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A SURVEY OF RECENT ADVANCES IN TRANSMISSION NETWORK SWITCHING

Los Alamos NATIONAL LABORATORY

Decision Applications Division

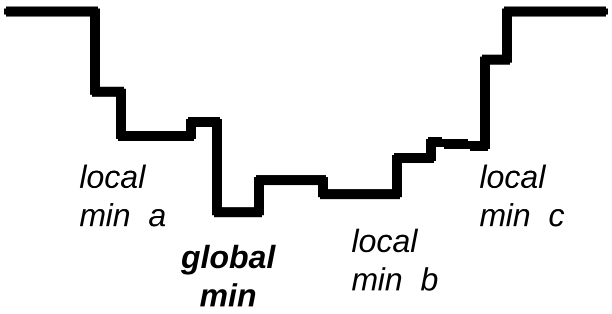
Transmission Switching

Slide 2

- Modify network configuration using a switching heuristic to improve a desired network metric
- Drive optimization using line power loss, economic loss, outage frequency, etc. objective functions
- Maintain network health using equality/inequality constraints and tolerances
- Avoid local minima in the search space using stochastic methods and smart tempering in the search heuristic

photo courtesy of Siemens AG

Objective Function[4]



Transmission Switching

- Exhaustive Search
  - Binary Integer Programming

bool	bool	bool	bool	bool	bool	bool	bool

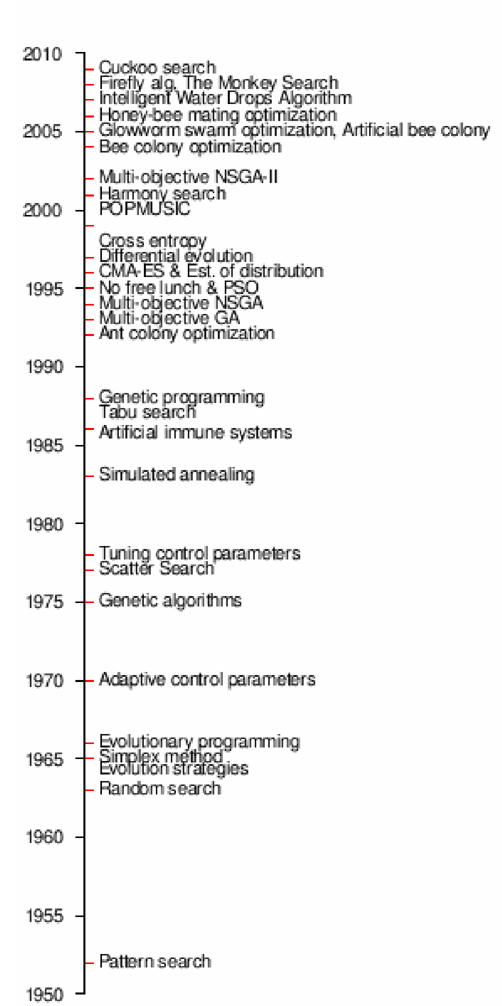
    - Binary valued switch variables
    - Simple modeling
    - Configuration restricted to the binary decision vector
    - Examples: genes in GA, switch vectors
    - Many MIP problems can be converted into BIP
  - Mixed Integer Programming

bool	int	float	bool	int	bool	bool	int

    - Real-valued or integer valued variables
    - More common in modern transmission switching
    - Can be used to solve BIP problems
    - Unique uses for MIP: multiple lines per edge or shunts per node

Transmission Switching

- Meta-Heuristic
  - A combinatorial heuristic optimization that reduces search based significantly compares to exhaustive search techniques
  - Most optimization strategies in the literature use some sort of meta-heuristic to drive optimization
  - A compromise between problem dimensionality and solution speed
  - Many of the heuristic procedures covered in this presentation date back at least 15 years, and as early as 1975 (genetic algorithm)
- Hyper-Heuristic
  - As problem complexity becomes less predictable hyper-heuristic procedures may allow us to optimize the algorithm to the model
  - As of this date very little research has applied hyper-heuristics to TS, most likely due to a much more increased overhead of computational resources
  - At this point hyper-heuristic is a purely speculative procedure for automatic transmission switching but may be worth investigation in future research



