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Guest editorial

Presenting the Special issue on Optimization and Combinatorics

The study of combinatorics and optimization (or operations research) continues to fascinate scientists from a variety of disciplines. At the center of focus is a special class of problems called nondeterministic polynomial-time complete problems (commonly called NP problems). For example, there has been no known exact solution to the classic Traveling Salesman Problem (TSP) except the exhaustive search. Furthermore, there are many everyday examples of optimization problems, such as scheduling classes in a school, planning delivery routes, assigning hospital beds, assigning aircrafts to terminals, etc.

One of the earliest attempts to solving the TSP is linear programming. Optimization based on linear programming began with Dantzig's development of the Simplex algorithm (1963) [1], and subsequent improvements by Khachian (1979) [2] and Karmarkar (1984) [3]. Meanwhile, pioneers such as Metropolis et al. (1953) [4], Kernighan and Lin (1970) [5], Karp (1977) [6], Kirkpatrick et al. (1983) [7], Geman and Geman (1984) [8], Hopfield and Tank (1985) [9], and Hinton et al. (1986) [10], also contributed much to the advancement in optimization and combinatorics.

Since the pioneer contribution by Metropolis in annealing, Kirkpatrick et al. in IC chip layout, and the Hopfield-Tank TSP solution, the neural network community has come to a full through Szu and Hartley's Fast Simulated Annealing in 1987 [11], and recently, the mean field annealing (MFA).

As perhaps self-evident in this current snapshot of 14 papers, such a flourished R&D indicates the recurrent emphases on applications, implementations, and basic theory. However, the grand challenge of optimization which one does in everyday life remains in the intuitive and computational solution of a nonlinear, adaptive and parallel approach to the global optimization – the fundamental unsolved problem, the second von Neumann problem (see paper: *Divide-and-conquer* orthogonality principle for parallel optimizations in *TSP* by Szu and Foo). The 'adaptivity' means: when more information/data measurement becomes available subsequently whether an early minimum solution can be re-computed with a minimum redundant effort. This is trivial if no interaction exists between new and old data, and we know that it is usually not true in our daily experience in decision making, e.g. in stock market, or in logistic arrangement. In short, can a nonlinear optimization be recursively 'divided-and-conquered'?

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In this regard, perhaps, fruitful directions lie along the spatiotemporal divide-and-conquer principle, i.e. a hybrid ANN consisting of the stochastic ANN and the traditional backprop ANN. This hybrid computational solution may overcome the local minima problem in multilayer perceptrons, and the slow-down learning at a temporal minimum near a flat energy landscape. Otherwise, the deterministic ANN algorithm can be used efficiently.

Another area of much interesting is the current multiresolution analysis approach leading to an interesting version of a multiresolution optimization. In other words, a coarse scale has a single minimum, while at a fine scale it breeds several minima. The question is: Can the scaling equation of wavelet analysis give us a handle on these minimization processes?

This special issue represents a relatively small but significant compilation of the growing interests in the applications of artificial neural networks for solving NP problems, ranging from vehicle routing, job-shop scheduling, satellite communication networks, to circuit partitioning.

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Guest editors

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