IBN AL- HAITHAM J. FOR PURE & APPL. SCI VOL.18 (2) 2005

A Study of Positive and Negative Parity States in ^{114}Te nucleus by the Interacting Boson Model .IBM by Neural Network(Back propagation multi-layer neural network) .

H. N. Hady and **H. R. Mohammed**
College of Education foe women ,University of Kufa

Abstract

Positive and negative parity states for ^{114}Te have been studied applying the vibration al limit U(5) of Interacting boson model (IBM-1) .

The present results have shown their good agreement with experimental data in addition to the determination of the spin/parity of new energy levels are not assigned experimentally as the levels 0^+_2 and 5^+_1 and the levels 3^-_1 and 5^-_1 .

Then back propagation multiLayer neural network used for positive and negative parity states for ^{114}Te and shown their membership to the Vibration limit U(5) the network implemented by MATLAB system.

Introduction

The interacting boson model (IBM) of Arima and Iachello(1,2) has been successfully applied to a wide range of nuclear collective phenomena(3) . The essential idea is that the low-energy collective degrees of freedom in nuclei can be described by proton and neutron bosons with spins of 0 and 2 . These collective building blocks interact(4,5) .

Different choices of the L=0 (s boson) and L=2 (d boson) energies and interaction strengths give rise to different types of collective spectra(6,7) .

In addition to the quadrupole d boson , other excitation modes are expected to play an important role in the description of the nuclear collective motion of particular importance is the collective 3^- mode(1).

Negative parity states are described in the IBM octupole model by adding a single angular momentum L=3 boson with intrinsic negative parity (an f boson) to the usual s-d model space(8) .

In order to construct state of octupole character, we consider a system of two different kinds of bosons (quadrupole d-boson) and (octupole f-boson) .

This is done in IBM-1 framework , in which neutron and proton degrees of freedom are not separately distinguished .The total number of bosons is conserved(1,8)

$N=n_s+n_d+n_f$ ....[1]

Where N is the total number of bosons , n_s , n_d and n_f are the number of s,d, and f bosons , respectively , and $n_f=0$ or 1 .
The most general Hamiltonian describing this system is(9)

$H=H_{sd}+H_f+V_{sdf}$ ....[2]

Where H_{sd} describes the positive parity core , H_f is the f-bosons Hamilton , and V_{sdf} describes the f-sd interaction .
The sd core Hamiltonian [U[5]dynamical symmetry] employed in this study is(5-7) .

$H_{sd}=\varepsilon_{nd}+a_1L^2+a_3T_3^2+a_4T_4^2$......................[3]
Where the f-boson Hamiltonian is given by(3,9) .
$H_f=\varepsilon_f+f^+.f+\theta_fN-Z_2[Q_f\times Q_{sd}]^{(0)}$..................[4]

ε_f is the energy of the L=3 boson , and θ_f and Z_2 are two parameters which label the interaction of the octupole bosons with the s and d bosons(1,3) .

The eigenvalue problem of U[5] limit for the system of s,d, and f boson can be sloved analytically , in that case the various states arrange themselves into two bands with energies(1,9) .

(N-band) $E=E_d+\varepsilon_f+n_dX_5$ ....[5]

(N'-band) $E= E_d+\varepsilon_f+n_dX_3-((2n_d-3)/5)\Delta_4$.................[6]

and the eigenvalues of the interacting d-boson (E_d) Hamiltonian(6) :

$$E_d=\varepsilon_d n_d+\alpha\frac{1}{2}n_d(n_d-1)+\beta(n_d-\upsilon)(n_d+\upsilon+3)+\gamma[L(L+1)-6n_d]......[7]$$

The parameters ($\varepsilon_d,\alpha,\beta,\gamma,\varepsilon_f,X_5,X_3$, and Δ_4) of equations (5,6, and 7) can be calculated from the experimental low levels(4,7) . The typical positive parity spectrum have been shown(3) in table(1) while in tabel (2) we show the typical negative parity states corresponding spectrum(1) .

In this figure the states arranged into "bands" are defined as follows(1,9) .

$$\left.\begin{array}{l} \text{N}-\text{band}\ \left|d^{n_d},Ld=2n_d;f;L=2n_d+3,M\right> \\ \text{N}'-\text{band}\ \left|d^{n_d},Ld=2n_d;f;L=2n_d+2,M\right> \end{array}\right\} \quad ....[8]$$

The other negative parity states which arise from the coupling d^{n_d} Ø f do not form aband structure since they are admixed to other states . Thus, loosing their collective character and systematic pattern(1) .