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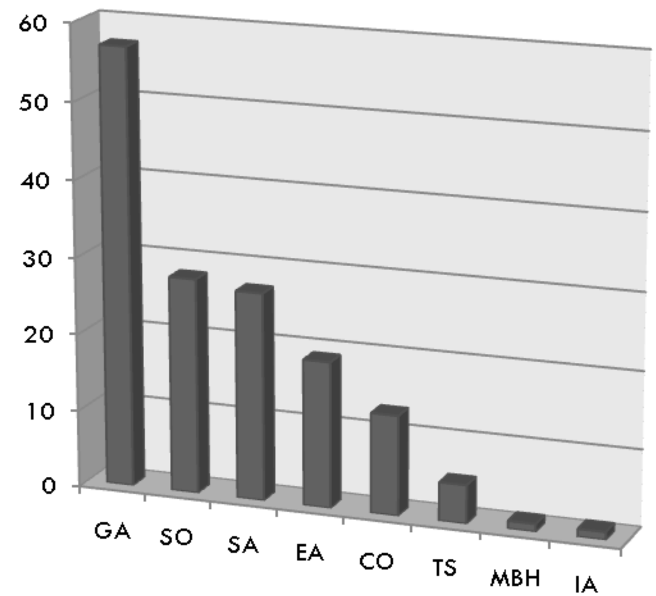
Approaches in Literature

- Genetic Algorithm (57*)
- Swarm Optimization (28)
- Simulated Annealing (27)
- Evolutionary Algorithm (19)
- Colony Optimization (13)
- Tabu Search (5)
- Memory Based Heuristic (1)
- Immune Algorithm (1)



** - # of results on IEEEXplore; searched for <method name> & "network loss reduction" & "power, energy, & industry applications"*

Network Fitness Criteria

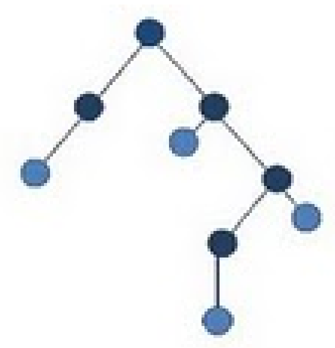
- Objective Functions
  - **Loss Reduction**
  - **Operation Expenditure**
  - **Load Balancing**
  - **Violation Penalties**
  - **Service Restoration**
  - **Network Overloads**
  - **Voltage Profile**
  - **Frequency Droop**
  - **Reliability**
- Constraints
  - **Line Current**
  - **Voltage**
  - **Phase Angle**
  - **Generation Limitations**
  - **Dispatch Control**
- Topology
  - **Avoid islanding (in most scenarios)**
  - **Maintain connection of all generation and load**

Radial vs. Meshed Network

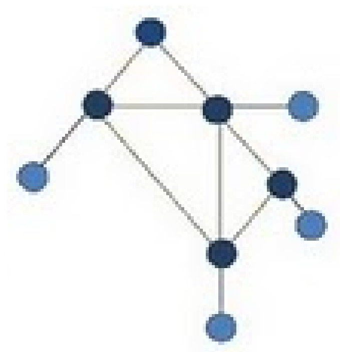
Slide 7

Radial Network

- Fast computation time
- Better convergence
- Simple power flow equations
- Radial networks are generally associated with distribution models



