Half-Lives for R-Process Nucleosynthesis Using the ANN Statistical Global Model

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" Numbers Rule The Universe "
PYTHAGORAS OF SAMOS

Introduction

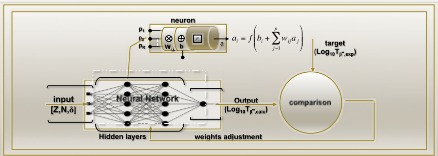
Statistical modeling of nuclear data within machine learning techniques provides a novel approach to nuclear systematics. Currently, there is an urgent need for **reliable estimates** of **β^--decay half-lives** of nuclei far from stability. This need is driven among others for the understanding of the **r-process** nucleosynthesis (mainly the element distribution and the time-scale). In this work [1], our recently developed **Artificial Neural Network (ANN)** statistical global model [2] of the β^--decay half-life systematics has been applied to the relevant to the r-process nuclei. We briefly report here our methodology and present and compare our results with the available experimental [3, 8-11] and the **theory-driven** values [5-7] in several regions of main interest. It seems that our new **data-driven** global model is very promising.

ANNs - Machine Learning Procedure

ANNs are structures, inspired from the corresponding biological neural systems, that consist of interconnected processing units (called **neurons**) arranged in a distinct **layered** topology. In analogy to the biological neural structures, the function of the network is determined from the connections between the units.

Static feedforward Neural Networks often have an **input layer** and one or more intermediate **hidden layers** of nonlinear processing units, followed by an **output layer** of linear units. The connection from neuron i to neuron j is characterized by a real number weight w_{ij}. The output a_i of neuron i is transmitted through this connection to neuron j and multiplies its strength by the weight w_{ij}, forming accordingly the weighted input $w_{ij}a_i$. Each neuron has additionally a bias b which is summed with its weighted inputs to form its net input. This quantity feeds the **activation function** f that produce the output a_j of neuron j.

Given two set of data, input/output pairs, ANNs are able to **learn** a specific nonlinear mapping by using a suitable **back-propagating (BP)** training algorithm and by adjusting the network weights and bias (as it schematically shown below). The goal of network training is not to learn an exact representation of the known half-lives itself, but rather to build a statistical model of the process which generates the half-lives. This is very important for a good **generalization** (prediction).



Objective: The minimization of the cost function E_D

$$E_D = \sum_{p=1}^{n}\left(\log_{10} T_{\beta^-,\exp} - \log_{10} T_{\beta^-,calc}\right)^2$$

Minimal Input for the Modeling of T_{β^-}

To what extent can mature learning machines (i.e. ANNs) properly decode the underlying β-decay half-lives systematics by only utilizing the hidden information inside of the minimal input Z and N nucleonic numbers?

Our β- Decay Global Model

We have therefore developed, continuing past similar efforts [4], a more sophisticated **Artificial Neural Networks** (ANNs) model for the half-life systematics of nuclei that decay 100% by the β^- mode in their ground states, using as input the atomic and neuron numbers (Z,N) and the corresponding parity (δ). The data sets are shown below.

Network	Architecture		Activation Functions
Static Feedforward Fully-connected	Size:	3-5-5-5-5-1	tanh-tanh-tanh-tanh-satlins
	Weights:	116	

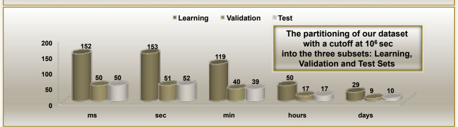
Mode	Training Technique	Initialization Method
Batch	LMO-BP Bayesian Regularization Cross-Validation	Nguyen-Widrow

Performance

Set	σ_{RMS}
Learning	0.53
Validation	0.60
Test	0.65
Overall	0.57

$$\sigma_{RMS} = \sqrt{\frac{1}{N}\left(\log_{10} T_{\beta^-,calc} - Log_{10} T_{\beta^-,exp}\right)^2}$$

Data Sets



Database	Dataset		Half-life Range	Decay Mode
NuBase2003 [3]	Cutoff	10^6 sec	0.15×10^{-2} s → ^{35}Na 0.20×10^6s → ^{247}Pu	100% β^-

