A Survey Of Optimization Techniques Being Used In The Field

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The rapid progress made in the application of optimization techniques to industrial processes has been driven primarily by the increase in global competitiveness and environmental regulations that force companies to make optimum use of their resources. The US Air Force has of late been coming under severe pressure to reduce expenditure in the form of reductions in budgetary allocations. There has therefore, been an increasing interest to optimize the operations of its various fleets. This paper surveys some of the optimization techniques currently in use in an attempt to analyze the strengths and weaknesses inherent in them and their applicability to a military operation.

Optimization may be defined as the process by which an optimum is achieved. The optimum may be that of an industrial institution or an objective function that models a similar entity. The factors that define the optimum will vary with the situation to which the optimization process is applied. Some examples of factors that may be optimized are cost, raw materials used, time required and pollution caused. Optimizations may be performed for obtaining local and global optima.

The increasing complexity of decision-making that increased competition has engendered has resulted in the implementation of enterprise-wide resource planning systems (ERP). These information systems have provided a wealth of information that is staggering in terms of sheer size. To achieve a competitive advantage firms must be able develop the means to use the information provided by these systems to improve their processes. However, decision-making is hampered by the presence of multiple objectives operating on different time scales, strategic environments and rates of change.

The US Air Force operates in a different competitive environment. However, it has of late been coming under severe pressure to reduce expenditure in the form of reductions in budgetary allocations. There has therefore, been an increasing interest to optimize the operations of its various fleets. To determine the optimization technique that would be most effective for the Air Force business model, we surveyed some of the optimization techniques currently in use. We attempt to analyze the strengths and weaknesses inherent in the different techniques and their applicability to a military operation.

This paper begins with an introduction to some of the terms commonly used in the industry and military when dealing with optimization in section 1. Section 2 describes some of the techniques that are used and describes a few recent applications of optimization in different industries and research areas. Section 3 evaluates the pros and cons of each technique. Section 4 summarizes the paper and concludes.

1. Introduction to Terminology Used

Attribute: An attribute is any parameter that has significant impact on the behavior of a system that is being optimized and is being controlled in an attempt to achieve an optimum.

Constraint: A constraint is used to refer to any condition that limits flexibility. In this case the extent to which an optimizer can vary the parameters that influence the outcome is limited by the constraint.

Objective Function: An objective function (also called a cost function) spells out the relationship between the outcome (objective) and the attributes mathematically.

Policy Level Objectives: These are macro-level objectives imposed upon a system due to strategic or operational necessities. These are broad, intuitive and articulate the tradeoff between different and sometimes antagonistic objectives.

Readiness: of a system is a measure of the number of units in the system that can perform to specifications with a given amount of certainty. This certainty is usually measured as the probability of occurrence with a required confidence level (usually 95%).

Markov processes: Simply defined a Markov process is one in which the rate of input and output are the same. Processes are usually treated as Markov processes because they resemble them or because they simplify the mathematics involved.

Multi-Level Optimization: We define multi-level optimization as being optimization that takes place on two different time scales or at different amounts of granularity. Usually the optimizer at the higher level makes use of the outputs of the optimizer at the lower level.

Multi-Objective Optimization: When the optimization tries to achieve multiple objectives, it is said to be multi-objective. Often in this type of optimization, one or more of the objectives are treated as constraints.

2. The Problem Being Tackled

The planning and allocation of resources in the Air Force has depended heavily on simulation software called LCOM (Logistic Composite Model) that provides estimates of outcomes based on a stochastic set of inputs. These inputs include labor, spares, capacity and policy requirements. An analyst will typically run multiple simulations with different scenarios and based on his/ her past experience come up with an educated guess about the optimal operating scenario. This scenario at present takes on average anywhere from two to three weeks. The lead-time needed for analysis decreases the accuracy of the estimates. Further the overhead imposed by the planning time hinders the ability of the Air Force to rapidly respond to changing requirements of the environment.

Advances in the field of optimization and in supercomputer processing power have made his problem more tractable in terms of time. By relegating the core optimization work to a machine the analyst could be better utilized in value enhancing activities such as risk analysis. Further by reducing the time needed to provide an estimate of the optimum it is hoped that the estimates themselves will be of greater utility in decision-making.

