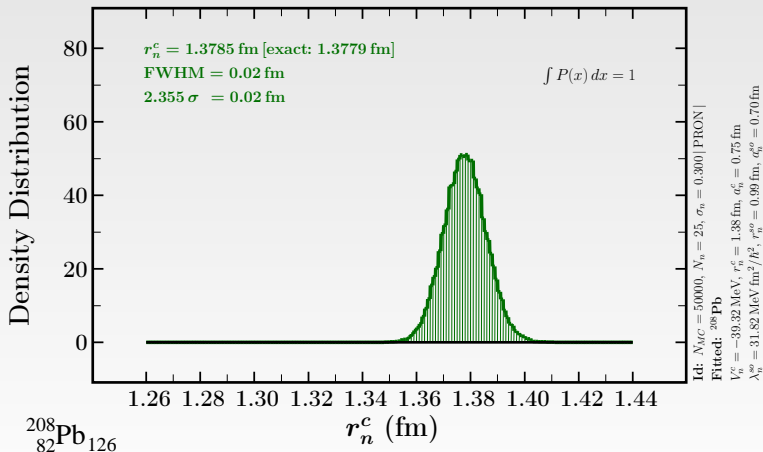


- Here: Sampling composed of 20 levels around the Fermi level

Uncertainties of the Optimal Parameters: r_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

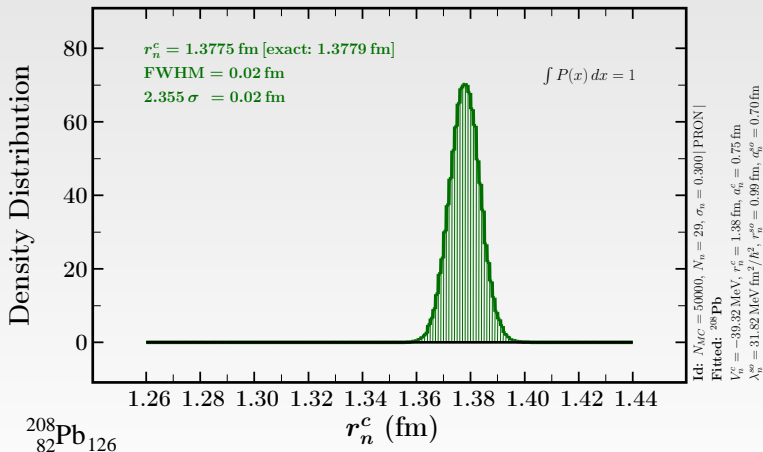


- Here: Sampling composed of 25 levels around the Fermi level

Uncertainties of the Optimal Parameters: r_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution



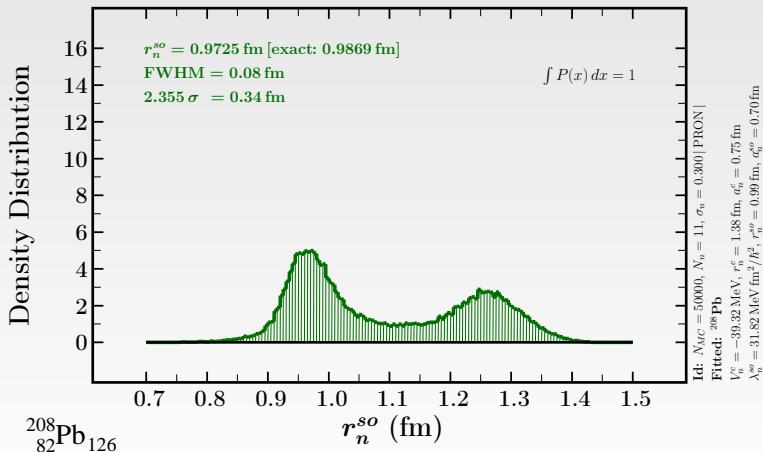
- Here: Sampling composed of 29 levels around the Fermi level

