

# Nuclear mass table based on Bayesian estimation of binding energy difference expressions

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# Local mass relations

## Introduction

Nuclear mass tables based on local mass relations are solutions of partial difference equations  $\hat{O}^n W(N, Z) = \tau(N, Z)$ . Example: transverse Garvey–Kelson mass equation (homogeneous PDE)

-	+	
+		-
	-	+

Z ↑

N →

$$\approx 0 \quad M(N+2, Z-2) - M(N, Z) + M(N+1, Z) -$$
$$-M(N+2, Z-1) + M(N, Z-1) - M(N+1, Z-2) \approx 0$$

This work as continuation of [Vladimirova et al., AIP Conf. 2377, 070003 (2021)] uses the residual  $pn$ -interaction energy

+	-
-	+

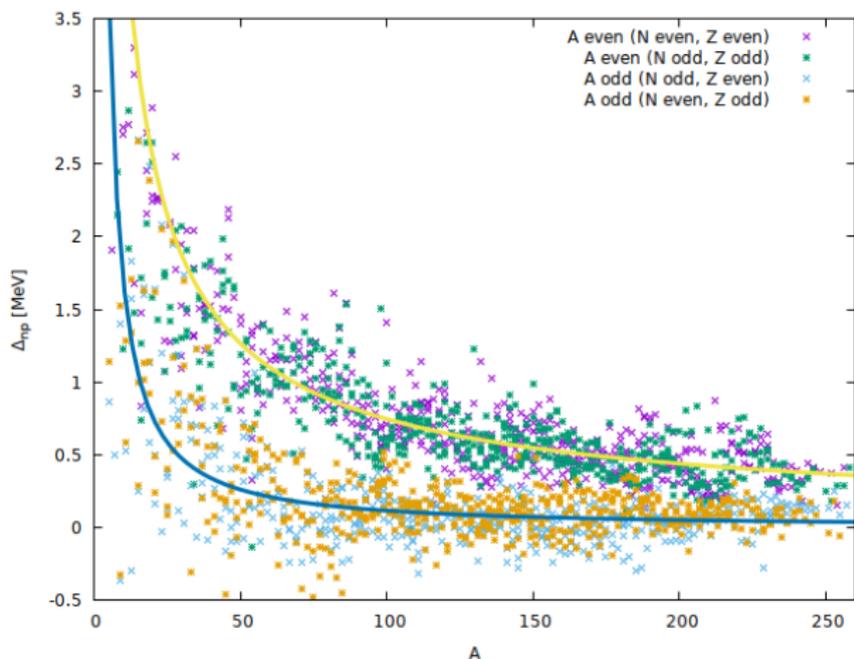
Z ↑

N →

$$\Delta_{np}(N, Z) = B_d(N, Z) - B_n(N, Z-1) - B_p(N-1, Z),$$

which determines an inhomogenous PDE.

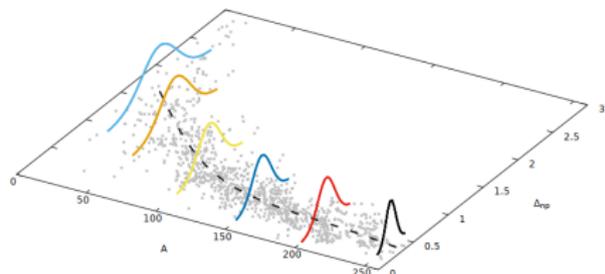
## Behaviour of $\Delta_{np}(A)$ for medium and heavy nuclei



*(Data from AME2020)*

As a function of the mass number  $\Delta_{np}$  separates into 2 branches for odd and even  $A$  and shows little dependence on shell effects or pairing.

## Estimation of $\Delta_{np}(A)$ using the Bayes theorem



$$P_{\text{post}}(\theta|x) = \frac{L(x|\theta)P_{\text{prior}}(\theta)}{P(x)}$$

$P_{\text{posterior}}(\theta|x)$  — posterior distribution of  $\theta$ ,  $x$  — observed data,  
 $L(x|\theta)$  — likelihood function,  
 $P_{\text{prior}}(\theta)$  — prior distribution of  $\theta$ ,  
 $P(x)$  — marginal distribution.