Radial Network



Meshed Network

Meshed Network

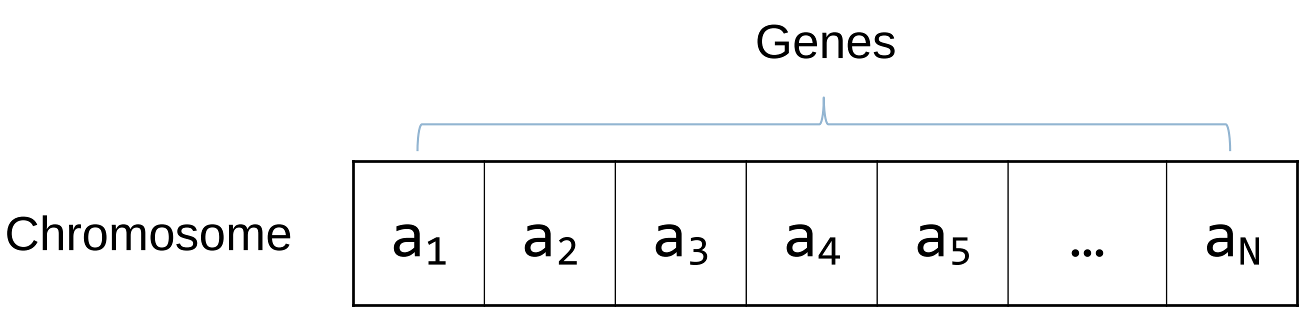
- More computationally intensive
- Possibility of lower convergence
- For compatibility with radial solvers meshed models can be converted to a radial model
  - Create loop break point (LBP) dummy buses
  - An extra calculation must be performed to readjust these dummy injections
- For our purposes we will perform OPF using conventional power flow software
- Meshed networks are more commonly seen in large transmission models

Transmission Switching Methodology

- Common Assumptions:
  - Line Loss is the primary metric for network health, but may also be complimented by other measures
  - In some instances meshed networks are reduced to purely radial networks, using loop edges as interchangeable switches, and ensuring radial topology
  - Models are balanced 3φ, use generalized 1φ model in simulation
  - DCOPF is used in order to reduce computation time
  - Optimality is not always guaranteed, most solutions are feasible and healthier than the initial model
  - Ensure all loads and generation are connected to the network on each iteration

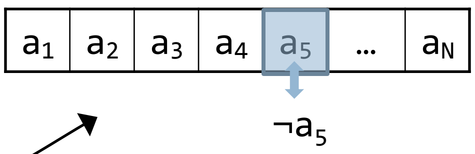
Genetic Algorithm[1]

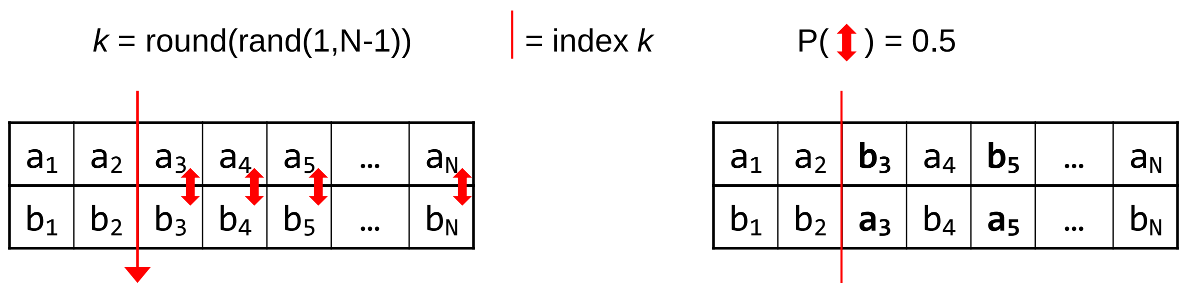
- Objective Function: loss reduction
- Candidate pool consists purely of available, initially open lines (represented by tie lines in the model)
- The genetic string "chromosome" is represented by a vector of "genes", binary values associated with the open/close position of each line in the candidate pool



Genetic Algorithm[1]

- Algorithm:
  1. Seed Population
  2. Reproduction
  3. Crossover
  4. Mutation
  5. Calculate Fitness
  6. Evaluate Convergence
     - Return to 2. if convergence criteria is not met





Genetic Algorithm[2]

