NOTICE

**CERTAIN DATA
CONTAINED IN THIS
DOCUMENT MAY BE
DIFFICULT TO READ
IN MICROFICHE
PRODUCTS.**

-13

Los Alamos National Laboratory is operated by the University of California for the United States Department of Energy under contract W-7405-ENG-36

TITLE: ENERGETIC ALPHA PARTICLE DEPOSITON IN A MAGNETIZED PLASMA

AUTHOR(S): DAVID PALMER SMITHERMAN, X-1

RONALD C. KIRKPATRICK, X-1

SUBMITTED TO SIXTH INTERNATIONAL CONFERENCE ON EMERGING NUCLEAR
ENERGY SYSTEMS
MONTEREY, CA
JUNE 16-21, 1991

DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government, or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

By acceptance of this article, the publisher recognizes that the U.S. Government retains a nonexclusive, royalty-free license to publish or reproduce the published form of this contribution, or to allow others to do so, for U.S. Government purposes.

The Los Alamos National Laboratory requests that the publisher identify this article as work performed under the auspices of the U.S. Department of Energy.

Los Alamos

MASTER
Los Alamos National Laboratory
Los Alamos, New Mexico 87545

ENERGETIC ALPHA PARTICLE DEPOSITION IN A MAGNETIZED PLASMA

D. P. Smitherman and R. C. Kirkpatrick

Los Alamos National Laboratory
Los Alamos, New Mexico 87545

ABSTRACT

The problem of energetic alpha particle deposition in a dense, magnetized deuterium-tritium (DT) thermonuclear fuel has been studied numerically for the case of coulomb interactions in cylindrical geometry. This was done by following the particle trajectories initiated at various radii and in different directions through the plasma and its imposed field until they had either left the plasma or deposited all their energy. The resulting complex particle trajectories in the static magnetized fuel make a detailed treatment of the problem computationally intensive. Therefore, we have attempted to use detailed modeling to produce a data base for a neural nets algorithm for incorporation in an ignition critical profile code. While the accuracy of the neural net in reproducing the detailed calculational results is not high, it is approximately 6000 times faster.

INTRODUCTION

The quest for controlled thermonuclear fusion in the laboratory has yet to be successful, and the search for a viable scheme has produced many ingenious experiments, some of which have given low

levels of thermonuclear neutrons [1], but are far from ignition or breakeven. Most of these experiments can be categorized as either inertial confinement or magnetic confinement. Inertial confinement is characterized by very small targets that must be driven to very high implosion velocities by very powerful drivers such as lasers, while magnetic confinement is characterized by very large devices that involve quasi-static operation to achieve long confinement times. Except that both are efforts to achieve significant fusion burn, the two categories have little in common. However, there has been a limited interest in a scheme that does not fit comfortably into either category. That scheme involves magnetized fuel.

Magnetized fuel relies on reduction of conduction losses by an embedded magnetic field (magnetic thermal insulation) and enhancement of the DT alpha deposition by the field, but not on plasma confinement by the field. Rather, the plasma is inertially (i.e., "wall") confined. Jones and Mead delineated the parameter space for magnetized fuel [2]. The definition of magnetized fuel is based on the cyclotron frequency, collision time product ($\omega\tau$). For $\omega\tau$ in excess of unity the plasma is said to be magnetized. It is possible that the

electrons are magnetized, but not the ions. Also, it is possible for the magnetic field to enhance the DT alpha particle deposition without having magnetic confinement or a magnetized ion component. Although Jones and Mead define an $\omega\tau$ for the alphas, the field times DT plasma radius (BR) is a more relevant parameter for small targets [3].

The energetic DT alpha particle can have a very complex trajectory in a magnetized plasma, and the energy deposited in one part of the plasma by alphas generated in another part of the plasma depends on both the temperature and density distributions in the plasma as well as the magnetic field distribution. In principle the aggregate of the trajectories can also alter the field distribution. A direct treatment of the alpha particle transport is a formidable problem in complex geometries, so that alternative approaches to transport have been used in some computer codes [4]. Here we report an attempt to use neural nets to model the results from a direct treatment of transport and thereby achieve a more accurate and efficient algorithm for inclusion in a laboratory microfusion simulation code.

DIRECT TRANSPORT

A code was written to follow the alpha particle trajectories through a static plasma with specified temperature, density, and magnetic field distributions in cylindrical geometry [5,6]. The plasma was divided into ten zones in which twenty particles from each zone were followed using the slowing down expression from Spitzer [5,7]. The energy deposited in each zone by the alphas originating in each other zone was then calculated by multiplying by the fusion rates from the originating zones.

This was similar to a Monte Carlo approach, but no random numbers were used. Rather, specific initial directions were chosen for the trajectories and the results were integrated over solid angles associated with each trajectory.