“Prior knowledge” + “data” → “posterior knowledge”

Treat experimental  $\Delta_{np}^{\text{exp}}$  at each point as random values with normal distribution  $\Delta_{np}(A) \sim N(\mu_A, \sigma_A^2)$ .

$$\ln L(\{\Delta_{np}^{\text{exp}}\}|\{\mu\}, \{\sigma^2\}) = \sum_{A=A_{\min}}^{A_{\max}} \sum_{\substack{\Delta_{np,i}^{\text{exp}} \\ \text{for this } A}} \ln N(\Delta_{np,i}^{\text{exp}}|\mu_A, \sigma_A^2)$$

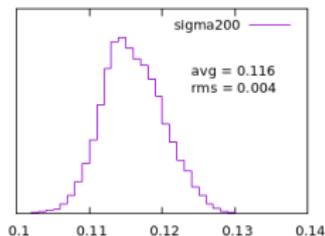
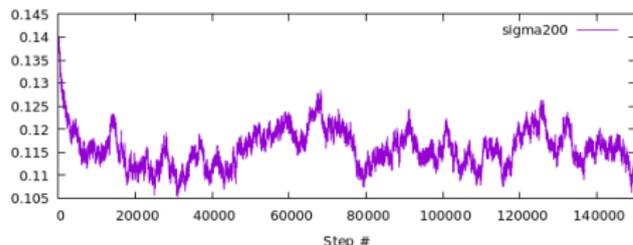
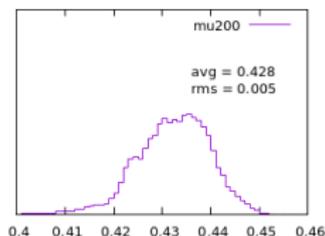
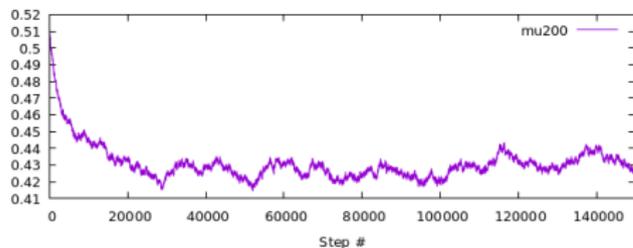
## Regularization condition

- ▶ Smoothness of  $\Delta_{np}(A)$  results from Tikhonov's regularization condition on  $\mu(A)$  and  $\sigma(A)$  and can be interpreted as prior knowledge.
- ▶ Originally, Tikhonov's regularization was formulated for the least squares method:  $\chi_{\text{reg}}^2 = \chi^2 + \tau \|\theta\|^2$ , where  $\tau$  is the regularization parameter. Penalty on high amplitude of  $\theta$ .
- ▶ Expressed as prior distribution:  
$$\ln P_{\text{prior}}(\theta) = -\tau \|\theta\|^2 = -\tau (\sum \mu_A^2 + \sum \sigma_A^2).$$
- ▶ Derivative:  $\ln P_{\text{prior}}(\theta) = -\tau (\sum (\mu_{A+1} - \mu_A)^2 + \sum (\sigma_{A+1} - \sigma_A)^2).$
- ▶ 2nd derivative:  
$$\ln P_{\text{prior}}(\theta) = -\tau (\sum (2\mu_{A+1} - \mu_A - \mu_{A+2})^2 + \sum (2\sigma_{A+1} - \sigma_A - \sigma_{A+2})^2).$$