Neural networks

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. The network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements(10).

Commonly, neural network are adjusted or trained, so that particular input leads to a specific target output . Typical many such input / target pairs are used , in this supervised learning, to train a network.

Back propagation: The standard backs propagation for designing the network has been used in this work.

The standard back propagation is a gradient descent algorithm, as is the Widrow- Hoff Learing rule, in which the network weighs are moved along the negative of the gradient of the performance function. The term back propagation refers to the manner in which the gradient is computed for nonlinear multi layer networks.

Typically, a new input Leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented.

This generalization property makes it possible to train network on a representative set of input / target pairs and get good results without training the network on all possible input/ output pairs.(11)

There are generally four steps in the training process:

1-Assemble the training data
2-Create the network object.
3-Train the network.
4-Simulate the network response to new inputs.(12)

We use two network ones for

a- Positive parity spectra and Second for
b- Negative parity spectra

The first network contains five sub nets multi- Layer perception are fed forward nets with. 8 nodes for Y- band, 5 nodes for X-band, 2 nodes Z- band , 2 nodes for β- band and 1 node for – band. These additional layers contain hidden units or nodes that are not directly connected to both the input and out put nodes.

The second network contains the sub nets multi- Layer perception are Fed for ward nets with 8 nodes for Y-band , 6 nodes for N- band , and 4 nodes for N^{-} - band.

Simulation process : The function sim simulates a network , sim takes the network input p, and the network object net, and neturns the network outputs a were a = sim (net ,p).

We use some tables for simulation network these tables are show on page .

Calculation

In the present paper we apply the U[5]limit of Interacting Boson model-1 (IBM-1) to compare its predictions for the positive and negative parity energy levels with experimental (13-16) data .

The values of IBM-1 parameters which gave the best fit to experimental(13-16) data are given in table (3) and low-lying quadrupole and Octupole bands energies for ^{114}Te nuclei are shown In Fig.(2) .

Learning process

Once the network weight and biases have been initialized , the network is ready for training. The training process requires a set of examples of proper network behavior network input p and target outputs t.

During training the weights and biases of the network are iteratively adjusted to minimize the network per for mance Function net-performfun. The defavlt performance Function for feed for ward network is mean Square error mse – the average. Squared error between the network outputs a and the target outputs t. As with momentum, if the new error exceeds the old error by more than a predefined ratio max – perf – inc (typically 1.04) , the new weights and biases are discarded. (17)

In addition, the Learning rate is decreased (typically by multiplying by Ir – des = 0.7). Other wise, the new weights , etc., are kept. If the new error is less than the old error, the learing rate is increased (typically by multiplying by Ir-inc= 1.05)

This procedure increases the learning rate , but only to the extent that the network can learn without large error increases . When a larger learning rate could result in stable learning , the learning rate is increased .

When the learning rate is too high to guarantee a decrease in error , it gets decreased until stable learning resumes .

In this work Backpropagation training with the Function traingda, which is called just like trained, except for the additional training parameters max- perf- inc , in- des , and Ir- inc.

The present resuits have shown their good agreement with experimental data for U[5] network (save in Ram memory with other network such as O(6) network and SU(3) network.

Discussion and Conclusion

The low –lying states in ^{114}Te Isotope display the characteristics of nearly spherical nuclei(18) collective excitations that occur in these nuclei at low energies are quadrupole and octupole vibrations Indeed , the ratio of the energies of 4^+ and 2^+ Yrast states is nearly two and indicates the vibrational character of these states . Furthermore , $\overline{3}$ states are known around (2.5) MeV in these nuclei(18,19).

The present work demonstrates that a microscopically based vibrational picture is quite successful to explain many aspects of the structure of ^{114}Te for the lowest 2^+ and 4^+ states this is not surprising in view of their pure phonon structure which was shown(20) .
The experimental 2^+_2 and 4^+_1 states at (1390.7 keV and 1483.3 keV) which are commonly considered as members of the two phonon triplets are well described in the framework of the IBM , this is not the case for the only experimentally found 0^+ state (1875 keV) in this energy region .

Concerning the three-phonon quintuplet it is easy to identify the experimental(13-16) 0^+ ,2^+,3^+,and 4^+ states at (1875 keV , 1800 keV,1975 keV, and 2026.1 keV) respectively , as members of this multiplet .

The situation of 6^+(2216.7 keV) state of the quintuplet is more complicated but the comparing of energy ratio of this state ($R_{6^+/2^+}$=3.1) with the values given by the ideal vibrator model(21) one sees that the ^{114}Te nucleus follow very well this vibrator description .