NEURAL NETWORK

We have used a neural network code developed at the Center for Nonlinear Studies (CNLS) at Los Alamos National Laboratory [8]. The neural network is a function approximation scheme that uses a set of Gaussian weighted Taylor expansions to approximate a given function. In this case it was used to approximate the results of the direct alpha particle transport calculations.

The expression used by the net is [8]:

$$\vec{\Phi}_o(\vec{x}_i) = \sum_j \frac{[\vec{f}_{jo} + (\vec{x}_i - \vec{x}_{jij}) \cdot \vec{d}_{ijj}][\vec{\rho}_j(\vec{x}_i)]}{\sum_j (\vec{x}_i - \vec{x}_{jij}) \vec{\rho}_j(\vec{x}_i)}.$$

where $\vec{\rho}_j(\vec{x}_i) = e^{-\beta(\vec{x}_i - \vec{x}_{jij})}$, and all the ρ 's are normalized using: $\vec{\rho}_j(\vec{x}_i) / \sum_j \vec{\rho}_j(\vec{x}_i)$. Here, i denotes a vector of inputs, j denotes a vector whose length is the number of Taylor expansion terms being used, and o denotes a vector of outputs. β is a constant, $\vec{x}_i$ is the input vector, $\vec{f}_{jo}$ and $\vec{d}_{ijj}$ are the first two terms of the Taylor expansion at the locations in parameter space determined by $\vec{x}_{jij}$, and $\vec{\Phi}_o(\vec{x}_i)$ is the output vector, which is the neural net approximation to the function.

In order to utilize the neural net as an efficient model of the computationally intensive transport process it must first be trained. Training means that sample transport calculations must be done and used as data points for calculating the coefficients ($\vec{f}_{jo}$ and $\vec{d}_{ijj}$) used to

approximate the transport results. The ranges of the multidimensional parameters over which the neural net will be used must be defined with all the data points lying within that range. It seems best to choose the training points within that range at random. Since the points about which the Taylor expansions are taken are coincident with the training (data) points, the first term of the expansion may be determined directly. It is simply the value of the data at that point. The derivative is not calculated, rather it is determined using an iterative scheme that minimizes the squared error between the net and the data points. Alternatively, the Taylor expansions could be randomly sprinkled in the parameter space and the first term could also be determined by the least squares error method, but for this application the former procedure was believed to be more accurate.

An alternative way to view the neural net is two sets of basis functions located at the same points in parameter space as the Taylor expansions. If the above net approximation is expanded, one obtains:

$$\Phi_o(\vec{x}_i) = \sum_j \tilde{\rho}_j(\vec{x}_i) \frac{f_{j0}}{\sum_j (\vec{x}_i - \vec{x}_{j0}) \tilde{\rho}_j(\vec{x}_i)} + \tilde{\rho}_j(\vec{x}_i) \frac{(\vec{x}_i - \vec{x}_{j0}) \cdot \vec{d}_{j0}}{\sum_j (\vec{x}_i - \vec{x}_{j0}) \tilde{\rho}_j(\vec{x}_i)}.$$

The first term is a Gaussian weighted by a constant, while the second term is a Gaussian times a linear expression. These two basis functions are used to reproduce the original functions (i.e., data) in a manner similar to approximation by splines or Fourier series. However, a neural net uses less training points.

NEURAL NET IMPLEMENTATION

Three codes were written for the implementation of the neural network: one to train the network by solving for the constants used in the expansion, one to estimate the average percentage error of the net, and one to compare the net output with the training data. These codes were first tested on simple problems before they were used to model the DT alpha particle energy deposition.

For the alpha particle deposition problem, the input vector consisted of the magnetic field strength B at the edge of the DT plasma, the radius R of the target, the density ρ of a particular zone, and the temperature profile $T(R)$ along a radius from the center to the edge of the plasma. The magnetic field was assumed to be generated by a uniform current density parallel to the axis of the cylindrically symmetric DT plasma. Thus the magnitude of the azimuthal field is zero at the axis, increasing linearly to full strength B at the edge of the plasma. We assumed the plasma to be isobaric, so that the density profile was the inverse of the temperature profile. The output vector consisted of the rate of change of the plasma temperature in each zone due to the DT alpha heating. Thus, for a problem with ten zones the net had thirteen inputs and ten outputs.

The parameter space selected for the first trial was $B = 0$ to $10T$, $\rho = 0.02$ to $0.2gm/cc$, $R = 0.05$ to $0.5cm$, and a central zone temperature between 1.8 and $80Kev$. The alpha particle deposition routine was used to generate about 500 data points for training the net. At first the net was trained on a few smooth, deterministic profiles. Although the net performed very well on any profile with a shape similar to that it had been trained on, it had large

errors for profiles of somewhat different shape. Random profile shapes for the set of training points seems to alleviate this difficulty.

