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MONTE CARLO TECHNIQUES FOR ANALYZING DEEP PENETRATION PROBLEMS*

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ABSTRACT

A review of current methods and difficulties in Monte Carlo deep-penetration calculations is presented. Statistical uncertainty is discussed, and recent adjoint optimization of splitting, Russian roulette, and exponential transformation biasing is reviewed. Other aspects of the random walk and estimation processes are covered, including the relatively new DXANG angular biasing technique. Specific items summarized are albedo scattering, Monte Carlo coupling techniques with discrete ordinates and other methods, adjoint solutions, and multi-group Monte Carlo. The topic of code-generated biasing parameters is presented, including the creation of adjoint importance functions from forward calculations. Finally, current and future work in the area of computer learning and artificial intelligence is discussed in connection with Monte Carlo applications.

I. INTRODUCTION AND CURRENT DIFFICULTIES

Deep penetration as applied to radiation transport is a somewhat nebulous term usually associated with fixed source calculations in contrast to those for reactor cores. There are no distinct correlations between penetration, deep penetration or very deep penetration, and mean free paths of penetrated matter. Pure penetration calculations are usually not three-dimensional and are relatively easy. Rather, it is the combination of penetration, streaming, and large angle scattering in systems with cavities and multileg ducts that have traditionally required Monte Carlo methods of solution. But Monte Carlo methods cannot generally be used to determine radiation paths through a geometrically complex shield, and some *a priori* knowledge of these paths must be available before beginning a calculation and introducing variance reduction procedures to direct particles along the "important" paths.

Other complications introduced into realistic shielding calculations are gamma-ray production from neutron interactions and the cross-section windows of nuclides such as iron and oxygen. Secondary gamma ray Monte Carlo dose calculations are sometimes low due to the fact that low-energy neutrons, which are usually unimportant to the neutron dose but very important to gamma-ray production, have not penetrated deep enough into the shield. Two of the most commonly used deep penetration techniques, exponential transformation and next-event estimation, if improperly applied may cause large portions of a shield to be skipped,

streaming even though the cross-section and production data are treated in great detail.

A final item in this discussion of general problem areas of deep penetration Monte Carlo is the concept of accuracy versus precision in the calculated results. There is the maxim that multiplying system calculations will always have enough particles available to calculate an accurate result within some precision (statistical uncertainty). The problem here is that an uncertainty of a few tenths of percent is often required. In contrast, for deep penetration an accuracy of a few hundred percent with an uncertainty of a few tens of percent may be acceptable. Often even in fairly well formulated deep-penetration calculations the primary goal of accuracy is not met, leading to low results due to undersampling in important regions of phase space. Poorly or improperly applied biasing techniques may only decrease the calculated uncertainty about the erroneous result without increasing the accuracy. Fortunately, the few situations which can give results much larger than the truth (e.g., collisions near point estimators or surface estimator grazing angles) also give very large uncertainties.

Most of the problems associated with accuracy and precision in any Monte Carlo calculation would exist even if the calculated uncertainties were theoretically correct. However, it is generally accepted that many techniques, such as exponential transformation and next-event estimation, have distributions which are not Gaussian distributed,[1-3] but the methods used to interpret the uncertainties are based on a Gaussian distribution. Even the casual users of Monte Carlo methods are aware that a change in a deep-penetration biasing parameter or only in the random number sequence may produce results which differ by more than that predicted by the calculated uncertainties. Attempts to improve on the method of code-calculated uncertainties have not been generally successful,[2] and this situation remains a serious theoretical problem.

Even in the case of actual Gaussian statistics, the calculated uncertainty in the form of one standard deviation of the mean result (σ, the square root of the variance) is often misinterpreted in determining the reliability of an answer. There is, of course, only a 68.3% probability that the answer lies within $\pm\sigma$ of the truth. One must go to $\pm 2\sigma$ (95.4%) or even to $\pm 3\sigma$ (99.7%) to establish more credibility.

In Section V there are presented several adaptive or learning techniques in which a code is able to automatically update various biasing parameters in the course of a calculation. Except in the case of completely excluding this learning phase of a calculation in the compilation of final results, there is at present no generally acceptable criteria for utilizing these preliminary results and their statistical errors.[2] This situation is similar to k_{eff} calculations where each generation is dependent on information calculated in the previous generations.