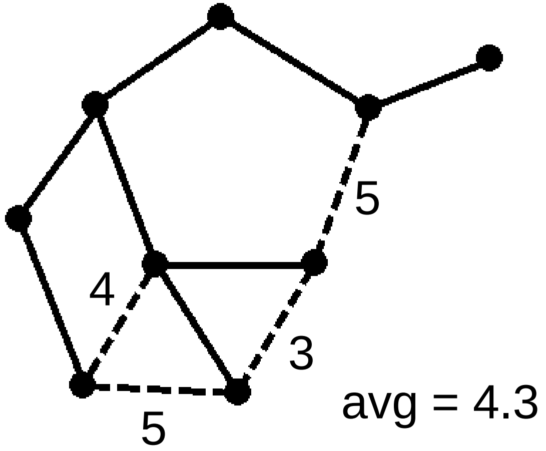
- Revisions:
  - Crossover
    - Matched pair gene swapping is random per gene, no indexing limit or restriction is placed
    - Previous crossover method favored front end gene elements

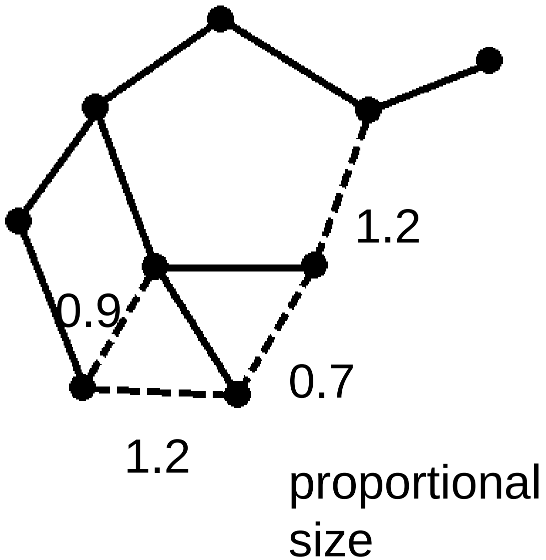
a_1	a_2	a_3	a_4	a_5	…	a_N
b_1	b_2	b_3	b_4	b_5	…	b_N

  - Mutation
    - Adaptive mutation; mutation rate decreases as minimum line loss of the population converges

Simulated Annealing[3][4]

- Objective Function: loss reduction
- Simulate the phenomenon of annealing as applied to materials, utilize entropic behavior to escape local minima
- In addition to generic SA a perturbation mechanism is introduced to guide the search using the knowledge of system topology, loop length and distance from switch determine the next switch selection

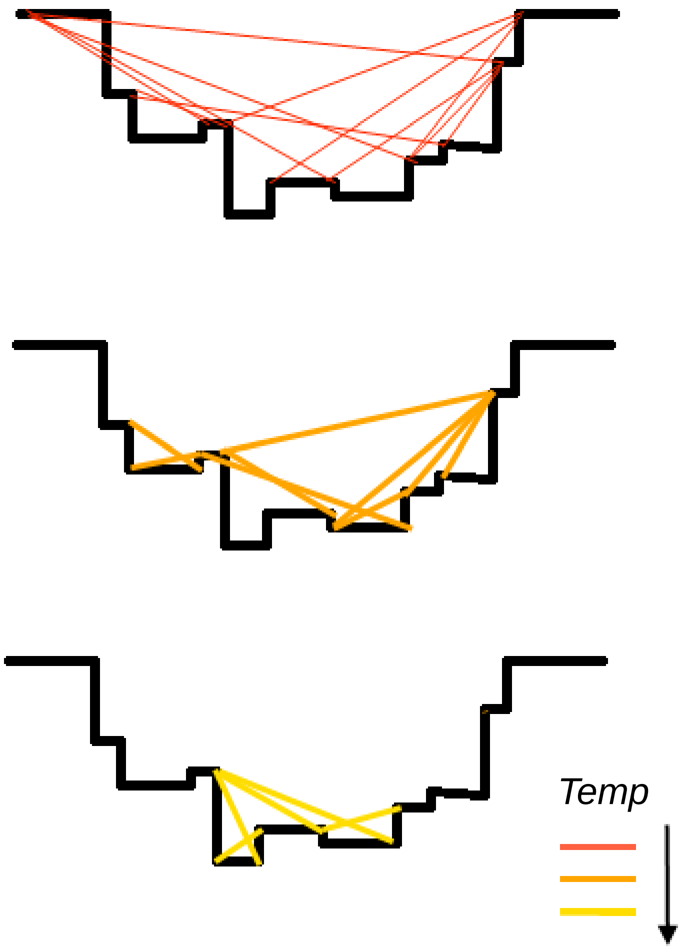




Simulated Annealing[3][4]