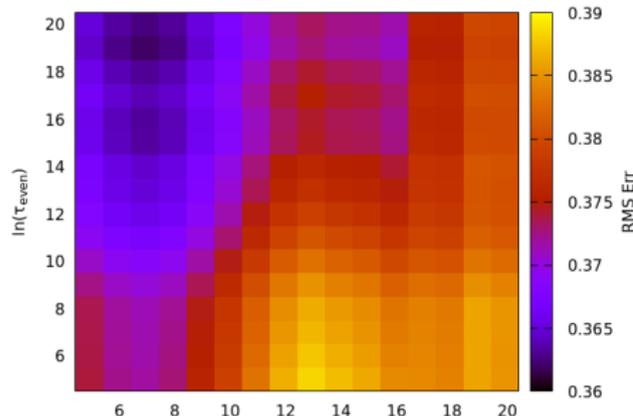
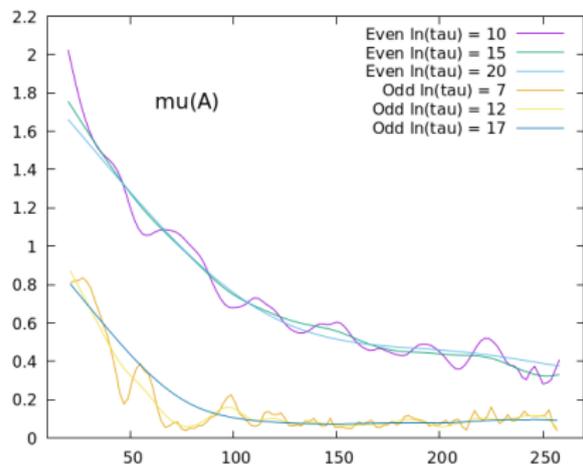
# MCMC method

Bayesian estimates of  $\{\mu\}$  and  $\{\sigma\}$  are obtained by sampling from the posterior distribution with the MH algorithm of random walk:

1. Randomly generate new  $\{\mu, \sigma^2\}_{t+1}$ .
2. Calculate  $\alpha = \frac{L(\{\Delta_{np}^{\text{exp}}\}|\{\mu, \sigma^2\}_{t+1})P_{\text{prior}}(\{\mu, \sigma^2\}_{t+1})}{L(\{\Delta_{np}^{\text{exp}}\}|\{\mu, \sigma^2\}_t)P_{\text{prior}}(\{\mu, \sigma^2\}_t)}$ .
3. Accept  $\{\mu, \sigma^2\}_{t+1}$  with probability  $\alpha$ , otherwise accept  $\{\mu, \sigma^2\}_t$ .
4. Go to step 1.



# Choice of regularization parameters

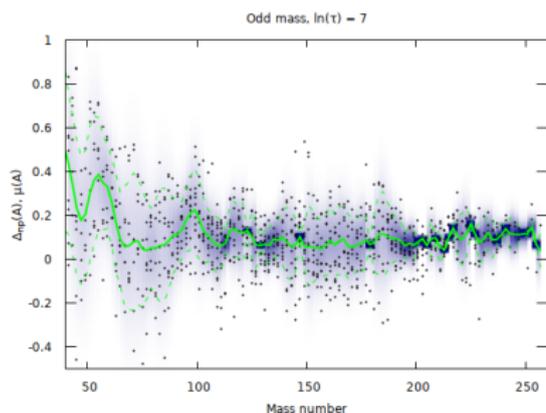
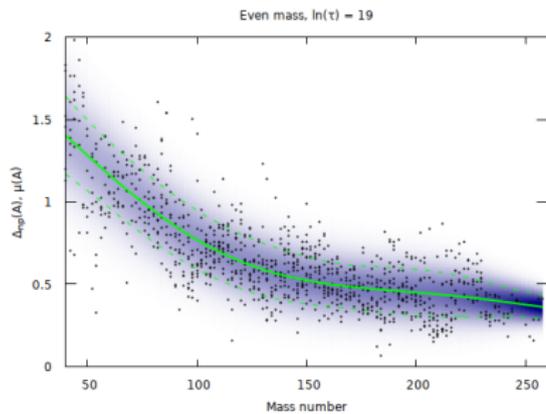


For each  $\tau_{\text{odd,even}}$ : use AME2016 to predict masses of 65 new nuclei in AME2020, calculate RMS error of prediction. Best  $\ln \tau_{\text{odd}} = 7$ ,  $\ln \tau_{\text{even}} = 19$ .

