CHAPTER 6

Conclusions

The explicit formulation of residual statics estimation as a nonlinear, rather than as a linear, inverse problem reveals the need for an initial guess in the estimation of statics corrections. In most applications statics are small; thus an initial guess of zero (in essence, *no* initial guess) for each shot and receiver static is sufficient for the attainment of the best statics solution. When near-surface anomalies are large, however, zero is not an appropriate first guess. Because the estimation of the resulting large statics requires the location of the global minimum of a multidimensional objective function, the presence of suboptimal local minima can lead to gross errors (cycle-skips) if the initial estimate of statics corrections is insufficiently close to the global minimum.

If no good initial guess can be made, the estimation of large statics corrections requires a method of optimization capable of locating the global minimum among many local minima, regardless of where the algorithm begins its search. Simulated annealing, one such method, is a Monte Carlo technique that performs a controlled random search. In applying simulated annealing to residual statics estimation, I have chosen to use the stack-power criterion of Ronen and Claerbout (1985) to quantitatively differentiate between statics solutions. The resulting Monte Carlo statics estimation algorithm searches through statics solutions that can either increase or decrease stack power, but the final solution is, with reasonable probability, the statics solution yielding the greatest stack power.

The results of this thesis establish that Monte Carlo statics estimation can be used successfully in a practical setting. Experimental tests were performed on both synthetic and field data. In both cases, the data contain severe statics that would normally result in cycle-skips after statics estimation. The results of Monte Carlo statics estimation, however, show that cycle-skipping need no longer be the difficult, if not insurmountable, problem it has previously been for automatic statics algorithms.

The objective of this work is to obtain useful solutions that alternative automated techniques cannot find. Although the use of thousands of iterations is computationally costly, it may nevertheless be a practical necessity. The number of possible solutions in a statics problem is immense—practically, infinity; thus the mere attainment of a reasonable solution is intriguing.

In residual statics estimation, the one-step heat-bath method is considerably more efficient than the Metropolis technique. Instead of randomly choosing among all possible shifts, the heat-bath method focuses specifically on cycle-skips. Yet, despite this improvement over the Metropolis method, the principal disadvantage of Monte Carlo statics estimation is still computational inefficiency. The nonlinear nature of the problem appears to preclude a truly fast method.

A more efficient technique might be possible, however, if the problem were posed differently. The Monte Carlo algorithm treats statics as a fully nonlinear problem, thereby extending the ability to estimate statics from a linear into a completely nonlinear realm. But perhaps the problem need not be fully nonlinear; for example, there should be a method that would more strongly discount the possibility of producing a highly disordered stack, at any stage of the iterative process. One efficient approach is indicated by the idea of seeding a crystal. Another approach, if prior knowledge of geologic structure were available, would be to maximize the power in a *dip-filtered* stack. In either case, random wandering would be limited, but not eliminated.

Experimentation is an integral element of the Monte Carlo approach. However, no systematic, empirical study of statics estimation by simulated annealing has yet been undertaken. Among the many unresolved issues is the algorithm's reliability: no two runs with identical parameters will exhibit identical behavior if different random numbers are used. Although global optimization with a given T may succeed, another attempt might fail. Thus far, the algorithm appears workably reliable: experimental trial and error is necessary to choose T, but the synthetic and field data examples show that successful runs can be obtained without excessive testing.

The success of Monte Carlo statics estimation is thus an empirical fact. For further research to be fruitful, however, it is necessary to know *why* the Monte Carlo method works. The structure of the residual statics problem appears to at least partially account for the success of simulated annealing in the estimation of large statics. The Monte Carlo algorithm essentially performs random sampling from a Gibbs distribution. The Gibbs distribution, originally discovered in statistical mechanics, is closely related to a spatial stochastic process in which conditional probabilities depend only on nearest neighbors. Because the surface-consistent constraint of statics estimation creates its own form of a nearest-neighbor system, calculations in the Monte Carlo statics algorithm can be organized such that changes in the objective function due to changes in a single parameter are easy to compute. The ease with which these computations are performed on a parameter-by-parameter basis appears central to the success of simulated annealing in residual statics estimation.

Applications of simulated annealing to other nonlinear inverse problems appears possible. Key criteria for applicability are whether the problem can be expressed in the form of a nearest-neighbor model, and, more importantly, whether repeated forward modeling can be efficiently performed.

The behavior of the Monte Carlo statics estimation algorithm can appear magical: from complete disorder, a relatively structured, ordered stack can appear. Transitions from disorder to order in physics produce much the same effect. To the extent that both phenomena are understood, both can be explained in the same way: for a system in equilibrium, low energy states are more probable than high energy states. This statement of probability does not fully discount the possibility of entrapment in a local minimum, but does strongly bias the search toward the deepest minima.