OPTIMIZATION METHODS IN PROCESS PLANNING

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Abstract: *CAx system is today basic stone of many engineering's works. But for success work must contain tools for optimization. In this article we talk about algorithm for implementation optimization tools to Cax systems.*
Key words: *CAPP systems. Optimization, GA, Stochastic principles, Simulated annealing*

1. INTRODUCTION

Theory without practice skill and application cannot be alive. Beside rising requests from products market and their dependencies on correct price, ecology load and another, the minimizing of initial costs is required. Optimization is way and know-how how to do it. Many steps beyond the men abilities the computer technology using is. Computer can to do many operations classified as computing, modeling and simulating better than any human.

Modules which in consists all modern CAPP systems, can be enriched by module for optimization of next product manufacturing.

2. USED METHODS

Stochastic principles are based on random searching principles of chosen status space. Each generated solutions account with fitness function is. If this solution is better as previous then is saved as the best, and the search being again. Search is work until beyond chosen iterations are done. This method is able escape from local extreme. For successfully optimization doing of bigger number of iterations is needed. Most often it is used for initial group initialization, which is processed by another methods.

Hill Climbing is the simplest method of these kinds. Each iteration consists in choosing randomly a solution in the neighbor hood of the current solution and retains this new solution only if it improves the fitness function. Stochastic Hill Climbing converges towards the optimal solution if the fitness function of the problem is continuous and has only one peak (unimodal function).

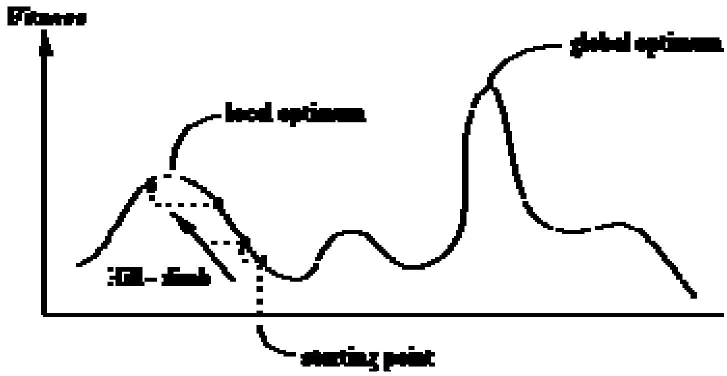

Fig. 1. Work of hill climbing algorithm

On functions with many peaks (multimodal functions), the algorithm is likely to stop on the first peak it finds even if it is not the highest one. Once a peak is reached, hill climbing cannot progress anymore, and that is problematic when this point is a local optimum. Stochastic hill climbing usually starts from a random select point. A simple idea to avoid getting stuck on the first local optimal consists in repeating several hill climbs each time starting from a different randomly chosen points. This method is sometimes known as iterated hill climbing. By discovering different local optimal points, it gives more chance to reach the global optimum. It works well if there are not too many local optima in the search space. But if the fitness function is very 'noisy' with many small peaks, stochastic hill climbing is definitely not a good method to use. Nevertheless such methods have the great advantage to be really easy to implement and to give fairly good solutions very quickly.

Tabu search is better as hill climbing algorithm abolish raised circular changes in browse nearest closed environment point of status place. A starting point for tabu search is to note that such a move may be described by a set of one or more attributes (or elements), and these attributes (properly chosen) can become the foundation for creating an attribute based memory. For example, in a zero-one integer-programming context these attributes may be the set of all possible value assignments (or changes in such assignments) for the binary variables. Then two attributes e and %, which denote that a certain binary variable is set to 1 or 0, may be called complementary to each other. Considering the number of attributes representing a move we may distinguish single-attribute moves (where every move is described by exactly one attribute) and multi-attribute moves (where every move may be described by more than one attribute). Following a steepest descent / mildest ascent approach, a move may either result in a best possible improvement or a least possible deterioration of the objective function value. Without additional control, however, such a process can cause a locally optimal solution to be re-visited immediately after moving to a neighbor, or in a future stage of the search process, respectively. To prevent the search from endlessly cycling between the same solutions, the attribute-based memory of tabu search is structured at its first level to provide a short-term memory function, which may be visualized to operate as follows. Imagine that the attributes of all explored moves are stored in a list, named a running list, representing the trajectory of solutions encountered. Then, related to a sub list of the running list a so-called tabu list may be introduced. Based on certain restrictions the tabu list implicitly keeps track of moves (or more precisely, salient features of these moves) by recording attributes complementary to those of the running list. These attributes will be forbidden from being embodied in moves selected in at least one subsequent iteration because their inclusion might lead back to a previously visited solution. Thus, the tabu list restricts the search to a subset of admissible moves (consisting of admissible attributes or combinations of attributes). The goal is to permit "good" moves in each iteration without re-visiting solutions already encountered.

Simulated annealing is a Monte Carlo approach for minimizing such multivariate functions. The term simulated annealing derives from the roughly analogous physical process of heating and then slowly cooling a substance to obtain a strong crystalline structure. In simulation, a minimum of the cost function corresponds to this ground state of the substance. The simulated annealing process lowers the temperature by slow stages until the system ``freezes" and no further changes occur. At each temperature the simulation must proceed long enough for the system to reach a steady state or equilibrium. This is known as thermalization. The time required for thermalization is the decorrelation time; correlated microstates are eliminated. The sequence of temperatures and the number of iterations applied to thermalize the system at each temperature comprise an annealing schedule. To apply simulated annealing, the system is initialized with a particular configuration. A new configuration is constructed by imposing a random displacement. If the energy of this new state is lower than that of the previous one, the change is accepted unconditionally and the system is updated. If the energy is greater, the new configuration is accepted probabilistically. This is the Metropolis step, the fundamental procedure of simulated annealing. This procedure allows the system to move consistently towards lower energy states, yet still `jump' out of local minima due to the probabilistic acceptance of some upward moves. If the temperature is decreased logarithmically, simulated annealing guarantees an optimal solution.

Genetic algorithms are general-purpose search algorithms based upon the principles of evolution observed in nature. Genetic algorithms combine selection, crossover, and mutation

operators with the goal of finding the best solution to a problem. Genetic algorithms search for this optimal solution until a specified termination criterion is met. The solution to a problem is called a chromosome. A chromosome is made up of a collection of genes, which are simply the parameters to be optimized. A genetic algorithm creates an initial population (a collection of chromosomes), evaluates this population, and then evolves the population through multiple generations (using the genetic operators discussed above) in the search for a good solution for the problem at hand.
We not deal about all methods for optimization. In last time are created new methods derived from genetic algorithm (Differential Evolution, Self Organization Migrating Algorithm) differed by some improvements which increase search capacity.

3. RESUME

Optimization methods have good chances for surviving in world of precise making technology. Aspects as ecology, costs, humanization, are conditions, which cannot be overlooked in any future time. Joining of this methods, contributed as theory research and experiment examines, should be covered into CAPP extension modules and allow us to make better solutions in width adequate to technology progress.

6. REFERENCES

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