Model	RMS Err [keV]
MCMC	361.9
No MCMC (LMR)	376.5
FRMD2016	909.2
HFB-17	729.6
DZ10*	815.2
DZ10GP*	289.1

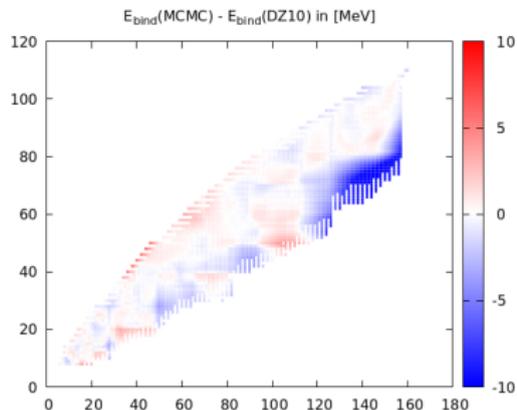
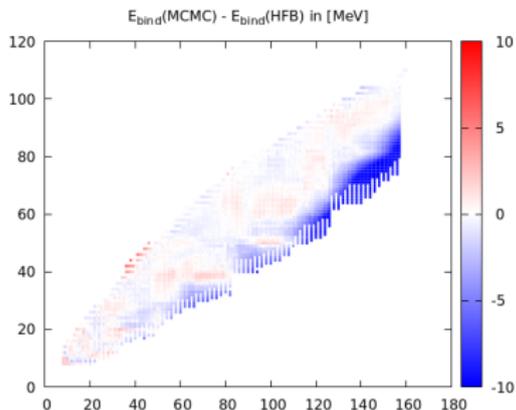
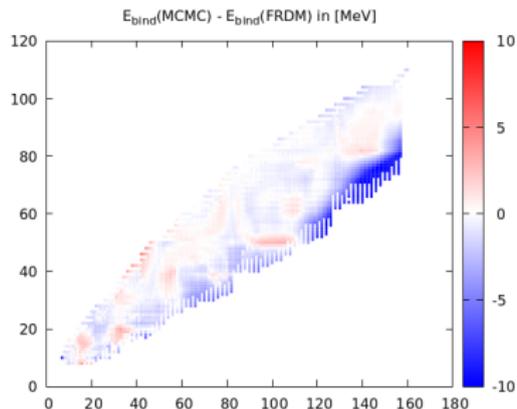
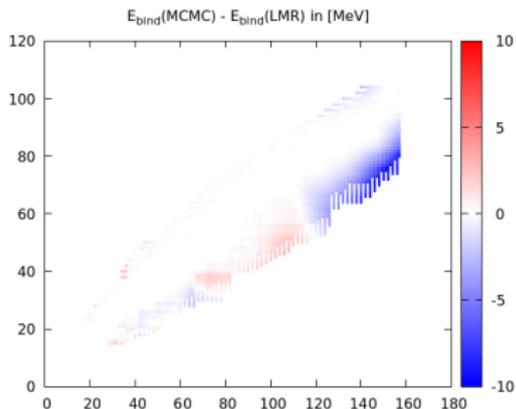
\* No  $^{46}\text{Mn}$ ,  $^{50}\text{Co}$ ,  $^{73}\text{Rb}$ ,  $^{211}\text{Pa}$  in DZ10(GP).

