Measures of Fault Tolerance in Distributed Simulated Annealing

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Outline

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Probabilistic and Meta-heuristic Algorithm.

Similar to Annealing in Metallurgy

- $P(E) = e^{\frac{-E}{kT}}$. where, $P(E)$ is Energy Function, T is Temperature, k is Boltzmann constant
- Energy Function has high value at Higher Temperature.
- Uses Metropolis-Hastings algorithm to generate its sample space.

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Algorithm

- Start with the system in a known configuration, at known energy E.
- while T is High {
- Perturb system slightly (goto new location on search space)
- Compute E, change in energy due to perturbation
- if($\Delta E < 0$) then accept this perturbation, this is the new system
- else accept this system with probability equal to Energy Function $P(E)$
- }
- stop when equilibrium is reached or T is low

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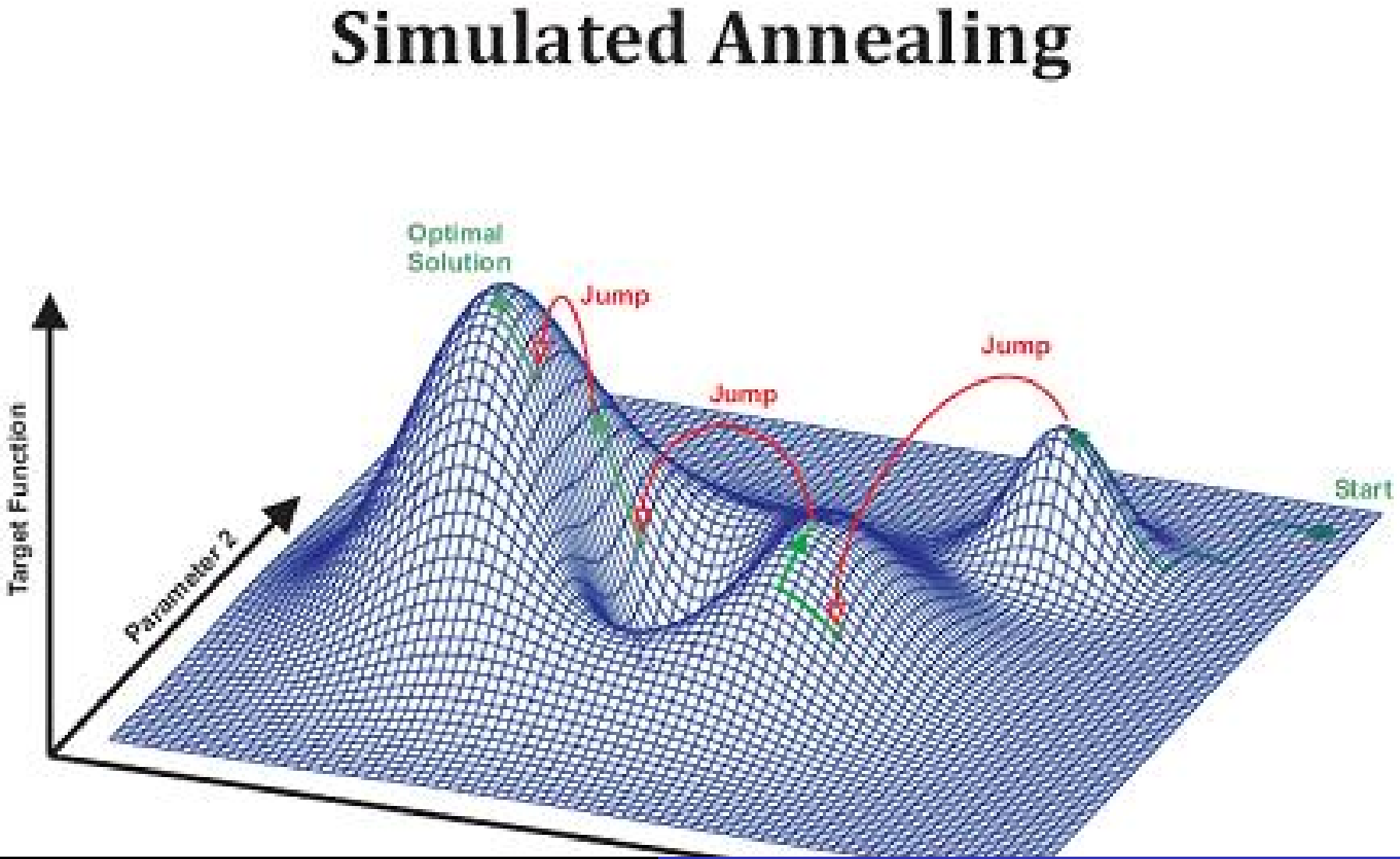
Search Space
Problem of local optima