This project will be implemented in three phases – the proof of concept phase, the validation phase and the implementation phase. The proof of concept phase will involve the selection of two optimization methods that would be most suited to handling the problem at hand. It will involve building a new model of the entire C17 fleet operations, independent of LCOM, and the optimization of the model with one of the two methods chosen. The second phase will involve the proof of concept and validation of both the optimization methods. The third phase will include the application of the optimization techniques so developed to LCOM.

3. Techniques Used and Some Recent Applications

The optimization problem can be stated mathematically as

$$x^* \in \mathrm{ARGMAX}_x \{f(x): g(x) = 0, x \in X\},$$

where $S = \{x: g(x) = 0, x \in X\}$ is the set of possible solutions.

Direct techniques are based on the derivative method in which the gradient of an objective function is calculated and set to zero to obtain points at which its value becomes maximum or minimum. The second derivative of the function is then used to determine whether the points so obtained are maxima or minima. Clearly, therefore, the objective function in classical & direct optimization must be continuous and twice differentiable. This requirement is generally not met in real world problems. Classical techniques however, have the advantage of being mathematically neat, simple to understand and easy to use. Due to the dynamic and discontinuous nature of the problem at hand classical techniques were clearly not of significant use. Some classical techniques include Gaussian elimination, Newton Raphson and Gauss Seidal methods.

Simulated Annealing

This technique draws its inspiration from the annealing process that many substances undergo while changing state. Typically, a substance, such as iron for example, when heated gains energy. This energy is gradually dissipated due to cooling. The temperature is thus a measure of the disorder in the iron. As it cools its molecules gradually, loose energy and gain order. This process continues until the system can achieve thermodynamic equilibrium. In the case of annealing a piece of iron, thermodynamic equilibrium would occur when the temperature of the iron is the same as the temperature of the surroundings. Simulated Annealing tries to mimic this process and therefore gets its name.

One of the difficulties in using Simulated Annealing is that it becomes very difficult to choose the rates of cooling and the initial temperatures for the system that is being optimized. This occurs primarily because of the absence of any rules for selecting them. The selection of these parameters depends on heuristics and varies with the system that is being optimized.

Industrial Application

Simulated Annealing has been used for a variety of optimization problems. These range from portfolio optimization to image processing. Belegundu and Constans [Ref. 14] have used simulated annealing to reduce noise pollution. They use a software called SOAR (Shell Optimization for Acoustic Radiation) to predict the vibration and sound power. The shape of a structure is modified until it becomes a 'weak radiator'. The simulated annealing algorithm is used to find the optimal distribution of mass locations from a noise perspective.

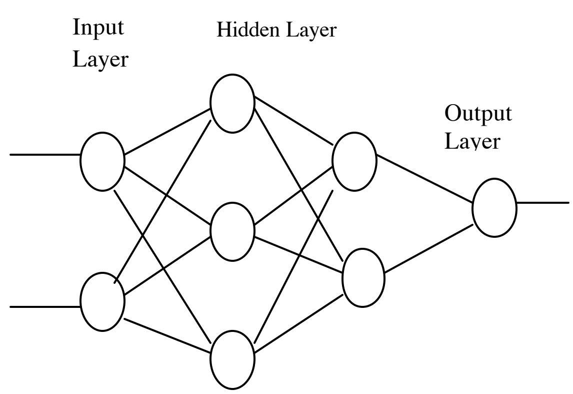
Cederberg and Collins, [Ref. 15] at the Naval Research Laboratory, have used simulated annealing to optimize the solution of inverse geoacoustic problems. The solutions are obtained with the help of self starter – an efficient forward modeling tool. Geoacoustic problems arise when a source and an array of receivers are separated by a water column with unknown parameters. These systems are used to probe the bottom of the ocean.

Greening at Datavision Computing Services together with Zakarauskas and Dosso of the Defense Research Establishment Atlantic Canada, [Ref 16] used simulated annealing to localize the sources of acoustic signals. They used a modified Bartlett processor, which matched the measured acoustic fields with computed values. The search for the parameters was then carried out using simulated annealing. They found that this simultaneous localization provided accurate positions and relative strengths for multiple sources.