Slide 13

- SA Algorithm:
  1. Initialize (temp, opt. config.)
  2. Set iteration limit per temperature/iteration schedule
  3. Move
     - Decrease – Accept
     - Increase – Accept/Deny depending on Temperature
  4. Detect Convergence
     - Criteria met - END
  5. Reset iterations, decrease temp, go to 2.

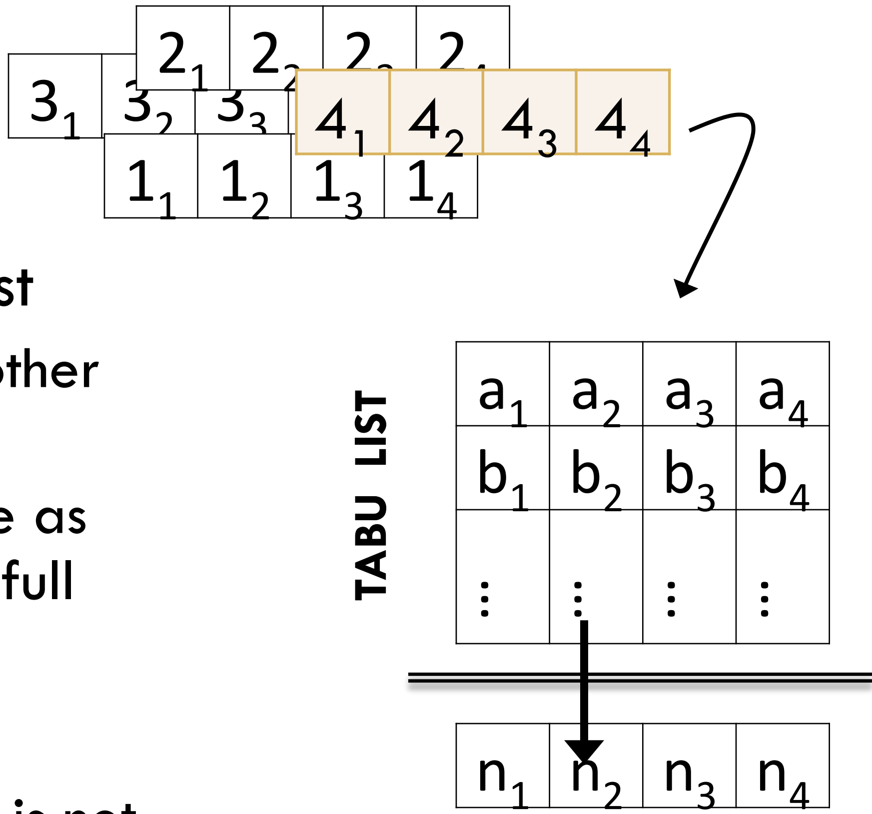


Tabu-Search[5][6]

- Objective Function: loss reduction
- Classical descent method of move, compare, update
- Tabu List provides a means of memorizing previous moves, moves that are “taboo” for new moves
- Perturbation mechanism is used to avoid local minima
  - Add/Subtract Move - random branch exchange followed by a complete sequence of branch exchange with all lines in the new loop, remove the line leading to minimum losses
  - Multiplicative Move - perform branch exchange on a random number of tie lines available for swapping
  - Constrained Multiplicative Move - limit the number of multiplicative moves

Tabu-Search[5][6]

- Algorithm:
  1. Initialize
     - Tabu List length
  2. Perform a move from the perturbation mechanism list
     - If move exists, perform a another move
     - Else add to tabu list and save as best candidate. If tabu list is full remove oldest member of list
  3. Check for convergence
     - Return to 2. if convergence is not satisfied

