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Engineering Analytics for selection of the Best Solution

Abstract

Selection of the best possible option when many alternatives are available is vital in decision-making process. In addition, the selection process becomes more complicated when the definition of 'Best' option changes with conditions and time – the problem becomes the optimization problem. With Engineering Analytics, CAPGEMINI PES (Product & Engineering Solutions) has developed unique expertise to solve such problems in optimization in diverse fields using various advanced techniques. Several client case studies can be solved using framework for the world leading client for operations planning, scheduling, and maintenance. The framework provide ready to use evolutionary search algorithms such as Simulated Annealing and Genetic Algorithm. The optimization framework using these evolutionary algorithms proposed by CAPGEMINI is expected to provide high degree of advantages in turnaround time for problems in optimization.

The framework encompasses end-to-end definition of the problem domain, modeling the problem in selected algorithm, defining the constraints for optimization, and customizing the objective function for optimal solution. This expertise is transformed to a generalized optimization platform that contribute to generating the solutions for diversified problems in optimization in much shorter periods. Such a framework essentially eliminate the need of complex mathematical formulations and derivative operations. To name few, application areas might be scheduling dependent and prioritized tasks, scheduling sequential and parallel operations, preparing optimal plans, etc.

1. Introduction

Optimization is a methodology to take the best decision when multiple options are available. Mathematically it is finding the best solution of constrained optimization problem, which (may) also have various local optima (maxima/minima). Therefore, optimization is a general problem and theoretically every problem can be modeled as an optimization problem. It spans almost all the domains like Machine Learning, Artificial Intelligence, Engineering designs, Planning and scheduling, Management, etc. There are numerous examples to list – selecting the right option from multiple availabilities, decision making based on given set of inputs, system design for maximum efficiency, planning set of operations for maximum revenue, and so on.

Solving such optimization problems essentially involved modeling the constraints as set of mathematical equations, goal of optimization as an objective function, and then devising the methodology to explore the complete search space for locating the optimal solution. IN turn, inherently it is iterative process and calls for solving the complicated derivative equations. The problem complexity becomes manifold in case of large number of variables and optimization constraints, non-linear constraints, highly complex hilly search space, and multiple contrary objectives to satisfy. In such cases, typical mathematical algorithms requires large time to mathematically model the problem and then solve using appropriate algorithm. Still there is a fear algorithm to get trapped in local optima or discontinuities in solution space thereby providing either no results or incorrect results.

Secondly, for most of the problems in practice, knowledge of solution space and behavior of constraints is either unknown or incomplete. In such cases, deterministic classical solutions like Mathematical Programming, Network Analysis, Branch & Bound, etc. are not suitable and one need to explore stochastic algorithms like Tabu search, Simulated Annealing, Genetic Algorithm, etc.

This paper explains the framework proposed supporting Simulated Annealing and Genetic Algorithms for solving the problems in optimization.

2. Solving Optimization Problem

Evolutionary algorithm is an umbrella term used to describe computer-based problem solving systems which use computational models of evolutionary processes as key elements in their design and implementation. These approaches cover the algorithms where solution evolves gradually towards better or desired characteristics. Genetic algorithms (GA) and simulated annealing (SA) represents such iterative processes whereby solution moves towards the desired goal gradually.