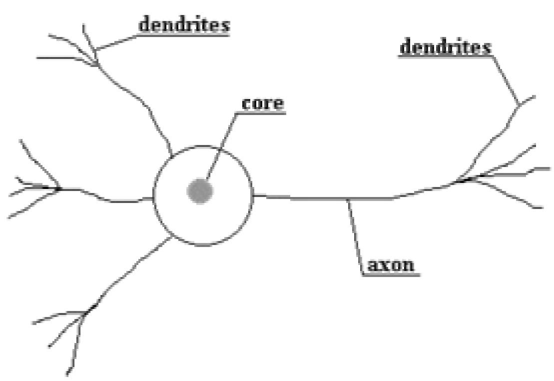
Boudet et al, [Ref. 18] at the Commissariat a l'Energie Atomique, used simulated annealing to design thin film filters. They assigned parameters such as the number of layers, tolerances for the target, incidence angles etc as parameters for the simulated annealer. Conditions like adhesion to the substrate were provided as constraints. The authors found that the simulated annealer converged in every case and that the accuracy of the optimum obtained depended upon the parameters chosen. They also report, interestingly that the solution needed no further refinement.

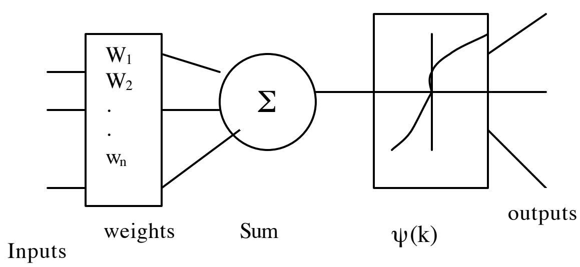
Neural Networks

There has been an explosion of interest in Neural Networks. They have been applied to modeling as well as to interpretation. The major reason for the universal appeal and utility of neural networks is that they are universal approximators. Neural networks derive their inspiration from biological neuron systems and the brain. A neural network consists of a number of sub-units called neurons. These are interconnected in parallel to form a network as shown below.



A typical neuron consists of inputs, a summing function, a limiting or threshold function and outputs. These correspond to the dendrons, the synapses, the cell bodies and the axons of a biological neuron. A diagram of an actual neuron and a artificial one is shown below.





For neural networks to perform any useful function they must be trained. The most common method of training found has been the backpropagation method [Ref 6 & 7] in which an error function is minimized by changing the weights of each synapse in proportion to the error calculated. The error being the difference between some target or desired value and the actual value (output) obtained. The analogy between the error function in backpropagation training and the objective function in optimization is too obvious to be missed. Hence, the application of neural nets to optimization problems is easy to expect.

Fundamental to the utilization of neural nets to optimization problems is the computation of the gradient of a cost/ objective function with respect to the parameters being optimized. For a constrained optimization, hard bounds can be introduced either on the inputs or on outputs depending on convenience. Another technique of limiting these problems is by using an exterior penalty function. The penalty function adds an additional function to the objective function that increases the cost of those regions that lie outside the constraints thereby making them infeasible.

A multi-criterion optimization problem is generally solved using the minimax method, a weighting method, a L_p-norm method, a goal programming method or more commonly an ε-constrained method. In the ε-constrained method one of the objectives is optimized while the others are treated as constraints. In the minimax method the optimization is carried out on each of the objective functions and the minimum of the result is taken as the optimum. In the weighting method each objective is assigned a scalar weight that signifies its relative importance to the other objectives. The optimization problem is then converted into optimizing the weighted sum of the different objective functions.

There have been several attempts to use neural networks to optimize discrete combinatorial problems. However, there have been reports of success as well as failure in obtaining optimal solutions using different methods developed. The conflicting reports need to be resolved with further research.

Industrial Applications

Lu and Markwood [Ref. 33] have developed and applied neural networks in the industry to control the weight of the coating applied in a hot dip coating line of a steel mill. They report significant savings in terms of reduction in coating weight, error between the target and actual coating weight and coating material used. They found that neural networks outperformed regression models and resulted in a 5% saving of Zinc.

Veluswami at Mittel Corporation, Canada, along with the Department of Electronics, Carleton University used neural networks to optimize high speed interconnects of VLSI circuits with electromagnetic simulation models.[Ref. 32] They found that the models once developed operate with minimal CPU time. They also demonstrate the savings in both CPU resources and advantages that neural networks have over existing techniques.

Yalcinoz and Short, [Ref. 31] report having used neural networks for solving dispatch problems in transmission systems. They found that the results that they obtained were very close to those obtained using the quadratic programming method.