Our new results from IBM-1 calculations are generally in good agreement with experimental(13-16) data . However , our much improved energy levels precision allowed us to remove some ambiguities for a detailed comparison with previous calculations see Raf.(13) .

References

1. Arim ,A. and Iachello, F. (1976), Ann. Phys ., 99: 253.
2. Iachello, F. and Arima, A., (1987). The Interacting Boson Model , Cambridge University Press , Cambridge .
3. Casten, R. and Warner, D. (1988) . Rev. Mod. Phys., 60 :389.
4. Wood , J.; Heyde, K.; Nazarewicz , W. ; Huyse , M. and Vanduppen, P. (1992).Phys. Reports , 215:101.
5. Jabber , J. (1989) . Decay schemes from the (n,γ) reaction on ^{151}Eu and ^{181}Ta, Ph.D.Thesis , London University .
6. Abrahams ,K.; Allaart, K. and Dieperink , A. (1981). B. Phys., 67: 53.

7. Abdul Ameer, A. (1991) . Investigations of nuclear energy levels in ^{82}Kr , ^{76}Se and ^{194}Pt , Ph.D. Thesis , London University .

8. Barfield , A.; Wood , J. and Barrett , B. (1986) .phys. Rev. C , 34 : 2001.

9. Scholten , O.; Arima, A. and Iachello ,F. , (1978). Ann. Phys. , 115 , 325.

10. Zurada , J. Introduction of artificial neural systems“ jaico publishing House , bombay.

11.Gluch, D.P. (1989).International Jovral of mini and Microcomputers Nol.11 . No. 3, pp 65-11.

12. Kinnere Brock, W. (1995), “Nevral network, Suneel Galgotia, India.

13. Moon ,C. and Kwon , J. (1998). Journal of the Korean Physical Society , 32: 666.

14. Moon , C.; Chae , S. ; Komatsubara , T.; Shizuma , T.; Sasaki , Y.; Ishiyama , H. Jumatsu , T. and Furuno , K. (1999). Nucl. Phys. A , 657: 251.

15. Lehmann , H.; Jolie , J.; DeCoster , C.; DeCroix , B.; Heyde , K. and Wood , J. (1997) . Nucl. Phys. A, 621, 767 ,

16. Sambatoro , M. (1982). Nucl. Phys., A380: 365.

17. Lippman, R.P. (1987) “ An introduction to computing with Neural Nets., IEEE ASSP , Magazine, pp4-22.

18. Schwengner , R.; Winter , G. ; Schauer, W. ; Grinberg , M.; (1997) .Becker , F.; Von Brentano , P.; Eberth , J.; Enders , J.; Von Egidy , T.; . Herzberg , R; Huxel , N.; Kaubler , L. ; Von Neumann- Cosel , P.; Nicolay , N.; Ott, J. ; Pietralla , N.; Prade , H.; Raman , S. ; Reif, J. ; Richter , A.; Schlegel , C.; Schnare , H. ; Servene ,T. ; Skoda , S.; Steinhardt , T. ; Stoyanov , C.; Thomas , H.; Wiedenhover , I. and Zilges , A. (1997) . Nucl . Phys. A 620 : 277.

19. Georgii , R.; VonEgidy , T. ; Klora , J.; Lindner , H.; Mayerhofer , U.; Ott, J.; Schauer , W.; Von Neumann-Cosel , P.; Richter , A.; Schlegel , C.; Schulz , R.; Khitrov , V. ; Sukhovoj , A.; Vojnov , A.; Berzins , J.; Bondarenko , V.; Prokofjevs , P.; Simonova, L.; Grinberg , M. and Stoyanov , Ch. (1995) . Nucl . Phys. A592 : 307,

20 Ott, J.; Doll, C.; Von Egidy , T.; Georgii, Rs.; Grinberg , M.; Schauer , W.; Schwengner , R. and Wirth , H. (1997) . Nucl. Phys. A 625 : 598

21. Scharff- Goldhaber, G. and Weneser , J. ,(1955). Phys. Rev. , 98;212

Table(1): positive parity spectra a-positive parity spectra (MeV).

Y-BAND	X-BAND	Z-BAND	β-BAND	-BAND
0	1.29	1.96	1.14	1.9
0.65	1.9	2.6	1.7	
1.3	2.7			
2.5	3.4			
2.8	4.2			
3.5				
4.4				
5.2				

Table(2): Negative parity spectra b-negative parity spectra (MeV).