It is helpful to examine a calculated result and its uncertainty for any anomalies as they are accumulated throughout a calculation rather than accept a final answer after some arbitrary number of histories. This is a standard procedure in k_{eff} calculations, which have their own unique uncertainty problems. Some general-purpose codes, such as MCNP,[4] provide these intermediate results as a standard feature. Although this type of analysis can be useful in the ultimate acceptance or rejection of a calculation, it should never be used as a

[redacted] reject certain combinations of batch results until some desired answer is attained.

II. BASIC CONCERNS IN DEEP PENETRATION CALCULATIONS

From a practical point of view, deep penetration calculations will give generally reliable results if the population density of particles remains roughly constant as they traverse the "important" volumes of the system between the source and detector (results) regions. The biasing procedures introduced to maintain the population reduce the statistical weight of the particles in proportion to the population loss of an analogue procedure, thus conserving the total weight in the system. All this is easy to realize in simple systems of one dimension, one energy, isotropic scattering, etc., where so many theoretical developments are verified and test comparisons are made. However, in realistic, three-dimensional systems the division of phase space into importance regions and the proper specification of the biasing procedure parameters can become an overwhelming task.

Of equal concern in maintaining the particle population density is doing so without too great a dispersion of statistical weight within the population. It is this weight that ultimately creates the desired results, and only a few very high weight particles can dominate the entire answer and give a very large variance, while the computation time on the many low-weight particles is wasted. If the differentiality of this population and weight control procedure is increased to include other variables such as energy ranges in addition to spatial regions, specification and implementation of the necessary biasing parameters can become prohibitive without automated computer-assisted procedures.

All general-purpose codes have available in the standard output, in addition to the desired final results, volumes of data to aid the user in determining the effectiveness of his biasing procedures. For complicated systems this information can be displayed graphically. The standard procedure is to run a few short calculations, examine this diagnostic output and make any necessary adjustment in the biasing, and then submit a final long calculation. There is no general recipe for success in Monte Carlo deep-penetration methods. Even groups of experts, after years of general experience and detailed studies of specific problem types, indicate that there is no substitute for experience regardless of theoretical considerations.[5]

It is well known that many biasing procedures actually increase the variance per history in a Monte Carlo calculation but reduce the computation time per history. Thus, the ultimate efficiency among various techniques is usually determined relative to the product of variance and computation time (or its inverse, the figure of merit). However, there is no general way to factor into this efficiency the preanalysis personnel and computer time necessary to produce a final calculation. But these intangible effects may be of principal concern in relation to program funding levels and deadlines. With the continual shift toward increased personnel costs in relation to computer costs, it is natural that as much of the preanalysis burden as possible be placed on the computer. Innovations in these topics will be discussed in a later section.

THE TRANSPORT PROCESS

The simplest concept for controlling the particle population throughout a system in a Monte Carlo calculation is by boundary splitting and Russian roulette. As particles transport into regions deemed to be more important (i.e., closer to the detector regions), they are split into more, lower-weight particles. If they revert into regions of lower importance, their number is decreased into fewer, high-weight particles by Russian roulette. In practice, there should be enough regions so that the particle population does not drop by more than a factor of 2 to 5 between boundaries in the important regions of the system between the source and detector. Otherwise, too many independent particles from the original source are lost, and the adjusted population may ultimately become highly correlated due to multiple splitting of a few particles.

The other commonly used technique in transport biasing is the exponential transform (a.k.a. path-length stretching, a misnomer since paths are sometimes shrunk). Although many forms of this technique have been devised, the most common is a directionally dependent form which artificially decreases the cross section in preferred directions and increases it in unpreferred directions. Thus, particles reach important parts of the system with fewer collisions and are not followed as far into unimportant regions as for the analogue case. However, the fluctuations introduced by the necessary weight corrections can sometimes cause a sufficiently large increase in variance so as to offset the time savings in the overall efficiency of the method. It is known that some form of weight control in the form of a weight window (restriction of all particle weights between an upper and lower limit for a given importance region by splitting and Russian roulette) improves the efficiency of the transform.[5] It is also known that improperly set weight windows can have the effect of negating the advantages of other biasing procedures and return the population and weight distributions to that of an analogue procedure. The weight window mean value for different importance regions must be set appropriately in relation to one another and to the source region, just as for boundary splitting and Russian roulette described above.