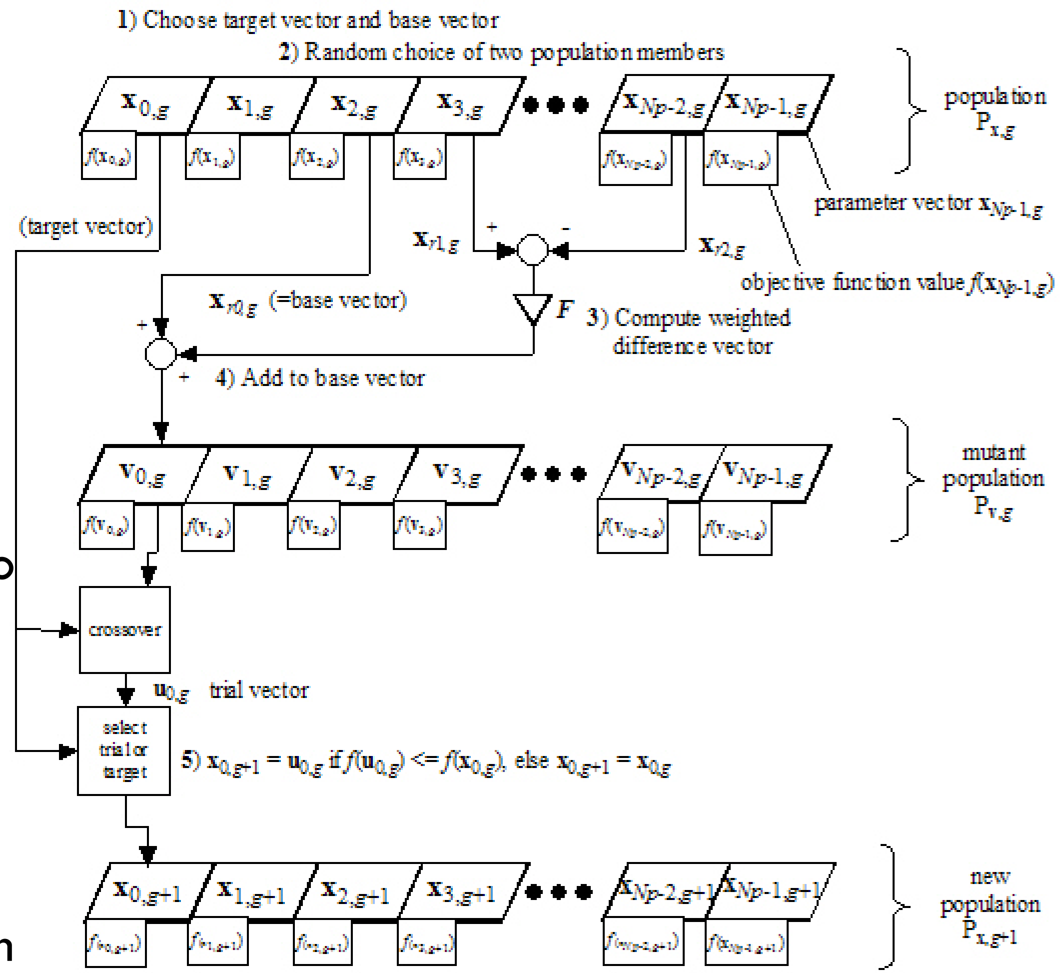


Differential Evolution[7]

- Objective Function: loss reduction/ violation penalty
- DE is a modified Evolutionary Algorithm utilizing a unique mutation method
- Differential vectors form a mutant population
- A scaling factor is used to perturb mutant individuals to an even greater degree

$$F^{t+1} = \begin{cases} c_d * F^t, \text{ if } {p^t}_s < 1/5 \\ c_i * F^t, \text{ if } {p^t}_s > 1/5 \\ F^t, \quad \text{if } {p^t}_s = 1/5 \end{cases}$$

- Scaling factor begins at F^0=1.2, and scales based on the frequency of successful mutations in a generation



Differential Evolution[7]