# Obtained estimates of $\Delta_{np}$

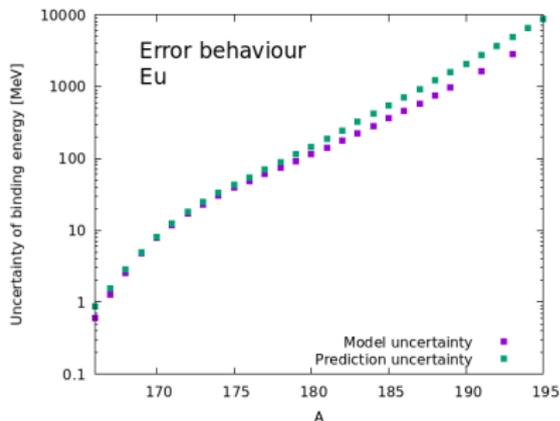
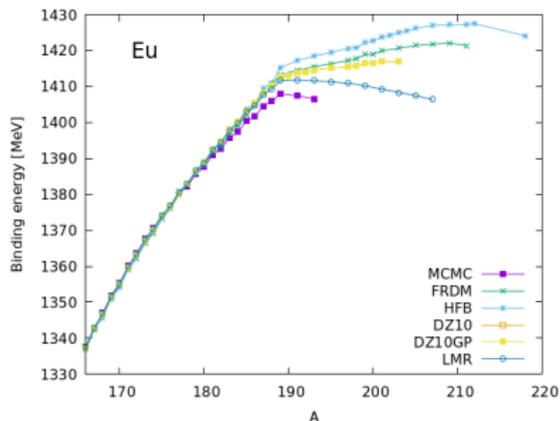
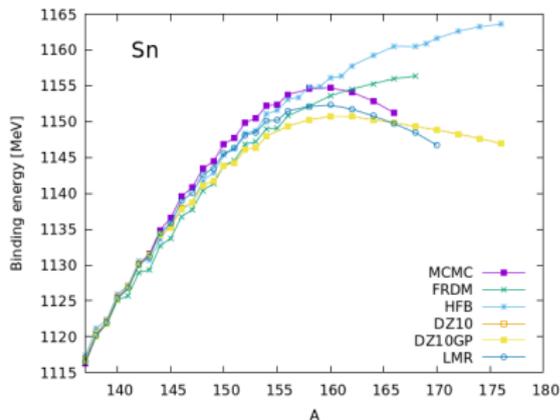
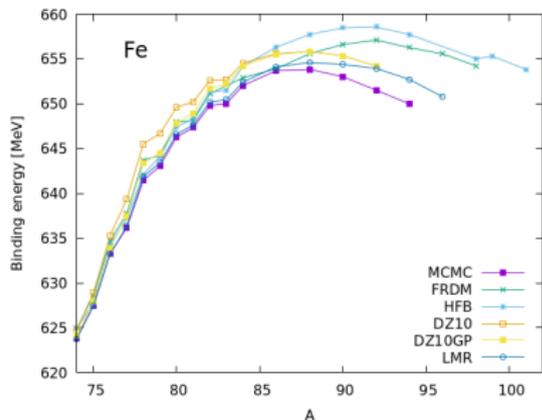


# Comparison of predicted binding energies

Use  $\Delta_{np}$  estimates to extrapolate AME2016

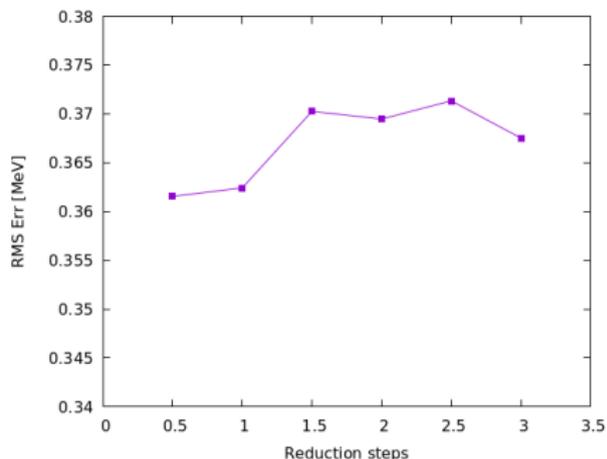
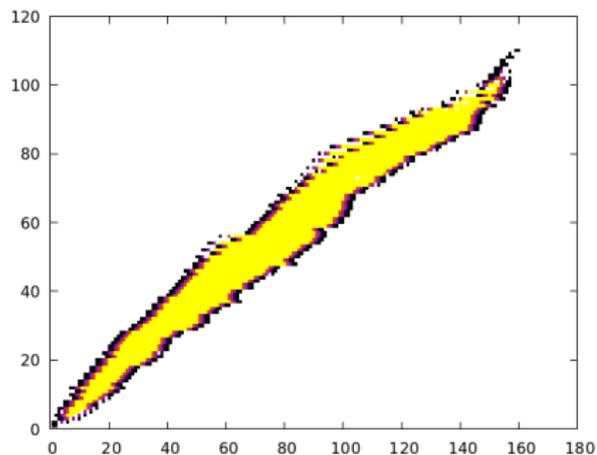