Spin-Orbit Radius Uncertainties

Uncertainties of the Optimal Parameters: r_n^{so}

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

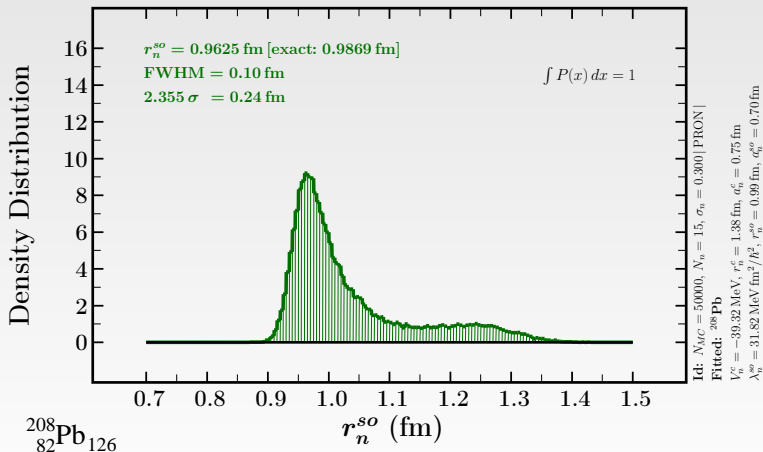


- Here: Sampling composed of 11 levels around the Fermi level

Uncertainties of the Optimal Parameters: r_n^{so}

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

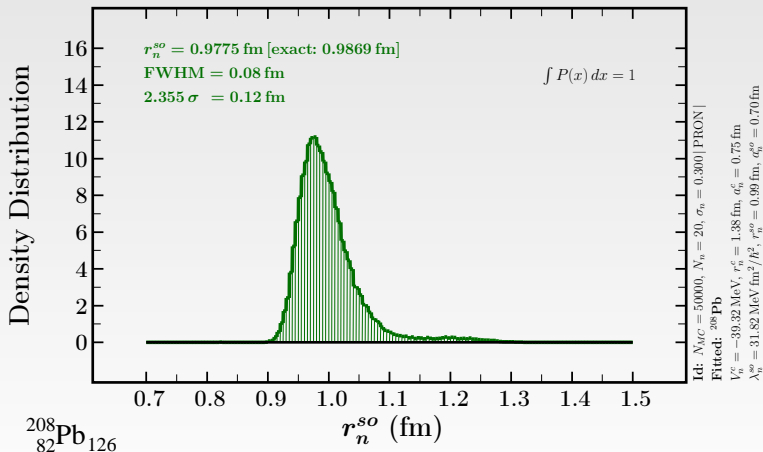


- Here: Sampling composed of 15 levels around the Fermi level

Uncertainties of the Optimal Parameters: r_n^{so}

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

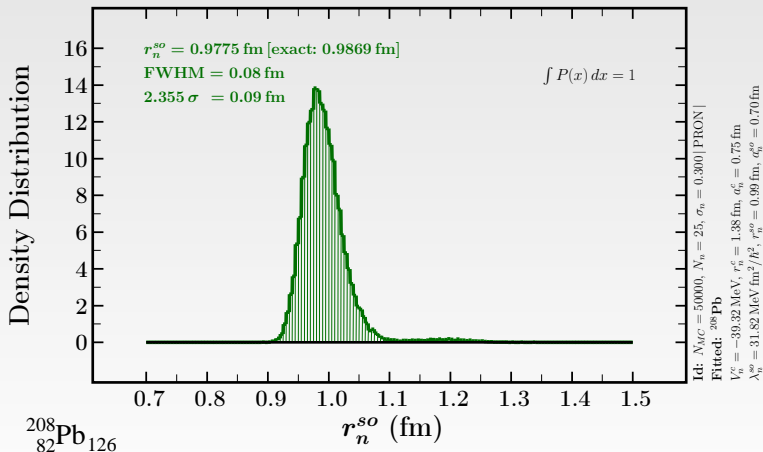


- Here: Sampling composed of 20 levels around the Fermi level

Uncertainties of the Optimal Parameters: r_n^{so}