Both methods of transport biasing, boundary splitting with Russian roulette and the exponential transform, together with various weight control devices, have been used successfully for many years. It would be difficult to establish which method is more efficient, and no such general theoretical studies have been made. The TRIPOLI code[6] has been specifically designed to utilize the exponential transform. The importance regions, the preferential directions, and the transform parameter are combined automatically so as to minimize the need for weight control, although there is a built-in weight window. It is well known that these techniques can produce accurate results of high precision, and they will be covered in detail in a latter presentation in this session.[7] But it can never be known how good are empirically set input parameters in terms of calculational efficiency as compared to some theoretically optimized procedure.

A two-dimensional multigroup Monte Carlo study of neutron leakage from a spent-fuel shipping cask indicates that there is no significant improvement in efficiency when the exponential transform is included in a calculation where the weight window for splitting and Russian roulette has been automatically set throughout the system from adjoint calculated importances.[8] In this study the transform parameter was determined in an optimal manner from a discrete ordinates adjoint event-value function, the correct adjoint function to be used in connection with the exponential transform. This optimized energy-, spatial-,

and directional-dependent parameter was found to never exceed 0.3 in a highly scattering system of steel and depleted uranium. But for gamma-ray transport in the same system, all optimized parameters exceeded 0.9. These same general effects are reported in an iron benchmark example in Ref. 9 (with a "forward-adjoint" generated weight window) where a uniform decrease in calculational efficiency resulted as the transform parameter was increased from 0.2. In a more absorbing medium (concrete) it was found that the exponential transform had (1) only a marginal beneficial effect when applied to neutrons in a coupled neutron-secondary gamma-ray calculation, (2) some benefit (approximate factor of 2) in a neutron only calculation, and (3) an even greater benefit when applied to gamma rays.

Some conclusions from this discussion indicate that the exponential transform performs best in absorbing systems with some control of large weight-correction fluctuations, with gamma rays being afforded more benefit than neutrons. This is consistent with the premise of the transform that the particle flux is attenuated exponentially and also with semi-empirical methods such as point kernels where gamma-ray scattering can be included with a fit to an exponential function and buildup factor.

For comparative purposes it must be pointed out that in these optimized studies the weight windows for splitting and Russian roulette were first set before introducing the transform. Thus, a substantial amount of transport biasing was already in effect before attempting to make an improvement with the transform. In contrast, for empirically determined input schemes the transform is the principal biasing device, and splitting and Russian roulette are used only when necessary for large weight fluctuations. No procedures have been reported where the optimization of the exponential transform was done first.

IV. SOURCE, COLLISION, AND ESTIMATION PROCESSES

Improving the transport process is the primary objective of biasing techniques in most deep penetration calculations. If this is done properly, the other aspects of the calculation can be treated fairly simply. But if the transport biasing is improperly or poorly applied, even very sophisticated techniques in the other processes are often to no avail.

Source biasing in any of the phase space variables is one of the most effective and easily implemented of any biasing procedure, even for fairly complicated systems. When there are no theoretical aids, such as adjoint results, empirically set biasing parameters can often increase the overall calculational efficiency by several factors over that from use of the natural source distribution. For complicated source distributions it may be necessary to segment the source in some way in order to adequately sample all important variables. The weight dispersions created by source biasing will be further dispersed by any subsequent biasing in other processes. The weight windows throughout the entire system must be set relative to that for the source region, which must not be so narrow as to negate the source biasing or too wide as to introduce large weight variations in the ultimate results. It may sometimes be necessary to make separate computer runs for different source phase space segments, with different biasing techniques and parameters, in order to control this weight dispersion.

In contrast to source biasing, effective collision biasing (of the outgoing energy and direction) is a difficult task. Many codes have an available

option, but this is usually the least used of all standard biasing procedures. A general scattering kernel is such a complicated function, as compared to most other distributions encountered in a Monte Carlo calculation, that empirically set parameters have not been found to consistently improve calculation performance. It has been found that implicitly biasing the energy and directional variables in other processes is generally preferable to altering the collision process explicitly.