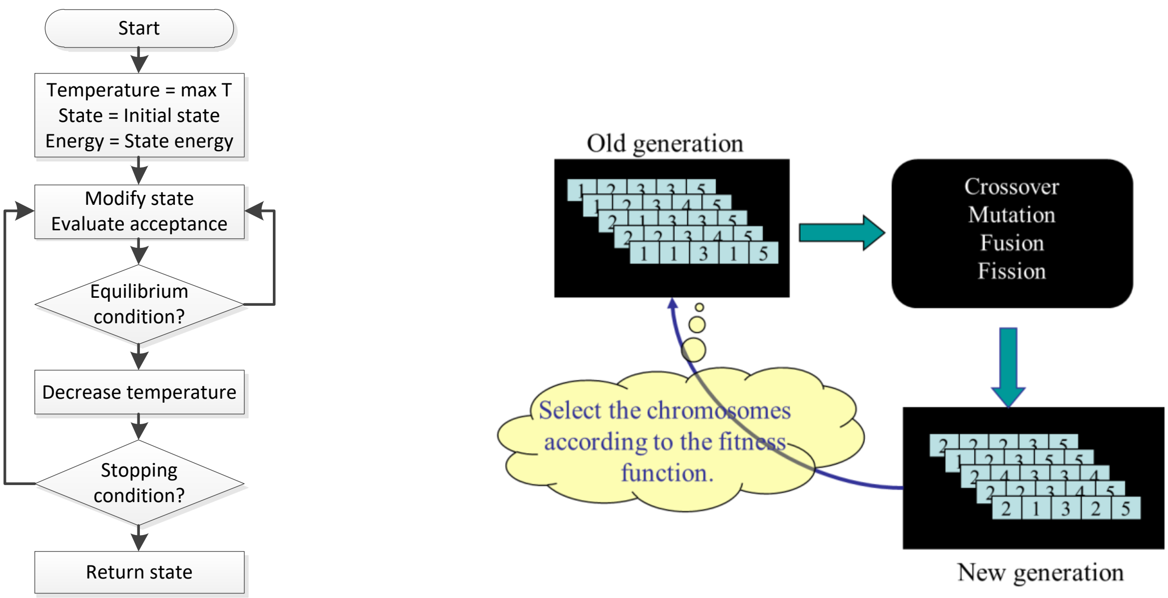
Annealing is a process of controlled cooling of an object so that eventually all the atoms occupy perfect sites in crystal lattice having the minimum energy, thereby removing the objectionable defects. Mathematically it is well described by Boltzmann statistics. Simulated annealing models this process of controlled cooling. It is a generic probabilistic approach for the global optimization problem, namely locating a good approximation to the global optimum of a given function in a large search space. The process talks about states, their energies, neighbors, and moves. A new solution is created by modifying only one solution with a local move and thus it is a Sequential algorithm. Whenever a move is made, an acceptance decision must be made before another move may be evaluated.

Biological evolution is the process describing how organisms evolve over time to adapt to the environment for better survival. Organisms produce off springs through biological reproduction (crossover). Typically, these offspring's have similar characteristics by virtue of inheritance; however, some may have some random variations due to the biological process of mutations. Some offspring survive and produce next generations while some do not. Those organisms that are better adapted to the environment have higher chance of survival. Therefore, over time, these generations become more and more adapted to the environment because the fittest of the organisms survive. This is the well-known principle of 'Survival of the fittest'. Based on this mechanism of biological evolution, John Holland from University of Michigan (1970's) developed a set of algorithms mimicking the evolution process. These algorithms are called Genetic Algorithms (GA). Genetic algorithms are the search procedures that operate on a population of solutions, which mimics natural selection to find increasingly better solutions.

As an evolutionary technique, simulated annealing and genetic algorithms both are quite well known global optimization techniques and being applied for wide range of problems. However, the performance of the either technique is solely problem dependent and is decided by the way problem is posed to the technique.

2.1 Algorithm Architecture

As discussed, these evolutionary search processes are iterative algorithm. The architecture of these algorithms is shown in Figure 1.



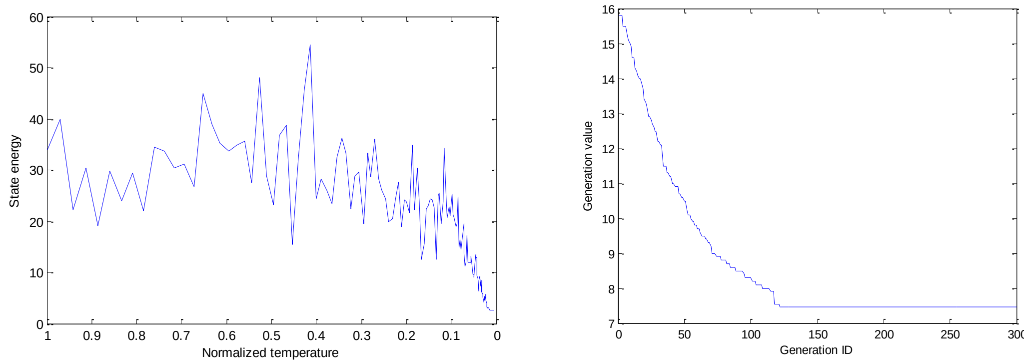
(a) Simulated Annealing (b) Genetic Algorithm

Figure 1: Algorithm architecture

Solving optimization problem with SA or GA follows the similar steps listed below –

