

The Basic GLSM Model

Many high-performance SLS methods are based on combinations of *simple (pure) search strategies* (e.g., ILS, MA).

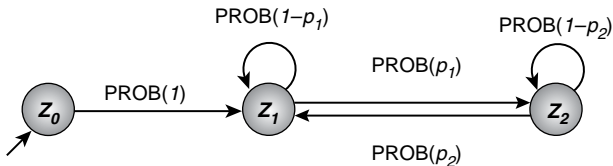
These hybrid SLS methods operate on two levels:

- ▶ **lower level:** execution of underlying simple search strategies
- ▶ **higher level:** activation of and transition between lower-level search strategies.

Key idea underlying Generalised Local Search Machines:

Explicitly represent higher-level search control mechanism in the form of a *finite state machine*.

Example: Simple 3-state GLSM



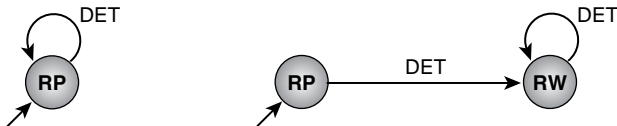
- ▶ States z_0, z_1, z_2 represent simple search strategies, such as Random Picking (for initialisation), Iterative Best Improvement and Uninformed Random Walk.
- ▶ $\text{PROB}(p)$ refers to a probabilistic state transition with probability p after each search step.

Generalised Local Search Machines (GLSMs)

- ▶ States \cong simple search strategies.
- ▶ State transitions \cong search control.
- ▶ GLSM \mathcal{M} starts in initial state.
- ▶ In each iteration:
 - ▶ \mathcal{M} executes one search step associated with its current state z ;
 - ▶ \mathcal{M} selects a new state (which may be the same as z) in a nondeterministic manner.
- ▶ \mathcal{M} terminates when a given termination criterion is satisfied.

Modelling SLS Methods Using GLSMs

Uninformed Picking and Uninformed Random Walk



procedure *step-RP*(π, s)

input: *problem instance* $\pi \in \Pi$,
candidate solution $s \in S(\pi)$

output: *candidate solution* $s \in S(\pi)$

$s' := \text{selectRandom}(S)$;

return s'

end *step-RP*

procedure *step-RW*(π, s)

input: *problem instance* $\pi \in \Pi$,
candidate solution $s \in S(\pi)$

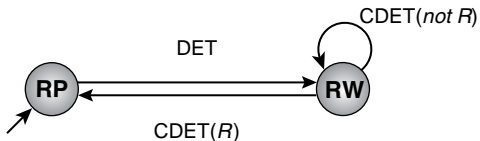
output: *candidate solution* $s \in S(\pi)$

$s' := \text{selectRandom}(N(s))$;

return s'

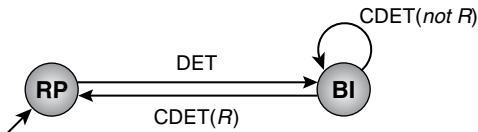
end *step-RW*

Uninformed Random Walk with Random Restart



R = restart predicate, e.g., $\text{countm}(k)$

Iterative Best Improvement with Random Restart



procedure *step-BI*(π, s)

input: *problem instance* $\pi \in \Pi$, *candidate solution* $s \in S(\pi)$

output: *candidate solution* $s \in S(\pi)$

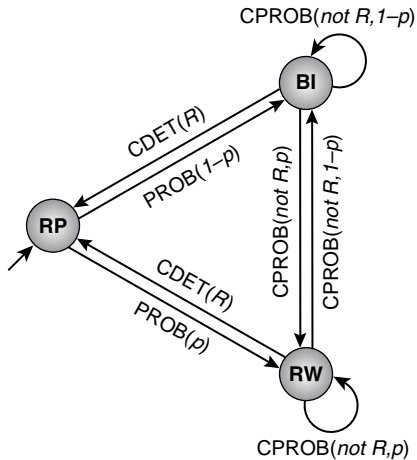
$g^* := \min\{g(s') \mid s' \in N(s)\};$