The collision biasing procedure in TRIPOLI will be presented in a following paper.[7] Recent work has been reported where the exponential transform weight fluctuation has been absorbed into a collision biasing scheme, but the actual application is limited to gamma rays.[10] In the shipping cask study mentioned in the previous section, it was found that optimized collision biasing, like the exponential transform, was ineffective when the weight window for splitting and Russian roulette was determined from an adjoint solution.

A conceptually simple form of angular biasing, designated DXANG,[11] has recently been made available to the MCNP code. Here, a spherical region, not necessarily part of the physical system geometry, is defined toward which it is desired to scatter particles. At each particle collision (and source event) a cone is defined by the solid angle $\Delta\Omega$ subtended at the collision site by the sphere. A secondary particle is created with a direction Ω chosen uniformly in the cone and with a weight adjusted from that of the primary particle before collision by multiplying by the easily-computed $\Delta\Omega$ and by the angular scattering probability $p(\Omega)$, as for a next-event point estimator. The primary particle continues normally, producing other particles at subsequent collisions, unless it actually scatters into the cone created for a secondary particle, in which case it is terminated. Each secondary particle becomes immediately another primary particle having the same transport, production, and termination characteristics as the particle which created it.

In this manner, many particles are directed toward some region of interest without the difficulties associated with conventional angular biasing. The extra weight accumulation of the many reduced-weight secondary particles is offset by the occasional termination of a full-weight primary particle. To control the proliferation of secondary particles a probability of creation can be assigned to each importance region. The DXANG method is never applied if a collision occurs inside the sphere.

This DXANG angular biasing technique with multiple spheres has been applied to a doubly bent 5 cm radius duct penetration of a high density (7.3 g/cm^3) concrete slab shown in Fig. 1. The importance regions were set empirically as well as the numbers indicating which one of the three spheres applied to collisions in a given region. However, a region-, energy-, and direction-dependent weight window was employed here that was created using the code-generated weight window described in Section V. The neutron leakage at the duct exit was calculated to be $3.13 \times 10^{-8} \pm 8.3\%$ in 5.93 minutes of CDC-7600 computer time. In contrast, a standard state-of-the-art MCNP calculation using a code-generated region and energy weight window gave $3.08 \times 10^{-8} \pm 14.5\%$ in 50.35 minutes, a factor of 25 difference in efficiency.

If all the random walk processes in a deep penetration calculation were treated correctly, or ideally, the estimation procedure would be a simple task. However, even for many well-formulated calculations this is not the case, and some form of next-event estimation is often used. Some of the statistical

anomalies associated with this estimator are discussed in the introduction. Next-event estimation often gives low results if the region in the vicinity of the detector is undersampled due to poor transport, and the problems associated with collisions close to a point detector are well known. Increasing the biased collision density in the detector vicinity for better sampling may remove the need for it, since analogue estimators might be applicable. A cure for the point-detector infinite-variance characteristic (due to close collisions) was first presented over twenty years ago, and many extensions to this technique have been devised as well as many approximations for use in the detector vicinity.[12]

The point estimator is ideally suited for detectors placed in voids or very low-density materials. The use of estimation probabilities, as for DXANG, can greatly increase the efficiency of the estimator, although care must be taken in creating empirical values in systems with streaming paths. Another simple procedure involves testing a partial contribution to the estimator before the time-consuming determination of the exponential attenuation term. This value, $WT*p(\Omega)/R^2$, is compared to a preliminary result compiled normally. A Russian roulette game is played if the incomplete estimation contribution is already below some fraction of the preliminary result. Upon survival, the geometry ray trace is made and the estimator is completed with the attenuation term and a correspondingly increased survival weight.

A final estimation technique to be discussed here, which also has characteristics of transport and collision biasing, is called DXTRAN in the MCNP code. A next-event estimator is used to deterministically transport particles from all collision and source points to spherical regions, known as DXTRAN spheres, which are superimposed over the problem geometry. The random walk transport is then continued inside the DXTRAN sphere. In a sense, DXTRAN is a form of angle biasing because at each collision particles are forced to go into the direction of the DXTRAN sphere. DXTRAN has proved beneficial in systems of widely separated volumes and exhibits many of the aspects of ordinary next-event point estimation. It has been utilized in MCNP much more than the once-more-collided point detector option.