Y-BAND	N-BAND	N^--BAND
0	2.5	3.2
0.65	2.9	4.06
1.3	3.4	4.6
2.5	3.8	5.3
2.8	4.4	
3.5	4.8	
4.4		
5.2		

Table (3) : IBM parameters In KeV for ^{114}Te nucleus

N_{toto}	Positive parity state par.				Negative parity state par.			
7	ε_d	A	β	γ	ε_f	X_5	X_3	Δ_4
	650	10	-16	3	2550	-300	-905.9	-2047.8

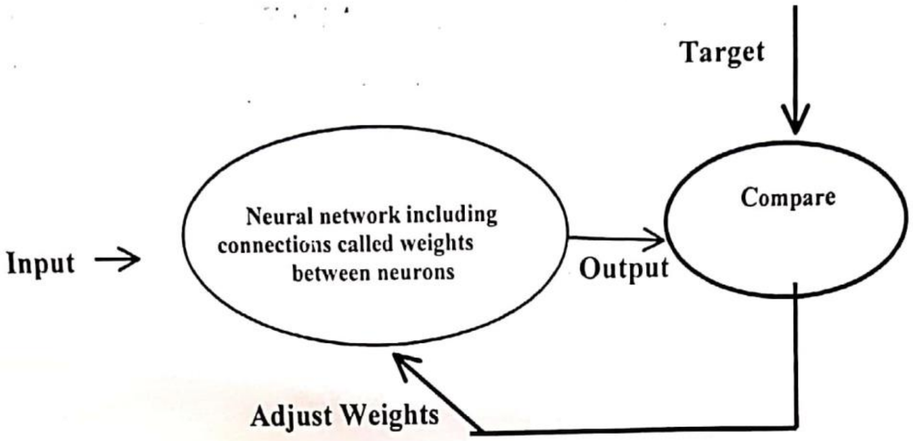

Fig.(1): Neural network including connections

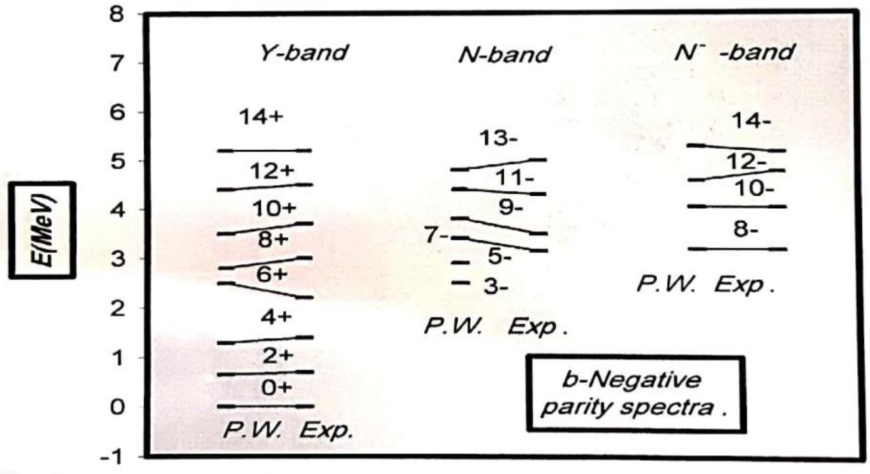

Fig.(2): Comparing experimental$^{(13-19)}$ and IBM calculations energy levels of ^{114}Te isotope

مجلة ابن الهيثم للعلوم الصرفة والتطبيقية المجلد 18 (2)2005

دراسة مستويات الطاقة الموجبة والسالبة التماثل في نواة ^{114}Te باستخدام نموذج البوزونات المتفاعلة IBM. باستخدام شبكة عصبية (شبكة الانبعاث الخلفي)

هيام ناجي هادي و هند رستم محمد
كلية التربية للبنات ،جامعة الكوفة

الخلاصة

تمت دراسة مستويات الطاقة الموجبة والسالبة التماثل لنواة ^{114}Te بتطبيق التحديد الاهتزازي U(5) لنموذج البوزونات المتفاعلة (IBM-1) ، و أظهرت النتائج الحالية التطابق الجيد مع القيم العملية أضافة الى تحديد زخم وتماثل مستويات طاقة جديدة لم تعيين عملياً كالمستويين 0^+_2 و 5^+_1 والمستويين 3^-_1 و 5^-_1 .

ثم استخدمت شبكة الانبعاث الخلفي لتحديد مستويات الطاقة الموجبة والسالبة في نواة ^{114}Te وانتماءها الى التحديد الاهتزازي U(5). تم تطبيق الشبكة العصبية باستخدام نظام MATLAB .