$s' := \text{selectRandom}(\{s' \in N(s) \mid g(s') = g^*\});$

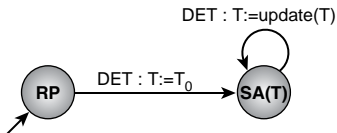
return s'

end *step-BI*

Randomised Iterative Best Improvement with Random Restart

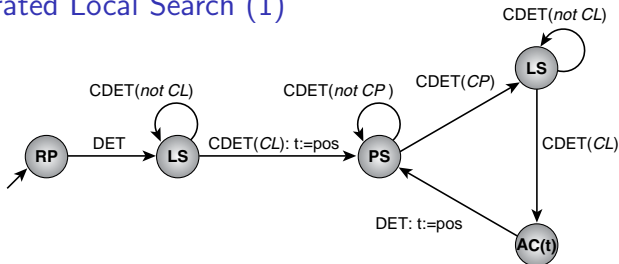


Simulated Annealing



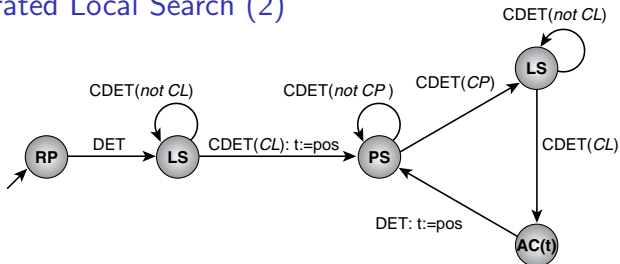
- ▶ Note the use of transition actions and memory for temperature T .
- ▶ The parametric state $SA(T)$ implements probabilistic improvement steps for given temperature T .
- ▶ The initial temperature T_0 and function *update* implement the annealing schedule.

Iterated Local Search (1)



- ▶ The acceptance criterion is modelled as a state type, since it affects the search position.
- ▶ Note the use of transition actions for memorising the current candidate solution (*pos*) at the end of each local search phase.
- ▶ Condition predicates *CP* and *CL* determine the end of perturbation and local search phases, respectively; in many ILS algorithms, $CL := lmin$.

Iterated Local Search (2)



```
procedure step-AC( $\pi, s, t$ )  
  input: problem instance  $\pi \in \Pi$ ,  
          candidate solution  $s \in S(\pi)$   
  output: candidate solution  $s \in S(\pi)$   
  if  $C(\pi, s, t)$  then  
    return  $s$   
  else  
    return  $t$   
  end  
end step-AC
```

Ant Colony Optimisation (1)

- ▶ General approach for modelling population-based SLS methods, such as ACO, as GLSMs:

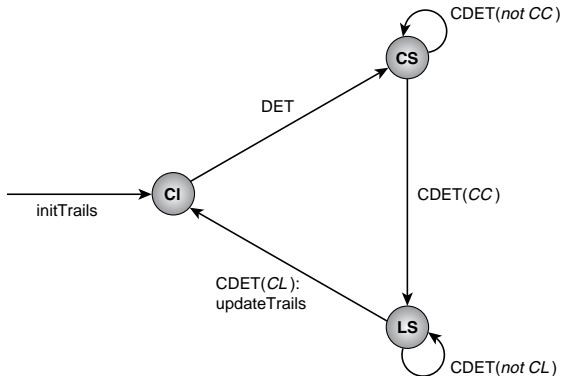
Define search positions as *sets of candidate solutions*; search steps manipulate some or all elements of these sets.

Example: In this view, Iterative Improvement (II) applied to a population sp in each step performs one II step on each candidate solution from sp that is not already a local minimum.

(Alternative approaches exist.)

- ▶ Pheromone levels are represented by memory states and are initialised and updated by means of transition actions.

Ant Colony Optimisation (2)



- ▶ The condition predicate CC determines the end of the construction phase.
- ▶ The condition predicate CL determines the end of the local search phase; in many ACO algorithms, $CL := lmin$.