Simulated Annealing (SA) is an effective and general form of optimization. It is useful in finding global optima in the presence of large numbers of local optima. “Annealing” refers to an analogy with thermodynamics, specifically with the way that metals cool and anneal. Simulated annealing uses the objective function of an optimization problem instead of the energy of a material.

Algorithm:

- Let $S = S0$
- *For $k = 0$ through k_{max} (exclusive):*
    1. $T \leftarrow temperature(k/k_{max})$
    2. *Pick a random neighbour,* $s_{new} \leftarrow neighbour(s)$
    3. *If* $P(E(s), E(s_{new}), T) \geq random(0, 1)$:

       $s \leftarrow s_{new}$
- *Output: the final state s*

Constraint satisfaction problems (CSPs): *A constraint satisfaction problem (CSP) requires a value, selected from a given finite domain, to be assigned to each variable in the problem, so that all constraints relating the variables are satisfied. Many combinatorial problems in operational research, such as scheduling and timetabling, can be formulated as CSPs. Researchers in artificial intelligence (AI) usually adopt a constraint satisfaction approach as their preferred method when tackling such problems. However, constraint satisfaction approaches are not widely known amongst operational researchers. The aim of this paper is to introduce constraint satisfaction to the operational researcher. We start by defining CSPs, and describing the basic techniques for solving them. We then show how various combinatorial optimization problems are solved using a constraint satisfaction approach. Based on computational experience in the literature, constraint satisfaction approaches are compared with well-known operational research (OR) techniques such as integer programming, branch and bound, and simulated annealing.*