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Artificial Intelligence Search Techniques for Optimization of the Cold Source Geometry*

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Artificial Intelligence Search Techniques for Optimization of the Cold Source Geometry

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Most Optimization studies[1−4] of cold neutron sources have concentrated on the numerical prediction or experimental measurement of the cold moderator optimum thickness which produces the largest cold neutron leakage for a given thermal neutron source. Optimizing the geometrical shape of the cold source, however, is a more difficult problem because the optimized quantity, the cold neutron leakage, is an implicit function of the shape which is the unknown in such a study. We draw an analogy between this problem and a state space search, then we use a simple Artificial Intelligence (AI) search technique to determine the optimum cold source shape based on a two-group, $r-z$ diffusion model. We implemented this AI design concept in the computer program AID which consists of two modules, a physical model module and a search module, which can be independently modified, improved, or made more sophisticated.

The physical model equations are solved using a special purpose two-group, $r-z$ nodal diffusion code.[5] The region occupied by the cold source, R, is taken to be a cylinder of radius 25 cm and height 50 cm that is surrounded radially and axially on one side (bottom) by 30 cm room temperature D_2O. A constant thermal flux (group 1) boundary condition (BC) representing the neutron input to the cold source is applied at the outer edges of the D_2O buffer region. Symmetry and vacuum BC are applied on the z-axis (left) and r-axis (top), respectively, for group 1. For the cold flux (group 2) vacuum BC are applied on all outer boundaries except for the symmetry condition on the z-axis. The cold neutron current on the top edge of R is the quantity to be optimized. The region R is divided into $N \times 2N$ computational cells of equal width and height. Each cell is permitted to contain liquid deuterium (lD_2), D_2O, or gaseous D_2, represented by the indices 0, 1, or 2, respectively, with the restriction that the lD_2 has to occupy a closed connected region with only D_2O on the outside and D_2 on the inside. Hence, any cold source configuration can be approximated on this discrete mesh, and is equivalent to an $N \times 2N$ integer array, S. The diffusion model described above is essentially a function Δ on the collection of arrays S to a real number equal to the cold neutron leakage from the cold source.

The analogy between the shape optimization problem and a state space search[6] is complete. The state space is the collection of all permissible arrays S. The evaluation function is Δ. An initial state, I, is any permissible S of our choice. A goal state, G, is a state S that maximizes the cold neutron leakage over the state space. Finally, the set of production rules that map any state S into another state S' during the search process are represented by the closed and connectivity restrictions on the lD_2 shape. The optimization problem can be stated as: search the state space for G. This is the fundamental problem in AI, and several techniques and strategies have been developed to produce satisfactory estimates of G at an acceptable cost.[6] The search module in AID uses a Nearest Neighbor strategy.[6] At each level of the search, the search module generates all permissible states from the current state using the production rules, evaluates each one using Δ, then compares the resulting cold leakage. If none is larger than the cold leakage of the current state, the search terminates successfully with G = current state. Otherwise, the state with the largest cold leakage is taken to be the current state and the search proceeds to the next level.

In order to demonstrate the capabilities of this new approach, we obtained optimum cold source shapes on two meshes: $N = 5$ with a variety of initial states, and $N = 10$. The two-group nuclear data were obtained by collapsing a 39-group cross-section set using Maxwellian weighting, where the energy boundary between the two groups is .05 eV. On the 5×10 mesh ($N = 5$), we used a number of choices as initial states and carried out the search. The optimization process consistently inserted lD_2 at points of large radius.

This is consistent with cylindrical one-dimensional results which indicated that the cold leakage increases linearly with the inner radius for a given thickness, and decreases far more slowly with thickness for a given inner radius. In other words, the penalty due to increasing the lD_2 thickness outwards at a given point in R is overcome by the gain due to increasing the cold source surface area. This is evident in Figure 1.a which represents the optimum state for $N = 5$, and has a cold neutron current 1.077 cm^{-1} sec^{-1}. In contrast, the optimized cold source in the Institute Laue-Langevin (ILL) facility[7] evaluated using our diffusion model has a cold neutron current .7279 cm^{-1} sec^{-1}, about 50% lower than the optimum shape. For the $N = 10$ case, we used an initial state that has an lD_2 cylindrical shell of thickness 2.5 cm, i.e., one computational cell, filled with D_2. The optimum shape, shown in Figure 1.b, superimposed on the $N = 5$ optimum shape, has a cold leakage of 1.161 cm^{-1} sec^{-1}, and is consistent with the $N = 5$ result, to within the resolution of the discrete mesh. The utility of our new approach is underscored by the large improvement in performance of the cold source determined by the Nearest Neighbor algorithm whose uncommon shape is practically impossible to foresee as a candidate design based on pure physical and engineering intuition.

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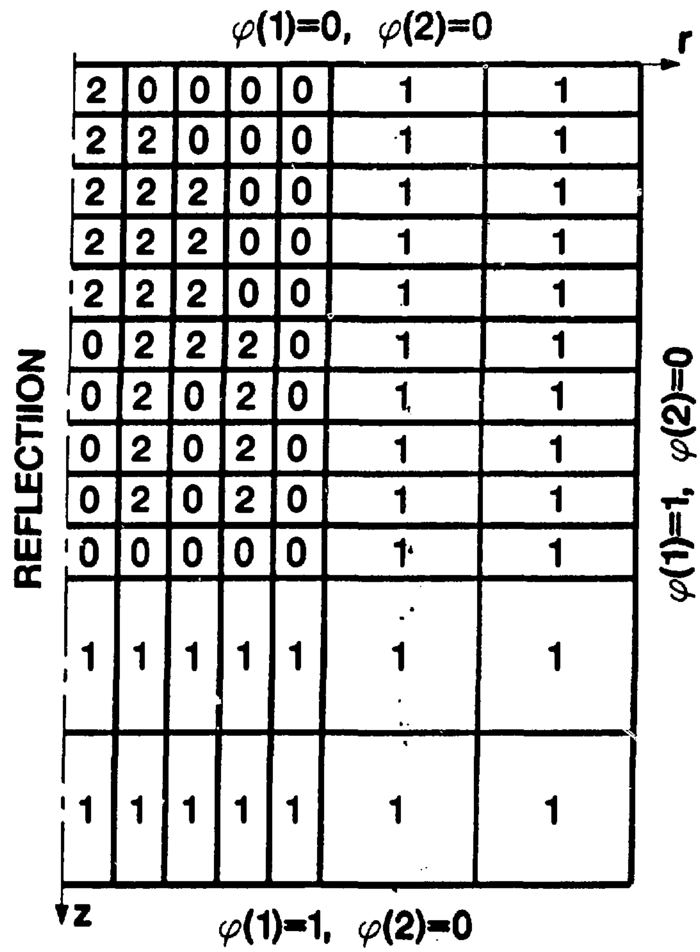
Figure Caption

Figure 1. The optimal shape of the cold source:

(a) The goal matrix G superimposed on a schematic of region R plus the D_2O buffer for $N = 5$ case;

(b) comparison of optimal shapes of the cold source determined for the $N = 5$ (////) and $N = 10$ (\\\\) cases, where the unhatched region for each case contains D_2.



φ(1)=0, φ(2)=0
r
REFLECTIION
φ(1)=1, φ(2)=0
z
φ(1)=1, φ(2)=0