V. DETERMINATION OF BIASING PARAMETERS

The use of empirically determined biasing parameters has been the primary method for implementing standard code options in deep penetration calculations. The use of adjoint results is always desirable when they are available, and variations of this theoretically optimal biasing function include approximate adjoint solutions of exact problems, such as with diffusion theory, and exact solutions to approximate problems, such as with discrete ordinates. It is possible to generate approximate adjoints by complete Monte Carlo adjoint calculations and use them to bias subsequent forward calculations. Iteration schemes have been devised where forward and adjoint results are used alternately. These methods are plagued with the practical problems of large statistical errors and long running times and the theoretical problem of propagation of the errors.

Between these two extremes there have been, and are now under development and testing, several learning, or adaptive techniques where biasing parameters are generated and improved upon during a calculation. Additionally, there is a large area of mathematically related variance reduction work sometimes having no direct relation to adjoint calculation results.

Among these learning techniques is an optimization procedure[13] which is essentially a perturbation method with the biasing parameter as the perturbation.[2] In principle, several parameters can be investigated simultaneously, and periodically throughout a calculation these parameters are updated to those giving the minimum variance to intermediate results. Pattern recognition techniques have been used to automate splitting and Russian roulette procedures[14] and for general transport and collision biasing.[15] In the last several years many mathematical investigations of a transport-like equation have been presented where the quantity of interest is the second moment (the variance) of the standard transport equation.[16,17] Although these developments are very interesting, their direct application by users of general purpose codes has never been widespread.

Some of the simplest of the learning methods are procedures for updating splitting and Russian roulette parameters in the course of a calculation by attempting to equally populate all appropriate regions of phase space.[18,19] Although these methods are in no way optimal, they are usually better than empirically set parameters for large systems, and they can be used as initial values for more exact methods.

Just such an exact method has recently been developed for the MCNP code with the creation of an optimal code-generated weight window.[9] This method uses the basic principles of phase space importance in computing adjoint fluxes simultaneously with a standard forward calculation. These adjoint fluxes are then used to automatically adjust the splitting and Russian weight parameters (the weight window) in subsequent runs. The creation of this self-adjusting procedure thus eliminates the need for empirically setting the weight window.

A final adjoint importance generation method to be discussed is the recursive Monte Carlo method.[20] Although it is not a learning technique in the sense of the previous methods, recursive Monte Carlo has, in principle, several advantages over the other methods. Since these other adjoint generation methods are run simultaneously with a forward calculation, they are tied to a specific source-response system. The statistical uncertainty of the generated adjoint information usually increases with increasing importance in the direction of the detector. Recursive Monte Carlo, on the other hand, begins at the detector and proceeds recursively in backward steps toward the source. The principal feature is that all steps are forward, non-deep-penetration calculations, and only one pass is made from detector to source. The system is divided by surfaces, generally on the order of one or two mean free paths apart, where the adjoint flux is to be determined. (An earlier, not generally successful attempt was made to have these surfaces set automatically by the code). Problems associated with this recursive method include difficulty in determining the surfaces and volumes in realistic three-dimensional systems and the treatment of statistical error propagation from one calculation step to the next. It must be remembered that in all these adjoint generation methods, only approximate adjoint fluxes are wanted for forward calculation biasing.

VI. OTHER ASPECTS OF DEEP PENETRATION CALCULATIONS

A fairly complete cross section of current work in Monte Carlo deep-penetration and related shielding areas is contained in the proceedings of the 1983 International Shielding Conference in Tokyo.[21] A review of these papers reveals that albedo Monte Carlo is a much-used technique, especially in Japan.

Much of this work was done with one-dimensional (azimuthal symmetry of the emerging particle) albedos determined from inexpensive invariant embedding calculations. The reported results are within a factor of 2-3 as compared to experimental results of difficult duct streaming problems. Earlier work[22] using two-dimensional, discrete-ordinates-computed albedo data indicates that to correctly predict the radiation streaming through a duct such as that shown in Fig. 1, the protruding interior corners and some portion of the duct wall in the exit leg must be modeled with standard particle transport.

It is also seen from the Tokyo proceedings and those of the 1984 Topical Meeting on Reactor Physics and Shielding at Chicago[23] that Monte Carlo analysis of any realistic system is often coupled with some other calculation method - discrete ordinates, diffusion theory, point kernel, or a separate Monte Carlo calculation. A much used scheme has been the DOT-DOMINO-MORSE[24] system developed in Oak Ridge, and it has been made more general in the MORSE-ALB[25] code system developed in Japan. Some coupling schemes with the TRIPOLI code have been presented, and an elaborate reactor shielding analysis system of various coupled methods has been developed in the United Kingdom.

