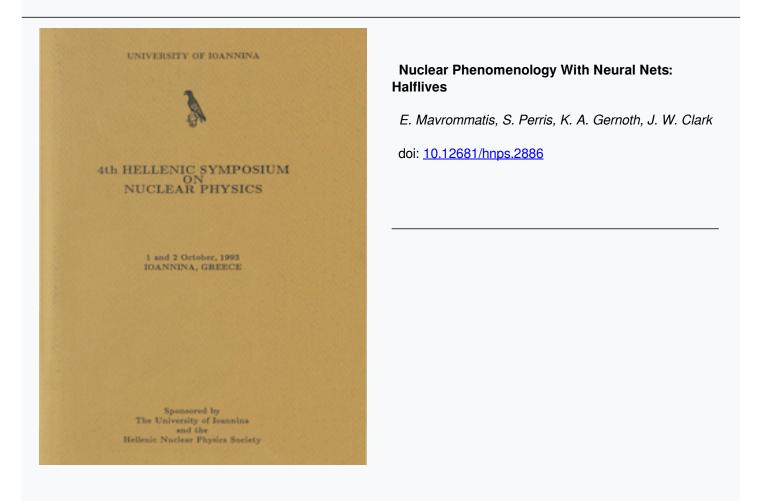




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NUCLEAR PHENOMENOLOGY WITH NEURAL NETS: HALFLIVES*

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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.

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