- Algorithm
  1. Initial Population
     - Create a population of configurations uniformly distributed on the entire parameter space
  2. Mutant Population
     - Randomly select 2-4 unique individuals, create a difference vector, multiply by scaling factor and merge it with a seed individual to create a mutant individual
  3. Population Crossover
     - Randomly pair a seed and a mutant.
  4. Choose best candidate of the generation
     - Determine the best candidate of the current generation. If the candidate is more fit than the best candidate of the parent generation, retain it. If not continue a new generation with the retained candidate.
  5. Perform migration if population diversity is not met in initial population of a new generation
     - Using the best candidate from the p a randomized mutation is performed to create a new population.
  6. Convergence check/Update scaling factor
     - Scaling factor is updated

Binary Particle Swarm Optimization

- Objective Function: maximize reliability
- Particles contain two vectors:
  - Position – binary vector containing switch information

$$\boldsymbol{x}_i(t) = \boldsymbol{x}_i(t-1) + \boldsymbol{v}(\boldsymbol{t}) \qquad x_{ij}(t) = \begin{cases} 1 \text{ if } \rho_{ij} < s(v_{ij}) \\ 0 \text{ for all else} \end{cases}$$

$$s(v_{ij}) = \frac{1}{1+\exp(-v_{ij})}$$

  - Velocity – real number vector dictating the movement of the particle

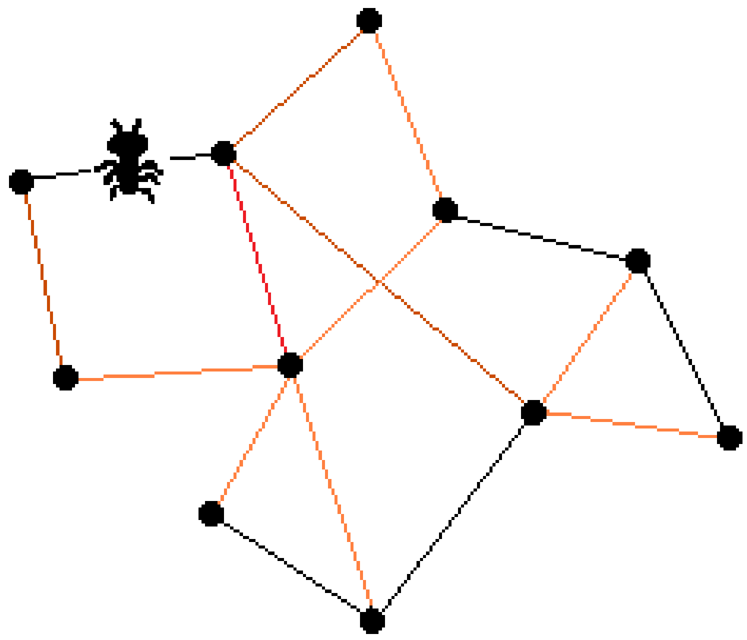
$$\boldsymbol{v}_i(t) = \boldsymbol{v}_i(t-1) + \varphi_1 \cdot r_1 \cdot \left(\boldsymbol{x}_{i,best} - \boldsymbol{x}_i(t-1)\right) + \varphi_2 \cdot r_2 \cdot (\boldsymbol{x}_{best} - \boldsymbol{x}_i(t-1))$$

Binary Particle Swarm Optimization

- Algorithm:
  1. Initialize
     - Create a population of randomly configured particles, nil velocity
     - Calculate initial reliabilities
  2. Perform feasibility check
     - Infeasible position vectors are given a heavy penalty in their fitness
  3. Update position and velocity vectors
  4. Particle with maximum reliability is saved and analyzed for convergence

Ant Colony Optimization[8]

- Objection Function: loss reduction
- Ant Colony Optimization models the hunt/gather/communicate dynamic search pattern of ants
- Distance and frequency of successful moves influence the movement of each "ant"
- Good moves increase the pheromonal value of a line



Ant Colony Optimization[8]