The use of albedo data and coupling methods has most often been associated with multigroup Monte Carlo codes (specifically MORSE[26]) due to energy group compatibility. The widespread use of MORSE has been made possible because of its discrete ordinate-type, multi-group cross section format. Until the promotion into the public domain in the last few years of codes such as MCNP and TRIPOLI, continuous energy codes have had, for a variety of reasons, installation dependent restrictions, especially in terms of cross-section data transportability. It is, of course, the cross section treatment which presents the most serious potential problems with multi-group codes. Data sets designed and weighted for specific applications are often used indiscriminately for many other applications. A particular problem arises in deep penetration calculations if only one weighting scheme is used in the shield. Just as for discrete ordinates applications, the shield should be divided into several regions, even if it is entirely one material, with appropriate cross section weighting in each region as indicated by the shape of flux spectrum determined from the fine group collapsing procedure. Similar problems to a much lesser extent can also arise in the use of "pseudo-point" cross section libraries available in many continuous energy Monte Carlo codes. These standard libraries can greatly decrease the computer memory requirements, and they have been shown to be adequate for integral results[5] but require adjustments for differential results.[27]

Another problem area with multigroup Monte Carlo is the occurrence of discrete ordinates-type "ray-effects" if fixed scattering angles (not fixed directions in space) are used. However, this phenomenon arises only for combinations of characteristics such as monodirectional sources, little or no multiple scattering, and low order polynominal cross section expansion. It is possible to obtain from multi-group calculations differential results in terms of nuclides and reaction types, although not to the extent of a continuous energy code, by manipulation of cross section, geometry, and response function input data.

Another potentially powerful deep penetration Monte Carlo method is the use of complete adjoint solutions, not just approximate adjoint importance functions for use in forward mode biasing. There are several problem types ideally suited for adjoint solution, but which require extensive biasing for forward solutions. The most notable example is a system with a large, extended source area of

relatively simple geometry and a small, concentrated, and geometrically complex detector region. Several continuous energy adjoint codes exist but have never been widely used, the gamma ray option being more amenable than that for neutrons. However, with the widespread use of multigroup Monte Carlo it is surprising that more use is not made of the adjoint option, which is conceptually no more difficult than the forward mode for problem setup and execution.

In practice adjoint calculations also require biasing or other special techniques, and a user's experience, intutition, etc., are often lacking in comparison to that for forward calculations. The appearance of flux terms, instead of current, in the basic equalities for forward and adjoint calculated integral quantities sometimes causes difficulty, or confusion, in creating adjoint sources and estimators. In most Monte Carlo applications flux is a quantity created in an estimation routine for multiplication with an energy dependent response function, but in the code the particle weight simulates current or collision density, not flux. Also, more attention must be given to the phase space variables other than energy in the adjoint source, response, and normalization than is normally necessary in the forward mode. One of the primary uses of adjoint methods in any calculational technique is the ability to obtain results from multiple sources from only one calculation regardless of the difficulty of the forward calculation. This procedure is, of course, the counterpart of that for multiple responses from one forward calculation.

The use of adjoint Monte Carlo also extends the options of coupling techniques for responses as well as for sources.[28] An application of this method has been employed in the ongoing program of dosimetric reevaluation of the atomic weapon radiation environments in Japan. Figure 2 shows a computer plot of the mock-up of a large, reinforced concrete building in Nagasaki. Doses interior to the building are determined by starting adjoint particles at specific locations in it and following them, or estimation trajectories, to a surrounding coupling surface a few mean free paths from the building. Here, the calculation is coupled with a forward two-dimensional air-over-ground discrete ordinates calculation, with the assumption that this free-field flux is unperturbed by the presence of the building. The source for the forward calculation is the weapon output, located approximately 500 m above and 500 m ground range from the building at the orientation shown in the figure.