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution



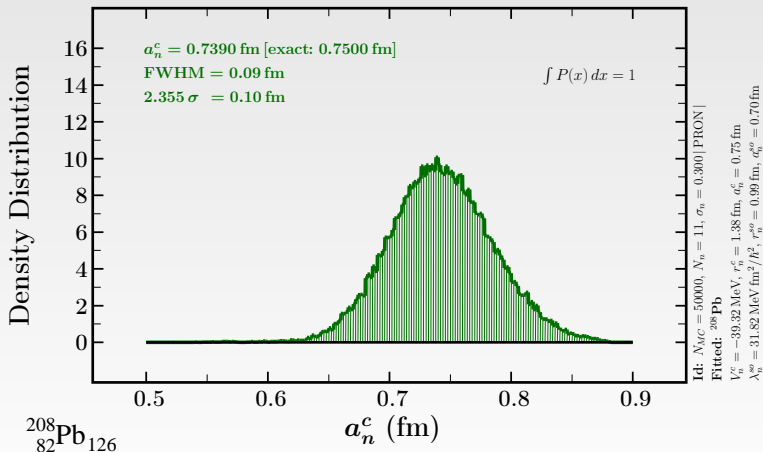
- Here: Sampling composed of 25 levels around the Fermi level

Diffusivity Parameter Uncertainties

Uncertainties of the Optimal Parameters: a_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

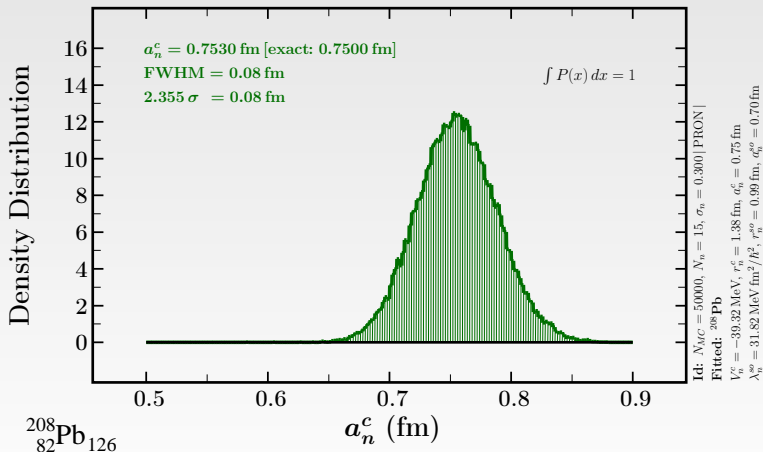


- Here: Sampling composed of 11 levels around the Fermi level

Uncertainties of the Optimal Parameters: a_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

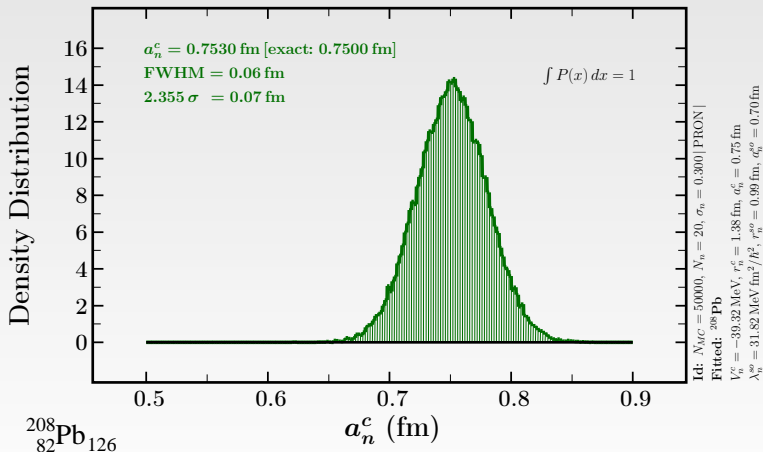


- Here: Sampling composed of 15 levels around the Fermi level

Uncertainties of the Optimal Parameters: a_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