Ko and Cho [Ref 31], report using neural networks to optimize face milling operations. They used two neural networks one for estimating tool wear length and the other for mapping input and output relations from the data during cutting.

Genetic Algorithms

These algorithms draw their inspiration from various hypotheses of biological evolution. Historically, such hypotheses have proposed that species evolve through a process of survival of the fittest. A population of a species (set of possible solutions in this case) is created. The members of this species are allowed to reproduce and recombine to produce new offspring. The fittest offspring are then selected to go on to the next stage namely, recombining and producing new offspring (or new solutions). The pseudo-code for this may be written as [from Ref 1]

```
Initialize the population
Evaluate initial population
Repeat
    Perform competitive
    selection
    Apply genetic operators
    to generate new solutions
    Evaluate solutions in the
    population
Until some convergence criteria
is satisfied
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There are a number of optimization techniques in the same family as genetic algorithms. They include genetic programming and evolutionary strategies.

Industrial Applications

Duponcheele and Tilley used genetic algorithms to optimize the shape of an automotive structural bumper beam. [Ref. 27] The used a variant of genetic algorithms called messy genetic algorithm. [Ref. 28] They carried out their evaluations in collaboration with ECIA, a car component manufacturer. The aim of a designer is to increase the moment of inertia of the cross-section with respect to bending and thus increase the absorption of kinetic energy. The optimization involves increasing this cross-section by increasing the mass of the beam and therefore its cost or changing the shape of the cross-section. The authors found that the performance of the messy genetic algorithm's design was consistently better than the existing ones.

Lee and Horner [Ref. 29] use group synthesis to model piano tones. A genetic algorithm is used by them to select nearly contiguous groups. Independent frequency deviations are provided to each group to simulate partial stretching. They found that the data required was reduced by half when compared to additive synthesis. Furthermore, the perceptual identity of sound was also preserved.

Higuchi and Kajihara report [Ref. 30] that MITI, Japan is developing Evolvable Hardware chips (EHW) as part of its real-world computing project. EHW is based on the idea of combining hardware with genetic algorithms to "execute reconfiguration" automatically. These chips are used in telecommunication equipment where they process compressed signals. They report that the GA is invoked each time the prediction performance of an EHW decreases due to changes in the data to be compressed. The GA searches for a better structure and autonomously reconfigures the hardware to changing environments. Based on their experience they conclude that the EHW concept with GAs can be applied to a wide variety of applications.

Tabu Search

This technique is based on the idea that humans behave in a seemingly random manner given the same learning environment. The correct behavior or solution is discovered over time by performing a given action, determining its consequences and using those consequences in performing future actions. Hence, tabu search must keep a track or 'list' of the paths it has traversed. Tabu search has two main stages. In the first stage it explores the state space coarsely and determines probable solutions. In the second stage, it searches in the environs of these probable solutions to determine which solution is the best. A detailed investigation on this algorithm can be found in [Ref. 21]. Vujic et al compared the performance of tabu search to the MonteCarlo method and found that tabu search was superior with respect to both the computational effort and the value of the objective function.

<u>Industrial Applications</u>

Lee and Ellis [Ref. 17] at the Graduate Institute of National Research and management and John Hopkins University respectively, provide some empirical comparisons of algorithms. They applied tabu search and other algorithms to optimize monitoring of network design to the Taiwan power system. They report that the primary objective in monitoring network design is to maximize information acquisition while minimizing cost. Accordingly they measured the performance of the algorithms based on the computational time or the cost and the effectiveness or frequency of obtaining good solutions. The algorithms they considered were the polytope method, simulated annealing and genetic algorithms. They found that simulated annealing and tabu search were superior in performance to the other methods.

Chang and Wen report [Ref. 24] that they had developed a mathematical model for 'trouble call' analysis and used tabu search to solve this problem. They tested their solution on a sample distribution system and found that the tabu search based method was efficient.

Tabu search has also been applied to scheduling m identical parallel processors with 'sequence dependent setup times' to minimize the total execution time [Ref. 25]. Their scheduling had three phases. In the first phase unassigned jobs were assigned to the processor. In phase 2 tabu search was used to improve upon the starting solution produced in phase 1. In phase 3 final adjustments were made to improve the solution obtained. The authors reported that this methodology resulted in producing "good quality solutions in reasonable running times" when compared with an exact procedure.