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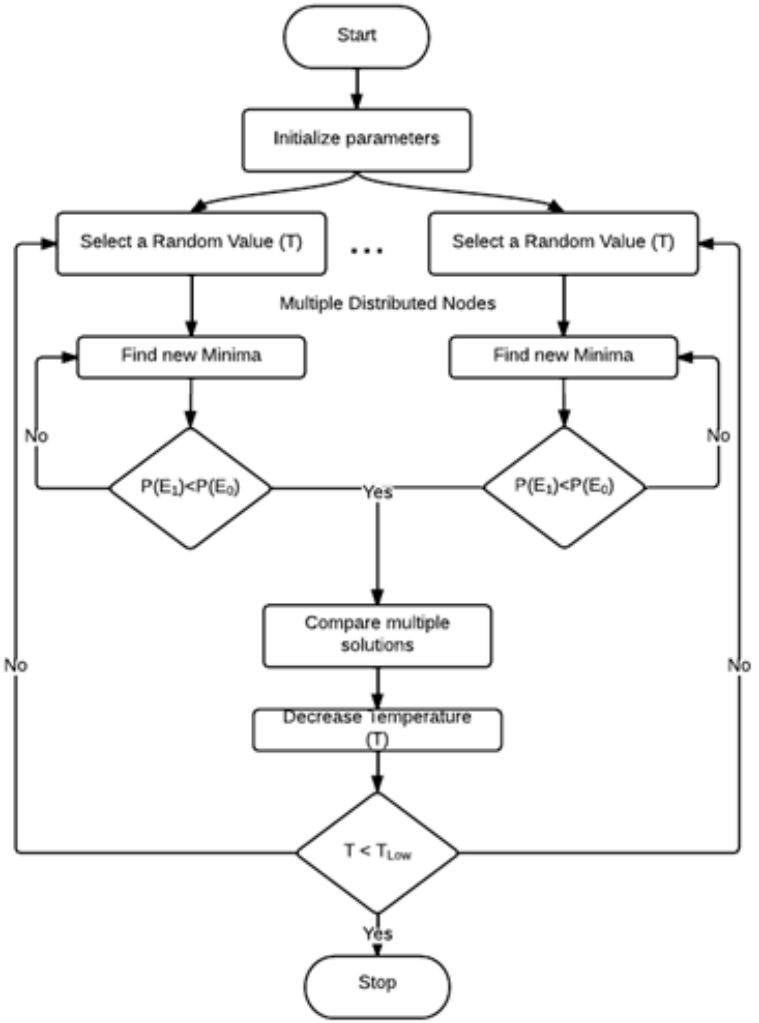
Distributed Simulated Annealing (DSA)

- MapReduce
  - (Radesnki 2012)
- CUDA
  - (Zbierski 2011)
- OpenCL
  - (Choong 2010)

DSA Algorithm

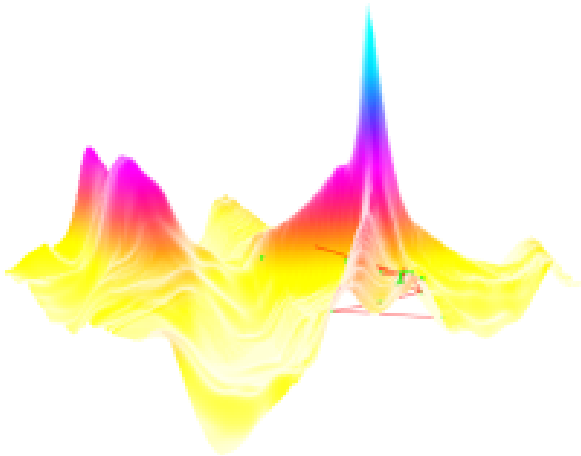
- Master/Host - Compare
- Cluster/Device - Search Solution



Outline

Sources of Design Faults

- Design Faults
  - Difficult Search Space
  - No memory of best solution (unlike Tabu search)
  - Pseudo Random Number Generator



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Sources of Operational Faults

Type of failure	Description
Crash failure	A server halts, but is working correctly until it halts
Omission failure *Receive omission* *Send omission*	A server fails to respond to incoming requests A server fails to receive incoming messages A server fails to send messages
Timing failure	A server's response lies outside the specified time interval
Response failure *Value failure* *State transition failure*	The server's response is incorrect The value of the response is wrong The server deviates from the correct flow of control
Arbitrary failure (Byzantine failure)	A server may produce arbitrary responses at arbitrary times

Source: Lecture Notes- Prof. Jalal Y. Kawash at Univ. of Calgary

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Independent Failure
-Loss of Node and Loss of Data
-solved by design of MapReduce

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Communication Faults

- Unreliable Communication
  - Incorrect result
- Insecure Communication
  - Incorrect result
- Costly Communication
  - Poor Performance
  - If the overhead of communication of nodes exceed the ratio of fraction of work to total Speedup then benefits of distribution of optimization is highly compromised
    - Amdahl's Law $\frac{1}{(1-P)+\frac{P}{S}}$

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Tolerance

- Adaptive vs Strategic
  - Flexible Adaptive Tolerant System
    - Can handle unprecedented failures
  - Strategic Fault Tolerance
    - Predictive handling
    - (Marin et al 2001 - Flexible)
  - Pooling of Search Space - Futile
    - Stochastic Search
  - Hashing of Intermediate results
    - No guarantee of having searched but quick ($O(n)$) verification
    - MapReduce - fast at hashing
    - Ganjisaffar et al, Tunning of MapReduce for DSA, achieved AUC $> 90\%$

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Recovery

- Cluster Replacement
  - Cold/Warm Standby - No use
    - Cannot perform backward error recovery
    - If temperature is still High, next search sequence is as good as any other
  - **Hybrid Replication Mechanism**
    - If Temperature is High - No result replication or broadcast
    - -Saves lot of time and space
    - If Temperature is Low ($T < T_{Low}$), convert some searching Node to reciprocating Nodes
    - Ensures when solution is found and if Node is dead, we will have a copy of the solution
    - -Reasoning: Higher Probability of finding optimal solution at lower T. Remember $P(E)$.
- Anomaly Node Detection
  - Several Machine Learning algorithms to detect anomalous

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