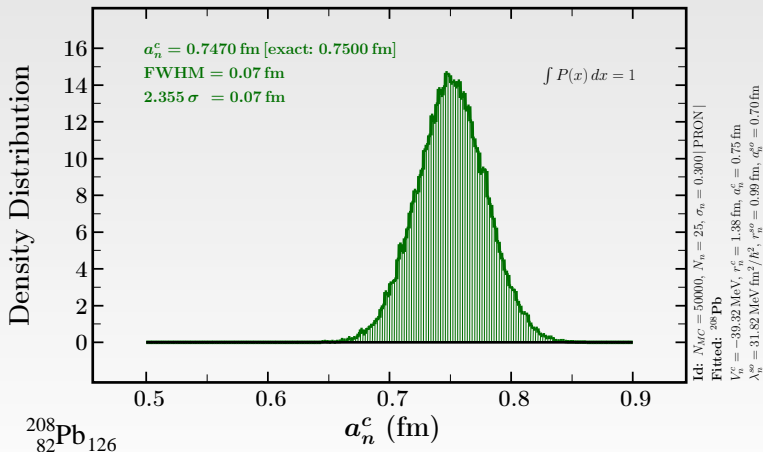


- Here: Sampling composed of 20 levels around the Fermi level

Uncertainties of the Optimal Parameters: a_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

Parameter Distribution

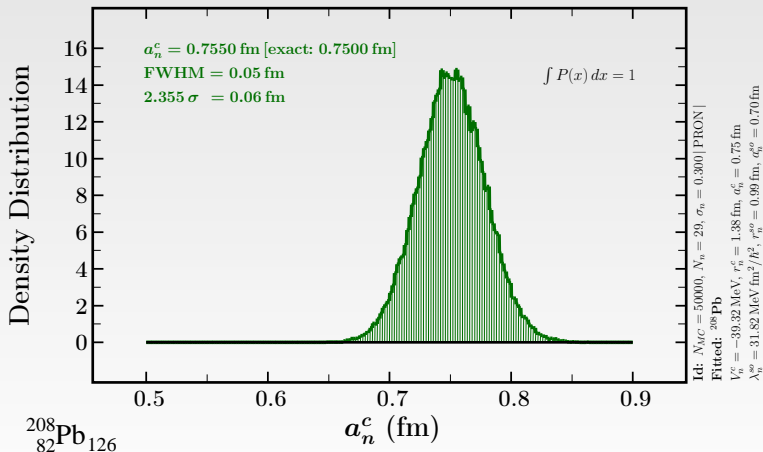


- Here: Sampling composed of 25 levels around the Fermi level

Uncertainties of the Optimal Parameters: a_n^c

- Pseudo-experimental levels: Parameter uncertainties \leftarrow increasing 'sampling'

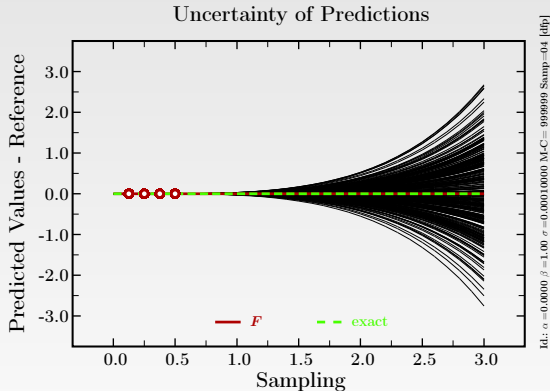
Parameter Distribution



- Here: Sampling composed of 29 levels around the Fermi level

Monte Carlo: Propagation of Uncertainties

- Monte-Carlo Simulation prediction curves, fitting the parameters to 4 sampling points. The exact solution curve has been subtracted for easy reading.



- Observe that the uncertainties near the sampling points are usually minute. Suppose that at 'sampling=2' – for the successful description we need the precision of 0.1. The simulation assures us that we **MUST NOT** use this exact theory at this required precision level.