# Comparison of predicted binding energies

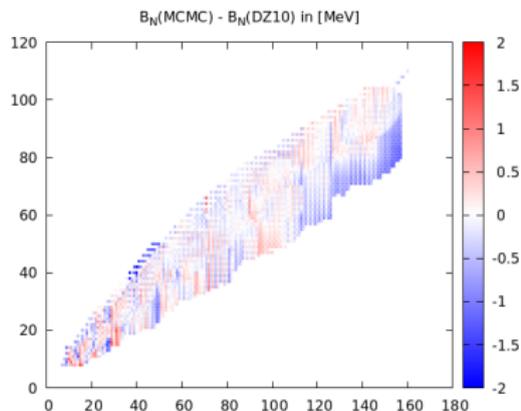
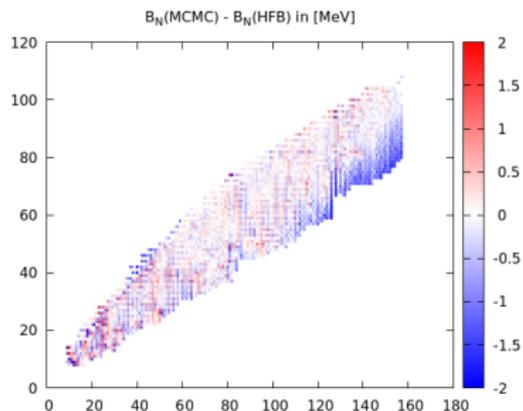
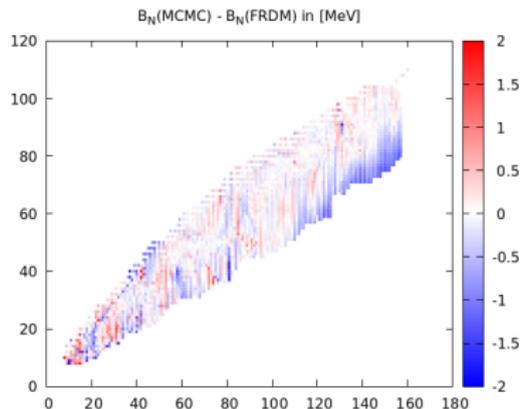
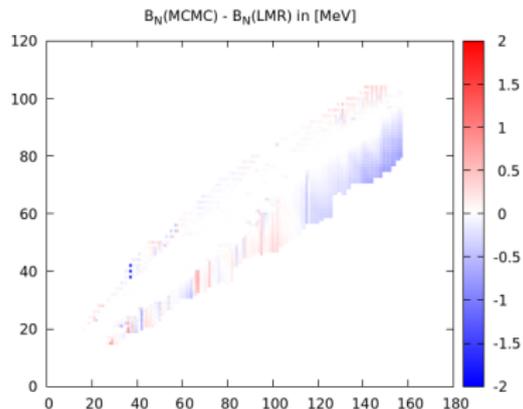


# Stability of prediction

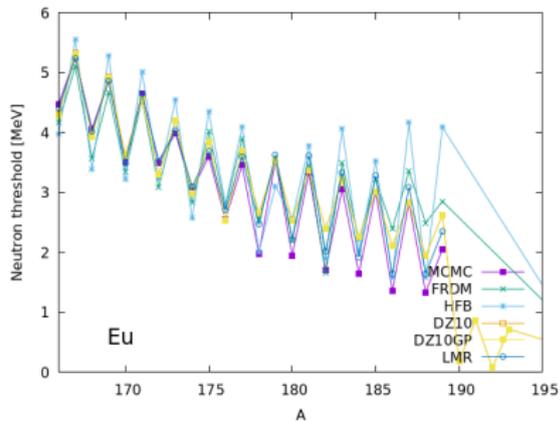
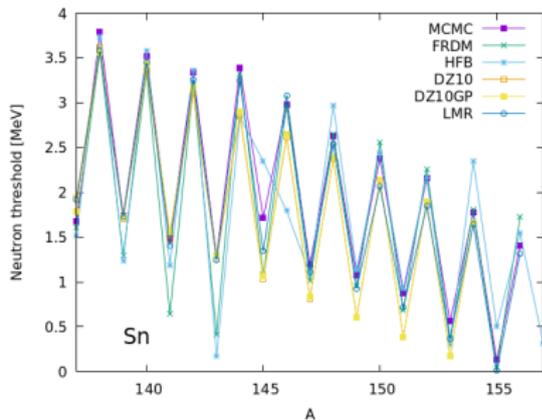
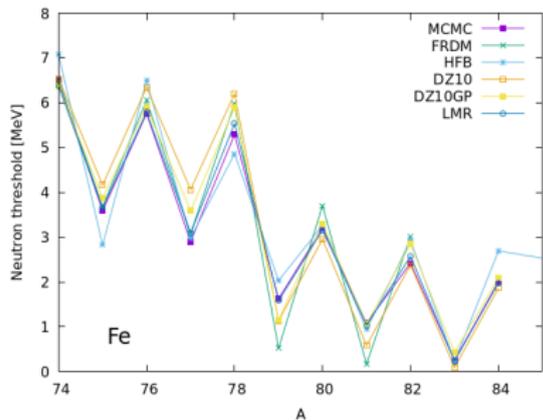
Reduce number of nuclei in AME2016 layer-by-layer, calculate RMS error.