He and Kusiak report [Ref. 26] that they used tabu search to configure an assembly system. They indicate the production of modular products requires a single assembly line. The assembly system must be designed to improve agility and cost efficiency. They set the aspiration value to the current minimum and use a stopping criterion of a fixed number of iterations. They found that their heuristic algorithm that used tabu search outperformed the general line balancing method.

Stochastic Approximation

While some non-classical optimization techniques are able to optimize on discontinuous objective functions, they are unable to do so when the complexity of the data becomes very large. In this case the complexity of the system requires that the objective function be estimated. Furthermore, the models that are used to estimate the objective function may be stochastic due to the dynamic and random nature of the system and processes.

Stochastic approximation techniques are not new. They had been first developed by Robbins and Munro in 1956.[Ref 2, 8] Their development however, has been slow due to their dependence on simulation and the accompanying computing power required.

The basic idea behind the stochastic approximation method is the gradient descent method. Here the variable that the objective function is to be optimized upon is varied in small increments and the impact of this variation (measured by the gradient) is used to determine the direction of the next step. The magnitude of the step is controlled to have larger steps when the perturbations in the system are small and vice versa.

$$x_1, x_2, \ldots . x_n \in I \ldots\ldots\ldots\ldots(i)$$

Stochastic approximation algorithms

$$c_i x_k + c_{i+1} x_{k+1} > L \ldots\ldots\ldots(ii \ldots i_n)$$

based on various techniques have been developed recently. They have been applied to both continuous and discrete objective functions. [Ref 3 & 4] Recently, their convergence has been proved for the degenerate case as well [Ref 9]. In their paper, L'Ecuyer et al [Ref 5] illustrate the behavior of stochastic approximation with different estimation techniques.

Industrial Applications

Simha R., and Kurose F., [Ref 19] with funding from DARPA and the Office of Naval Research used stochastic approximation to minimize the call setup time. They attempted to achieve this by balancing the load on call processors. They compare the performance of two stochastic approximation techniques when applied to a circuit switched or a packet switched network.

Mixed Integer Programming(MIP)

Integer programming is used for optimizing linear functions that are constrained by linear bounds. Quite often, the variables that are being varied can have only integer value (e.g. in inventory problems where fractional values such as the number of cars in stock are meaningless). Hence, it is more appropriate to use integer programming. Mixed integer programming is a type of integer programming in which not all of the variables to be optimized have integer values. Due to the linear nature of the objective function it can be expressed mathematically as

$$\min \sum_{j,k=1}^{n} C_j X_k$$

where C is the coefficient matrix and X is the attribute vector of attributes $x_1 \dots x_n$. Also (i) and ($ii..i_n$) are the constraints in the equation above. Typically, MIP problems are solved by using branch and bound techniques to increase speed.

Industrial Applications

Mixed Integer programming has been used extensively at American Airlines. In their paper [Ref. 10], Ranga et al, at American Decision Technologies, describe the optimization of crew pairings. American Airlines, in 1992, had about 25,000 pilots and flight attendants. Their yearly cost was estimated at around $1.3 billion. The authors reported that the use of MIP in their optimization code (named TRIP) and subsequent enhancements resulted in savings of $20 million per year over the period 1985-90 and $3-5million from 1990-92. The code implemented in Fortran and C used an existing IBM optimization subroutine library.

In his paper [Ref. 11] Ciriani found that MIP when used to optimize the modeling techniques used at IBM 'significantly improved performance'. He reported using MIP as a preprocessor and found that combinatorial problems with a flat objective function seemed to benefit from heuristics. He also concluded that model formulation can provide a better integer polytope approximation if methods like coefficient tightening are used. Dillenberger and Wollensak [Ref 13] report that the use of mathematical programming techniques (such as MIP) in the decision support system of IBM's Sindelfingen plant was successful.

Ballintjin, [Ref. 12] at Shell Laboratories reports that MIP models that were used to control mode switching at acceptable levels generated attractive schedules. However, the solution times obtained were not satisfactory.

4. The Pros and Cons of Each Technique

While classical techniques would obviously not be applicable to the problem we have at hand, stochastic techniques seem, intuitively, to be appropriate for our purpose. The literature survey demonstrated that each technique had its strengths and weaknesses. It also demonstrated that the performance of each algorithm would be heavily dependent on the nature of the problem itself and the heuristics that we used.