***Our dataset** consists of **838** nuclides: **503 (~60\%)** of them have been **uniformly** chosen to train the network (**learning set**), **167 (~20\%)** to validate the learning procedure (**validation set**) and the remaining **168 (~20\%)** to evaluate the accuracy of the prediction (**test set**).*

Results - Comparisons

WP Nucleus	T_{β^-} (ms) Exp. Data [3, 13]	ANN Model [2]	pnQRPA +ffGT [5]	pnRQRPA +ff [6]	DF3+ CQRPA [7]
$^{78}Ni_{50}$	110 (+100,-60)	57	224	150	108
$^{79}Cu_{50}$	188 ± 25	115	157	-	257
$^{80}Zn_{50}$	545 ± 16	371	1.26 (s)	970	839
$^{129}Ag_{82}$	44 ± 7	77	32	-	56
$^{130}Cd_{82}$	162 ± 7	158	502	299	147
$^{131}In_{82}$	280 ± 30	307	139	-	201
$^{132}Sn_{82}$	39.7 ± 0.5 (s)	3 (s)	23.8 (s)	472.5 (s)	29.8 (s)

*β^--decay half-lives ($T_{\beta}-$) for main r-process **waiting-point** nuclei at N = 50 and N = 82 regions as given by the ANN Model [2], in comparison with the experimental values, as well as with the pnQRPA+ffGT calculations by Möller et al. [5] and the DF3+CQRPA model by Borzov et al. [7].*

Nucl.	$T_{\beta}-$ (ms) Exp. [3,9-11]	ANN [2]	QRPA +ffGT [5]	Nucl.	$T_{\beta}-$ (ms) Exp. [3,9-11]	ANN [2]	QRPA +ffGT [5]
^{70}Fe	94 ± 17	180	262	^{111}Mo	200 (+40 −35)	145	808
^{73}Co	41 ± 4	104	31	^{115}Tc	73 (+32,-22)	84	71
^{78}Ni	110 (+100,-60)	57	224	^{118}Ru	123 (+48,-35)	69	212
^{79}Cu	188 ± 25	115	157	^{121}Rh	151 (+67,-58)	91	62
^{81}Zn	290 ± 50	165	517	^{124}Pd	38 (+38,-19)	124	289
^{84}Ga	85 ± 10	214	268	^{130}Ag	35 ± 10	38	32
^{85}Ge	540 ± 50	329	806	^{133}Cd	57 ± 10	57	185
^{87}As	610 ± 120	448	699	^{135}In	92 ± 10	76	70
^{91}Se	270 ± 50	174	39	^{138}Sn	150 ± 60	113	336
^{94}Br	70 ± 20	194	33	^{137}Sb	450 ± 50	355	1.3 (s)
^{99}Kr	40 ± 11	35	61	^{138}Te	1.4 ± 0.4 (s)	1.6 (s)	7.9 (s)
^{102}Sr	69 ± 6	60	123	^{141}I	430 ± 20	569	1.4 (s)
^{102}Rb	37 ± 5	47	13	^{147}Xe	130 ± 80	195	89
^{105}Y	160 (+85 −60)	58	46	^{148}Cs	146 ± 6	279	154
^{107}Zr	150 (+40 −30)	75	177	^{150}Ba	300	453	402
^{110}Nb	170 ± 20	100	206				
σ_{rms} ($Log_{10}T_{\beta}$-)						**0.28**	**0.45**

*Half-lives of the **heaviest measured** r-process nuclides in the region of 26≤Z≤56, derived from the ANN Model [2], are compared with the experimental values and the pnQRPA+ffGT calculations by Möller et al. [5].*

Nucleus	$T_{\beta}-$ (s) Exp. Data [8]	ANN Model [2]	pnQRPA+ffGT [5]	DF3+CQRPA [7,8]
^{194}Re	1 (+0.5,-0.5)	20.8	70.8	2.1
^{195}Re	6 (+1,-1)	23.9	3.3	8.5
^{196}Re	3 (+1,-2)	8.8	3.6	1.4
^{199}Os	5 (+4,-2)	13.6	106.8	6.6
^{200}Os	6 (+4,-3)	21.7	187.1	6.9
^{198}Ir	8 (+2,-2)	57.6	377.1	19.1
^{199}Ir	6 (+5,-4)	73	370.6	46.7
^{202}Ir	11 (+3,-3)	8.6	68.4	9.8
	σ_{rms} ($Log_{10}T_{\beta}$-)	**0.77**	**1.33**	**0.39**