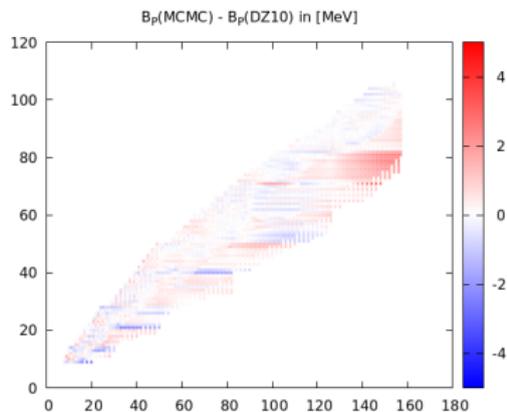
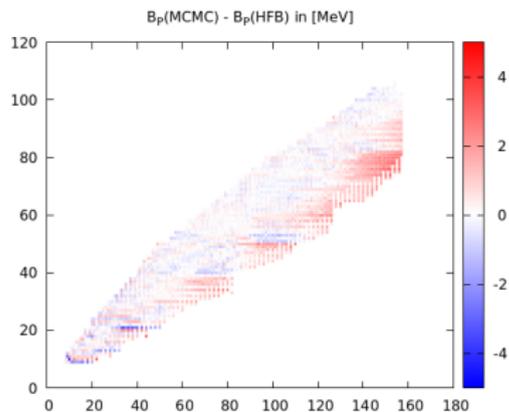
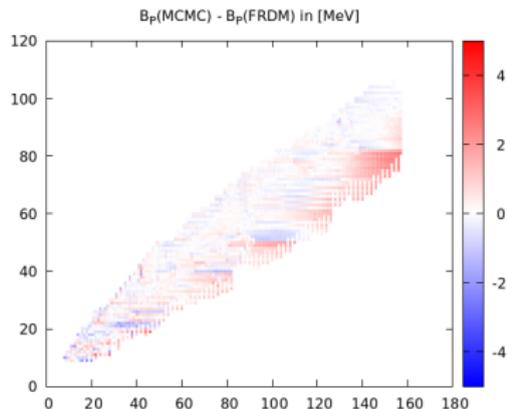
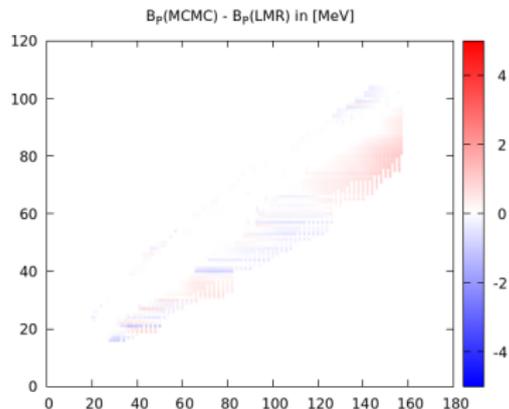
# Comparison of predicted neutron thresholds



# Comparison of predicted neutron thresholds



# Comparison of predicted proton thresholds



# Conclusions

- ▶ Nuclear mass model based on Bayesian estimation of  $\Delta_{np}$  is described.
- ▶ Very simple Monte-Carlo computation method: no numeric minimization, root finding, etc.
- ▶ Obtained RMS error value of 0.36 MeV is an improvement in comparison to the older version.
- ▶ Error scales quadratically with number of steps.
- ▶  $\Delta_{np}(A)$  shows preference for non-smooth behaviour for odd- $A$  nuclei.

Thank you!