- Algorithm:
  - Initiate
    - Individuals start out on a random loop element, pheromonal value of all loop elements is initially equal
    - The authors also initialize the search with a super-ant using quick optimal path search tool
  - Move
    - The ant moves to another loop element based on two factors: pheromonal value and distance. These two values are weighted through tuning
    - A good move will update the pheromonal value of the line element, increasing the likeliness it will be utilized by other ants
    - Eventually all the individuals create a unique radial network, the best of these individuals is selected as the heuristic spark for the next iteration
    - The network configuration is perturbed on each iteration by randomly branch swapping several loop elements, the number of swaps is usually around 2-5% of the ant population
  - New generation
  - Stop search when convergence criteria is met for the best individuals

Economic Trans. Topology Control[9]

- ObjFunc = (sum of load payments) – (generation gross margin) – (merchandising surplus)
- Nodal price – evaluated using generation, load and network limitations
- Merchandising Surplus – a product of nodal price matrix and excess generation (gen – load)
- Switches available in the search space include only lines that are initially open
- Profitable and Un-Profitable lines are evaluated, Un-Profitable lines are selected as switch candidates
- Power transfer distribution factor (PTDF) and line outage distribution factor (LODF) are calculated to determine the economic effects of a line outage which in turn determine which line to cut in the next iteration.
- Stopping criteria is either unlimited or limited to *I* iterations

Other Methods

- Immune Network - http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1193637
- Artificial Neural Network - http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=252662
- Rank Removal - http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4436100
- Fuzzy Reconfiguration - http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=756119
- Tabu-Mutation Hybrid - http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=756120
- Unbalanced Phase Swapping for Distribution Networks - http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4104582

Literature Methodology

	GA	SA	Tabu	DE	ACO	ETTC
16-bus	**8.9**			**8.9**		
19-bus	**15.7**	**15.8**				
30-bus	**31.2**					
32-bus			**31.1**			
33-bus					**31.1**	
69-bus			**39.7**			
70-bus					**11.1**	
96-bus				**11.7**		
IEEE-118			**16.0**			**9.7**
135-bus					**12.7**	
148-bus		**19.5**				
362-bus		**79.0**				
1692-bus	**19.4**	**33.4**				

% Reduction by Model

Approach to the Problem

- TransEx is pimarily transmission expansion tool, with some parameter restrictions can it be retooled for Optimal Transmission Switching?
- TransEx uses two heuristic methods for optimization: Limited Discrepancy Search and Randomized Discrepancy Bounded Local Search
- We will be comparing LDS and RDS with other methods
  - Test Systems:
    - IEEE-14 (debug purposes)
    - RTS-96 73 bus system
    - Modified RTS-96 73 bus system
    - IEEE-118 (most common metric, for later benchmarking)
- Most methods presented performed switching optimization on radial distribution networks; we will be focusing on meshed networks

TransEx Configuration

- Existing Corridors:
  - MaxLines = number of lines in model corridor
  - MinLines = 0
- No new corridors, lines shunts, transformers, voltage upgrades, etc.
- Linear DCOPF
- LDS and RDS
- Static Line and Bus constraints
- Objective Functions:
  - Load Shedding
  - Line Overload
  - Line Loss
  - Economic Loss (future simulation)

RTS-96 Modifications

- As established by O'Neill et al.[18] RTS-96 test system is frequently modified for optimal switching analysis
- Modifications:
  - Remove line (11-13)
  - Shift 480 MW from buses 14,15, 19, 20 to 13
  - Add generation capacity to:
    - (1) – 100 MW
    - (7) – 100 MW
    - (15) – 155 MW
    - (23) – 155 MW
  - Decrease thermal capacity of line (14-16) to 350 MW

Results

LDS Results

	Time (min)	Initial Loss (kW)	Final Loss (kW)	Reduction (%)
IEEE-14	2.326	15.994	2.559	84.0
RTS_96	4.235	361.998	322.178	11.0
RTS_96m	5.791	423.915	377.522	10.9

RDS Results

	Time (min)	Initial Loss (kW)	Final Loss (kW)	Reduction (%)
IEEE-14	2.312	15.994	2.559	84.0
RTS_96	7.623	361.998	350.192	3.26
RTS_96m	-	-	-	-

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