***Recently measured**, by T. Kurtukian-Nieto et al. [8], β^--decay half-lives ($T_{\beta}-$) of eight **heavy** nuclei close to the neutron shell N = 126 and around A = 195, are compared with the results derived by the ANN Model [2], the pnQRPA+ffGT calculations by Möller et al. [5] and the DF3+CQRPA model by Borzov et al. [7,8].*

Conclusions & Prospects

Our data-driven, theory-thin, **ANN** statistical global model of **β^--decay half-lives** should provide a valuable, robust additional tool to **complement** the **r-process clock** and **matter flow** studies, as well as to contribute to the exploration of β^--decay half-lives of very neutron-rich nuclei in the existing and future experimental facilities.

We plan further studies of nuclear properties relevant to r-process: i.e. masses, neutron capture cross-sections, with the already developed ANN and SVM techniques. We also plan further studies of nuclear properties using Artificial Intelligence's more mature learning strategies, such as **committee of machines** (CoM) - a collection of different feedforward ANNs instead of a single ANN, with a view to refine current results.

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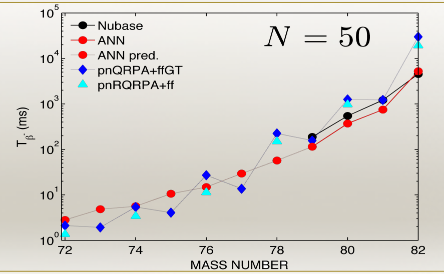
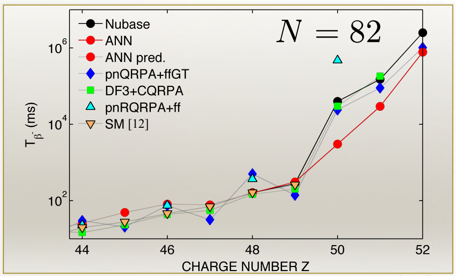
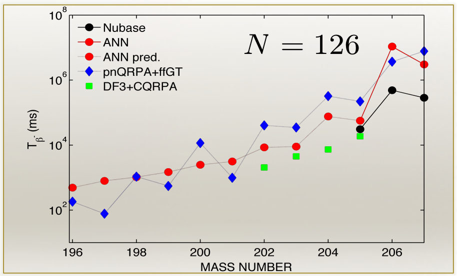


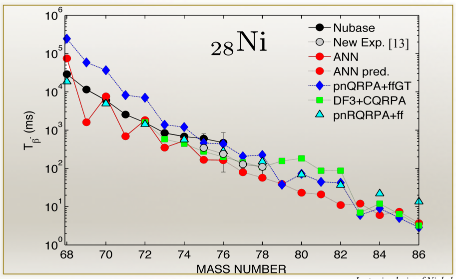
Isotonic chain of N=50



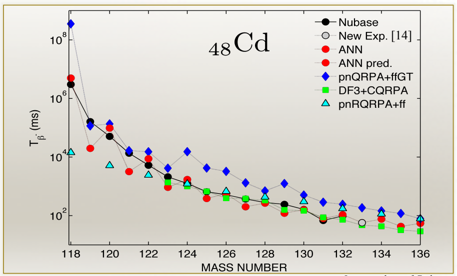
Isotonic chain of N=82



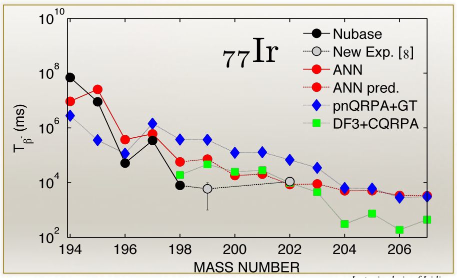
Isotonic chain of N=126



Isotopic chain of Nickel



Isotopic chain of Cadmium



Isotopic chain of Iridium