VI. ON-GOING AND FUTURE WORK

The plot in Fig. 2 represents current state-of-the-art geometry and computer graphics capabilities available or planned in most general-purpose Monte Carlo codes. This picture was drawn by the JUNEBUG diagnostic module of the MARS "array of arrays" geometry system in the MORSE code. The exterior vertical and horizontal lines represent the array into which each part of the building may be modeled in any detail independent of the rest of the building. Any repeating or symmetric portions are modeled only once and placed in the array as often as necessary.

For several years at meetings such as this, the topics of supercomputing, vectorization, parallel processing, computer aided design, etc., have been and are extensively covered. At Saclay there is presently an ambitious program under way, in connection with the next generation of the TRIPOLI code, to provide the user with an interactive computer capability which should reduce complicated deep penetration problem setup time from what now might take many

man-hours to only a few minutes. This program, when complete, will effectively constitute an "expert system," which will not only give the user assistance in the mechanics of problem setup but will also offer specific technical advice from an accumulated data base of problem types. The standard practice of a few short runs, with subsequent data adjustment from the intermediate results for a final long calculation, will now be approached more systematically.

There will, of course, continue to be developments in Monte Carlo theory and the creation of new techniques to handle specific problems. A current effort at Los Alamos is directed toward attempting to bias the random number space rather than the physical phase space.[29] If successful, this technique would make Monte Carlo variance reduction truly problem independent. The computing hardware will always get "bigger and faster" so that it is possible to run more histories or batches. The emergence of a new generation of user-friendly software such as just described and the availability of complete and reliable importance parameters as described in Section V will help to make deep penetration Monte Carlo calculations more of a pure science and less of an art.

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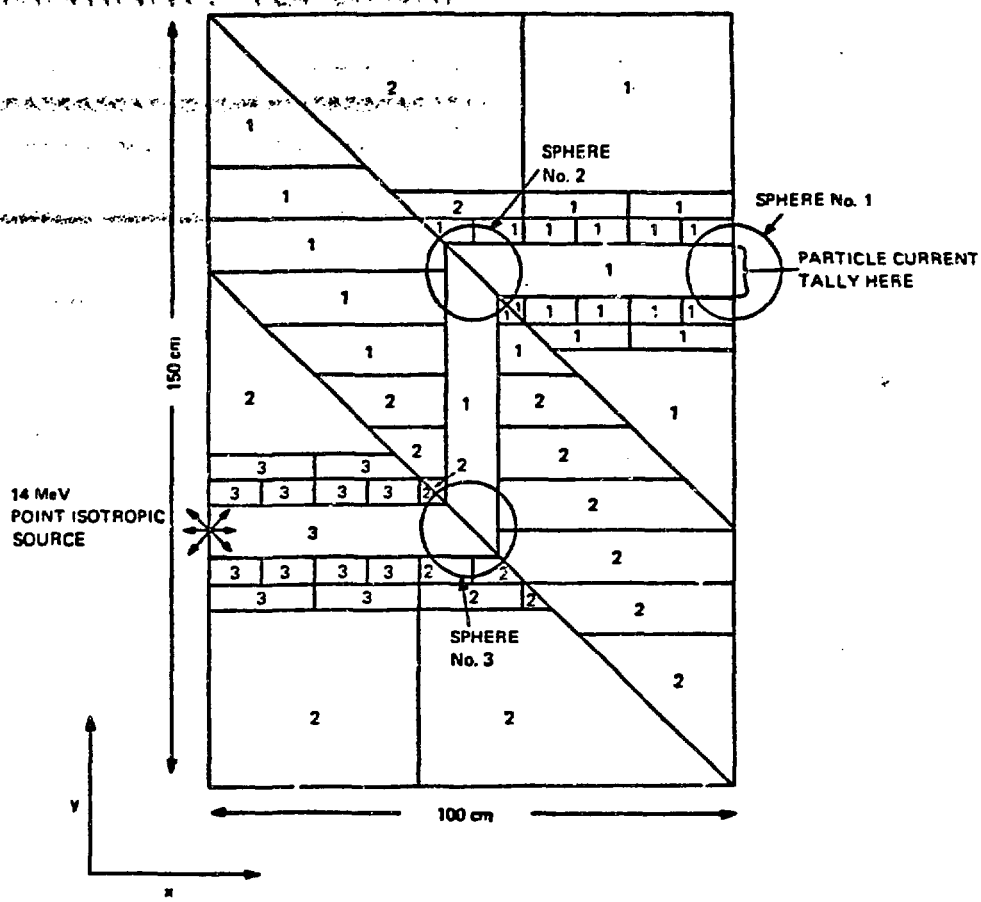

Fig. 1. Multileg duct with DXANG spheres.