1. Modeling the problem in selected algorithm domain
    a. Simulated Annealing (SA) – Define state and state energy, define operators to modify the state
    b. Genetic Algorithm (GA) – Define chromosome, define operators to modify chromosome like cross over, mutation, fusion, and fission
2. Modeling optimization goal as objective function
    a. State energy in SA can itself be an objective function. In some cases, it can be more complex mathematical function of the state energy
    b. In case of GA, fitness function is the objective function
3. Defining constraints for optimization
    a. These defines boundaries of the search space. Can be modeled as linear or non-linear mathematical equations, or inequalities.
4. Specify and tune the algorithm parameters for optimal solution
    a. Simulated Annealing (SA) – Definitions of cooling profile, state equilibrium condition, and stop criteria
    b. Genetic Algorithm (GA) – Definitions of population size, probabilities of chromosome modification operations, stop criteria

As an example of minimization, as search progresses the state energy (in case of SA) or fitness value (in case of GA) decreases towards the minimum possible. Typical convergence characteristics for these two search engines are depicted in Figure 2.



(a) (b)

Figure 2: Convergence characteristics for (a) SA and (b) GA algorithm

For stopping criteria, there are multiple options to stop the search process. For example, we can stop the search after fixed number of iterations or there is no change in the solution for last few iterations.

2.2 Optimization Framework

The framework provide customizable components for modeling the problem to be solved in optimization using evolutionary approach, as depicted in Figure 3.

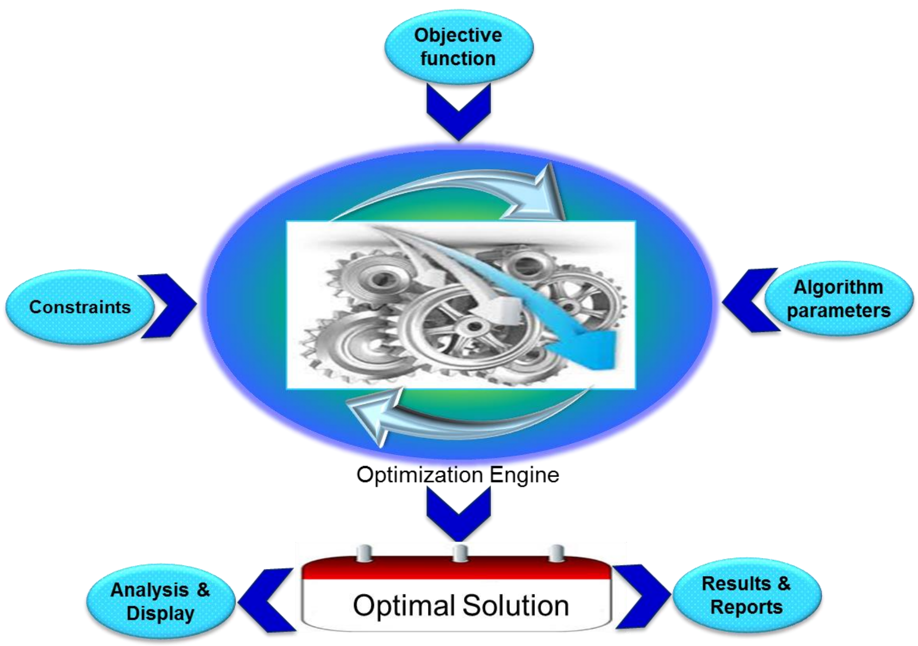


Figure 3: Proposed optimization framework architecture

Optimization engine can be configured for either of the algorithms, SA or GA. Optimization framework provide a way to define the corresponding algorithms components (state, state energy, chromosomes, and fitness functions), constraints, and objective functions. Framework also support results and reports, graphical display and performance analysis functionalities helping to tune the algorithm parameters for generating optimal solution for given problem. All these components of optimization engine are shown in Figure 4.

