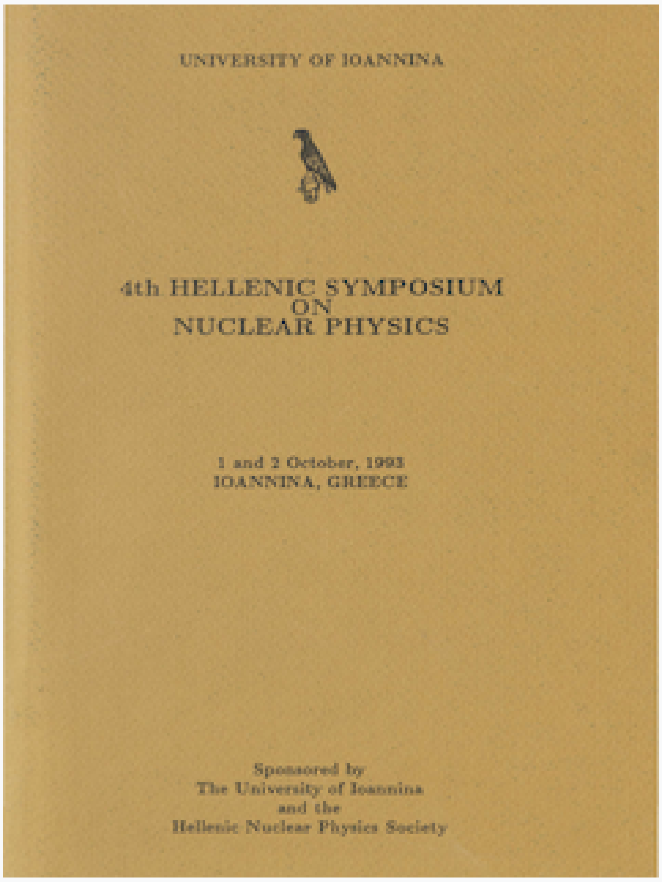
HNPS Advances in Nuclear Physics

Vol 4 (1993)

HNPS1993



Nuclear Phenomenology With Neural Nets: Halflives

E. Mavrommatis, S. Perris, K. A. Gernoth, J. W. Clark

doi: [10.12681/hnps.2886](https://doi.org/10.12681/hnps.2886)

NUCLEAR PHENOMENOLOGY WITH NEURAL NETS: HALFLIVES*

E. MAVROMMATIS and S. PERRIS
Physics Department, Division of Nuclear and Particle Physics
University of Athens, 15771 Athens, Greece

K. A. GERNOTH
International Center for Theoretical Physics
Trieste, Italy

J. W. CLARK
Department of Physics, Washington University
St. Louis, Mo 63130 USA

Abstract

A phenomenological approach to the analysis of nuclei that implements multilayer feedforward networks of model neurons has recently been developed [1,2,3]. Backpropagation and the closely related conjugate-gradient algorithm [4,5] are applied to teach such networks the systematics of a given nuclear property using a suitable training set selected from the existing database. The networks are then asked to predict the property for test muclei absent from the training set. With proper architecture and coding schemes for input and output data, learning can be accomplished with high accuracy. Predictive performance can equal or surpass that of conventional theoretical approaches provided the test nuclei are not too different from those of the training sets.

Neural network phenomenology has been successful in a number of specific problems including discrimination of stable from unstable nuclides, learning and prediction of atomic masses, analysis of neutron separation energies of odd-N nuclides, assignment of spin and parity to nuclear ground states and computation of decay-mode branching ratios in the decay of unstable nuclides [1-3]. We have obtained preliminary results from computer experiments aimed at developing neural network models that capture the systematics of the lifetimes of unstable nuclear ground states. To the best of our knowledge, there exist no global phenomenological models of the later. Work is in progress to improve the performance of our neural networks both in learning and prediction.

References

[1] S. Gazula, J.W. Clark and H. Bohr, Nucl. Phys. A540 (1992) 1.
[2] K. A. Gernoth, J.W. Clark, J.S. Prater, and H. Bohr, Phys. Lett B300 (1993) 1.
[3] J.W. Clark, K.A. Gernoth and M.L. Ristig, in Condensed Matter Theories Vol. 9, ed. J.W. Clark, A. Sadig, and K.A. Shaoib (Nova Commack,NY 1994), in press; and K.A. Gernoth and J.W. Clark, submitted to Neural Networks.
[4] D.E. Rumelhart, G.E. Hinton and R.J. Williams, in Parallel Distributed Processing, Vol. 1, ed. D.E. Rumelhart, J.L. McClelland, et al. (MIT Press, Cambridge, 1986).
[5] J. Hertz, A. Krogh and R.G. Palmer, Introduction to the Theory of Neural Computation (Addison-Wesley Redwood City, CA, 1991).

----

* Presented by E. Mavrommatis