..A very detailed geometry mockup was used in initial Monte Carlo calculations:

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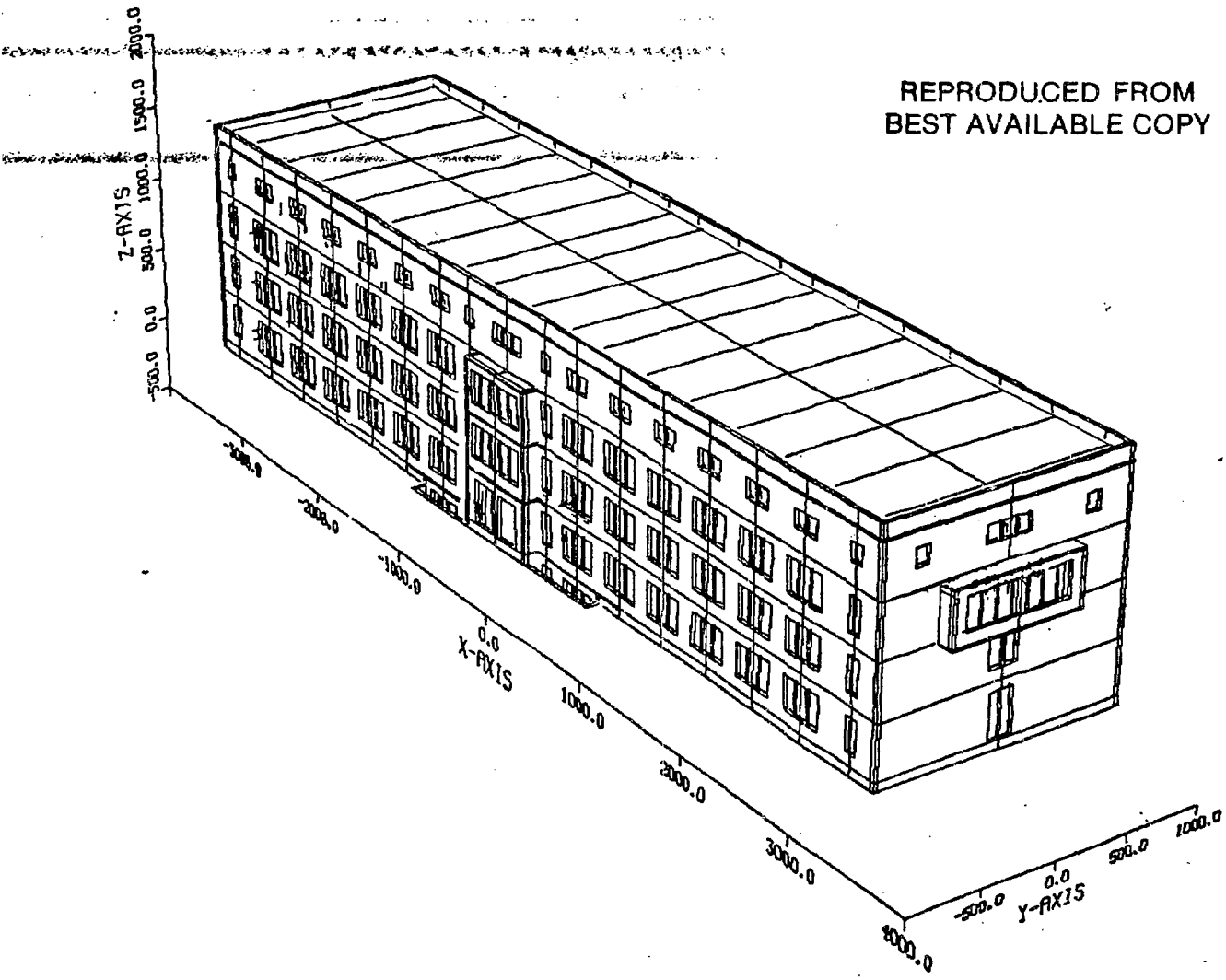

Fig. 2. Reinforced concrete building in Nagasaki.