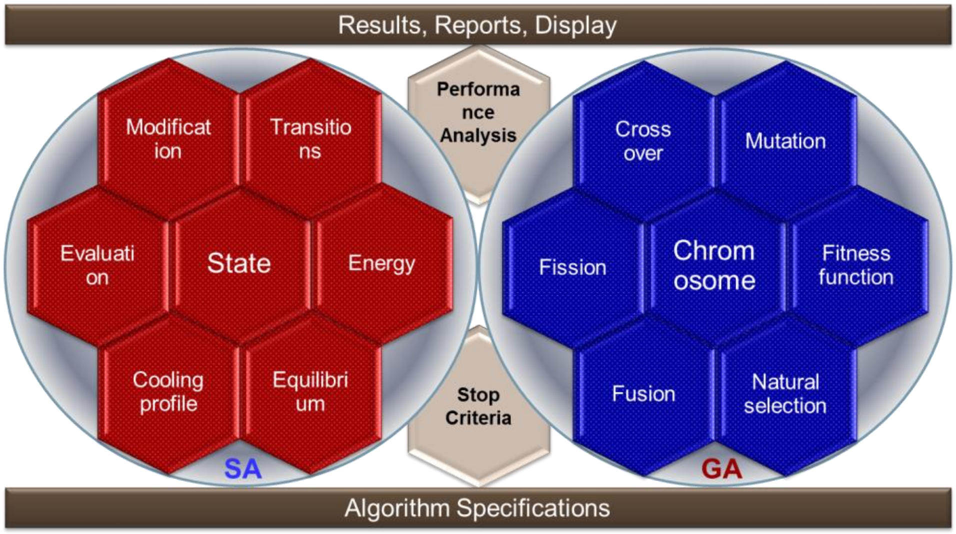


Figure 4: Optimization engine components

2.3 Key Features

CAPGEMINI's Engineering Analytics optimization framework come with the following features –

1. Open Architecture
2. Support for global optimization algorithms – Simulated Annealing and Genetic Algorithm
3. User configurable algorithm designs
4. Can be modeled most of the optimization problems – combinatorial optimization and continuous optimization
5. Scalable architecture – large size optimization problems and multi-objective optimization can be modeled

2.4 Key Benefits

Optimization results are characterized in terms of guarantee of optimal/near optimal solution, ruggedness of the algorithm, potential to handle contrary non-linear constraints, and rate of convergence. Available literature survey highlights the potential of selected evolutionary algorithms to perform best reference to the specified characteristics, decided by the problem design modeled in algorithm. For example, a sufficient low cooling profile always ensures the optimal/near optimal solution irrespective of the search space complexity. All such features directly enhance the business potentials of proposed framework supporting state of the art optimization algorithms.

Ideally, any problem can be posed as an optimization problem. Therefore, there are ample examples in different domains where the framework provide the benefits. Some of the examples are –

1. Analytics - System identification, Digital filter design, Pattern identification, Data clustering, Decision automation
2. Automotive – Model optimization for model predictive controls in engine control, vehicle dynamics control, Structural optimization of automotive chassis

3. Communication network – Network design optimization, Coloring the optical network in WDM communication, Traffic routing , Carrier allocations in cellular network
4. Dispatching fleet of vehicles in supply-chain management – Logistics optimization, fleet optimization, inventory optimization
5. Design and process optimization

The framework can be extended to all the business verticals handling such optimization problems. It is expected to provide business benefits in terms of –

a. Reduced efforts in building the optimization solution
b. Fast turn-around time for client requirements
c. Increased customer confidence and satisfaction by providing more insights into problem and solution via –
    i. Quick experimentations for exploring unknown search space
    ii. Relaxation from complex mathematics

3. Summary

This paper discusses CAPGEMINI's Engineering Analytics Optimization Framework, which theoretically has proven potential to meet industry requirements for solving global optimization problems. CAPGEMINI brings unique benefit to its customer by combination of user configurable evolutionary algorithms with software architecture and this transformed to such generalized framework for solving global optimization problems. The solution discussed in this paper provide flexible optimization platform for quick experimentation which is an essential step towards solution of optimization problems. CAPGEMINI proposition described in this paper brings major benefit to its customer with reduction in turn-around time for solving the practical problems in optimization.

4. How CAPGEMINI Optimization framework bring value to CAPGEMINI business/vertical

CAPGEMINI Optimization Framework provide the new business opportunity for solving optimization problems in all major verticals e.g. Networking and communication, Heavy Equipment & Machinery, Automotive, Consumer Appliances, Energy, Chemical Process Engineering, Logistics optimization and Controls, etc. This initiative will add value especially in data analytics e.g. process modeling and control, asset management, scheduling and maintenance problems, energy utilization, supply chain management and optimization, to name few.

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Doctorate in Photonics and Sensors with 27 years of research experience in multiple domains. With a strong background in physics, mathematics and statistics, has expertise in customized algorithm developments, modeling and simulation, data/video/speech analytics & cognitive science, image & signal processing, controls and optimization, and Machine learning/artificial intelligence.

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Over 32 years of multi-sector industrial experience delivering innovative solutioning and industrialization of cutting edge technologies spanning IoT, M2M, engineering analytics, process and machine automations, sensing and controls, Product and system engineering. Responsible for the growth and support of Engineering Analytics Practice. Managed Innovation Centre and Analytics Centre of Excellence.