Since the output training vector contained values of temperature rates that ranged from 10^{-10} to 2 Kev/ns, the manner in which the data was normalized before it was used to train the neural net had an impact on the net's error. Linear and logarithmic normalization were both used, with the logarithmic normalization producing a flatter dependence of the percentage error on the magnitude of the output. Because the error was much lower for larger values of temperature rates due to DT alpha particle deposition (the output of the net), the linear normalization is preferable. When the temperature rates are very low, a large percentage error has little effect on the net temperature rate, since it is then mainly determined by the other heating and cooling terms (bremsstrahlung, conduction, compression, etc.).

For a given number of basis functions there is an optimum value for the width of the basis functions. For that optimum width the error in the net is minimized. Generally, the higher the density of the basis functions in the parameter space, the better the approximation, but there is a point of diminishing returns. In an attempt to find the lowest possible error, the net was trained numerous times with different numbers and widths of basis functions. The optimum values selected for the range of parameter space cited above were 200 basis functions with an average β of eight. This produced a weighted error of about 15 to 20 percent. To obtain the most accurate assessment of the net's error, it is necessary to test the net against data it is not trained on. This is shown in figure 1. The net is very efficient. The code that provides the

neural net approximation to the DT alpha particle deposition is only about 70 lines of FORTRAN as compared to the 650 lines needed for the particle tracking algorithm used before, but now used only to generate the training data for the neural net in a separate code.

Fig. 1. An example of the net's output compared with data it wasn't trained on for the inner zone as a function of magnetic field strength.

The time required to calculate the DT alpha heating was 10 to 30 Cray YMP minutes, but dropped to only 0.01 seconds for the neural net approximation. Once it has been trained the and the coefficients for the expansions are read into the neural net algorithm in the main code, the net provides a very efficient approximation, albeit not highly accurate, of the DT heating rate at each point in the problem. The best strategy seems to be to use the neural net algorithm for surveying parameter space within the range that the net was trained, searching for promising islands for magnetized fuel targets, and then to use the detailed particle tracking

algorithm to confirm and refine the results obtained with the neural net algorithm within the more limited range of the islands.

COMMENTS

The neural net described here has not been extensively tested. For some problems (e.g., identification of ignition critical profiles [6]) the net's 15 to 20 percent weighted error may prevent convergence to a profile. Also, it is not safe to use the neural net algorithm outside the range of parameter space for which it was trained. However, the latter restriction is no more severe than that of equation of state tables. For accuracy over a large range of parameter space it may be necessary to train the net over several restricted ranges and switch in different coefficients as results are required for different restricted ranges for which the nets were trained.

The neural net approach to speeding up the calculation of DT alpha heating in the presence of a magnetic field is effective only for cases in which the number of calculations using the neural net algorithm to approximate the heating greatly exceeds the number of detailed calculations needed to train the net.

ACKNOWLEDGEMENTS

We appreciate the assistance of Dr. Roger Jones in developing the net used here, as well as many of his many helpful suggestions. Also, we appreciate the unfailing assistance of Dr. Robert Webster and the elucidating discussions with Dr. Henry Fisher.

REFERENCES

1. Widner, M. M., "Neutron Production from Relativistic Electron Beam Targets," Bull. Am. Phys. Soc. 22 (1977) 1139.
2. R.D. Jones and W.C. Mead, "The Physics of Burn in Magnetized Deuterium-Tritium Plasmas," Nucl. Fusion 26 (1986) 127.
3. R.C. Kirkpatrick & I.R. Lindemuth, "Ignition and Burn in Inertially Confined Magnetized Fuel," Sixth Int. Conf. Emerging Nucl. Energy Systems, accompanying paper (1991).
4. G.B. Zimmerman and W.L. Kruer, "Numerical Simulation of Laser-Initiated Fusion," Comments on Plasma Phys. and Controlled Fusion 2 (1975) 51; UCRL-50021-72-2 (1972) 131.
5. R.H. Loveberg, "Retention of D-T Alpha Particles in the High Density Z-Pinch," unpublished (1989).
6. D.P. Smitherman and R.C. Kirkpatrick, "Ignition Critical Profiles for Magnetized Fuel ICF Targets," Bul. Am. Phys. Soc. 34, (1989) 1920.
7. L. Spitzer, Physics of Fully Ionized Gases, (London: Interscience Pub., 1956), p.78.
8. R.D. Jones, Y.C. Lee, C.W. Barnes, et al., "Functional Approximation and Time Series Prediction with Neural Networks", Los Alamos National Laboratory Report LAUR 90-21 (1990).

END

**DATE
FILMED**

11/105191