The major strengths of simulated annealing, [Ref. 35] are that it can optimize functions with arbitrary degrees on non-linearity, stochasticity, boundary conditions and constraints. It is also statistically guaranteed of finding an optimal solution. However, it has its disadvantages too. Like GAs it is very slow, its efficiency is dependent on the nature of the surface it is trying to optimize and must be adapted to specific problems. The availability of supercomputing resources, however, mitigates these drawbacks and makes simulated annealing a good candidate.

Neural networks have the advantage that the entire operations process can be treated as a black box. This would ease the burden of having to model the entire system. It has, however, the disadvantage of requiring us to gather data and training the network. Furthermore, the performance of the optimizer would be heavily dependent on the quality of the data used.

Genetic algorithms perhaps seem to be the most popular algorithms at present. Their advantage lies in the ease of coding them and their inherent parallelism. The use of genotypes instead of phenotypes to travel in the search space makes them less likely to get stuck in local minima. They have, however, certain drawbacks to them. GAs require very intensive computation and hence are slow. They are also not guaranteed to give an optimal solution. There are examples to show that simple random mutation may be superior to GAs in some cases [Ref. 34]. The lack of proofs demonstrating the ergodicity of GAs is one factor that makes this technique unsuitable for our problem.

Tabu search had the advantage of not using hill-climbing strategies. Its performance could also be enhanced by branch and bound techniques. However, the mathematics behind this technique was not as strong as those behind neural networks or simulated annealing. Furthermore, a solution space would have to be generated. Hence, tabu search would require a knowledge of the entire operation at a more detailed level. Battiti and Tecchiolli [Ref. 22] had compared Simulated Annealing and Tabu Search on the Quadratic assignment problem. They found that tabu search does require extra overhead in terms of memory usage and adaptation mechanisms compared to Simulated Annealing. However, it avoids the "traps" inherent in simulated annealing such as attraction basins and hence did work better in their case. Paulli J., [Ref 23] reports, on the other hand, that simulated annealing is significantly better than tabu search. He cites the excessive memory overhead as well as the time required by tabu search to form a search trajectory as being the main causes of the poor performance.

Stochastic Approximation did not have as many applications reported as the other techniques. This could have been because of various factors such as the lack of a metaphorical concept to facilitate understanding and proofs that are complex. It has recently shown great promise, however, especially in optimizing non-discrete problems. The stochastic nature of our model along with the complexity of the application domain makes this an attractive candidate.

Mixed integer programming was found to have the widest application. It was preferred to routing airline crews and other similar problems that bore a close resemblance to the problem we had at hand. Furthermore, the mathematical rigor we were looking for was well established. However, as the nature of our problem is continuous and dynamic we preferred to use either Simulated Annealing or Stochastic Approximation.

5. Summary and Conclusions

This paper has surveyed a wide range of applications to determine which optimization technique has proven to be most successful. This knowledge will be applied in choosing one of these techniques to optimize a simulation model of the operations of the Air Force. The paper has briefly enumerated the strengths and weaknesses of each technique and elaborated in some detail the techniques themselves.

Due to the very nature of the application, the optimization methodology would have to meet certain requirements. It must be able to provide a ninety-five percent statistical confidence level for its estimates of the global optimum. Second, it must be fault tolerant and able to produce realistic results even in the event of minor inconsistencies in the input set. Third it should be able to come up with a good approximation of, at a minimum, the local minima when constrained to execute in a given time frame. Fourth, it should be robust enough to deal with noisy inputs and underlying stochastic models. Lastly, the ease of implementing a highly secure version is most desirable. The implementation must in no way compromise the security of the underlying hardware and software systems.

While the authors appreciated the strengths of each technique, Stochastic Approximation and Simulated Annealing best fit our application. We chose simulated annealing due in part to the fact that it lent itself naturally to optimizing a scenario-based simulation [Ref 20]. Another reason that influenced our choice included the fact that the mathematics behind Simulated Annealing is based on the rigorous theory of Markov chains. Additionally, several convergence proofs have existed for it in technical literature for quite a few years. Finally, Simulated Annealing variants such as Adaptive Simulated Annealing and Quenching provide a quick 'first pass' solution. More elaborate simulated annealing techniques such as enhanced simulated annealing [Ref. 36] provide a clean mechanism with parallelism inherent in it to achieve speed up.

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