Application of Emerging Metaheuristics in Power System Field

Dr.ir. J.L. Rueda Torres

26th June 2015
Outline

1. Problem complexity
2. Why metaheuristics?
3. Emerging algorithms
4. Applications
1 Problem complexity

Generic formulation

Minimize/maximize

Objective function

\[ OF = \sum_{r=1}^{p} w_r \cdot f_r(x) \quad (1) \]

subject to

Constraints

\[ g_i(x) \leq 0, \quad i = 1, \ldots, m \quad (2) \]

\[ h_j(x) = 0, \quad j = m + 1, \ldots, n \quad (3) \]

considering the search space given by

Bounds

\[ x_k^{\text{min}} \leq x_k \leq x_k^{\text{max}}, \quad k = 1, \ldots, D \quad (4) \]

Solution vector

\[ x = [x_1, x_2, \ldots, x_D] \quad (5) \]
1 Problem complexity

Types of optimization problems

Problem type
- Single objective/multi-objective
- Constrained/unconstrained
- Continuous (real numbers).
- Combinatorial (countable items - integer numbers).
- Mixed-integer.

Problem Complexities
- High dimensional search space
- Non-convex, discontinuous search landscape
- Multimodality
- High numerical accuracy, high nonlinearity.
- Lack of analytical expressions
- High computational burden
1 Problem complexity

- global optimum
- Solution/particle
- infeasible space
- search space
- feasible space
1 Problem complexity

Some synthetic problems:

(CEC’15 expensive optimization competition)

Source: http://www.ntu.edu.sg/home/epnsugan/

Shifted and Rotated Weierstrass Function

Properties:

- Multi-modal
- Non-separable
- Continuous but differentiable only on a set of points
1 Problem complexity

Optimization benchmarks

Test beds with synthetic problems can be found at

http://www.ntu.edu.sg/home/epnsugan/
(under EA Benchmarks / CEC Competitions)

- These problems are useful for the design of metaheuristics
- Performance of metaheuristic algorithms compared against state-of-the-art algorithms

Effectiveness in power system problems?
1 Problem complexity

The no free lunch theorem (NFL)


“All optimization algorithms perform equally when averaged over all possible problems”

- The algorithm A is better for some problems, but there are some other problems on which algorithm B performs better.
- Do not assume that an optimization algorithm that works well on benchmark functions will work well on real-world problems
2 Why Metaheuristics?

Basic notions

- ‘Meta’ – Greek for ‘upper layer methodology’.

- Use of high level scheme to guide the search process while subordinating and combining strategically different procedures derived from classical heuristics, artificial intelligence, or nature-inspired evolutionary techniques.

- Metaheuristic algorithms range from simple local search to complex learning processes.
2 Why Metaheuristics?

Basic notions

- **Main challenge:** Tradeoff between exploration (diversification) and exploitation (intensification) to improve the rate of convergence and to achieve global optimality.

- **Exploration:** Generate diverse solutions so as to explore the search space on a global scale.

- **Exploitation:** Focus the search in a local region knowing that a current good solution is within this region.
2 Why Metaheuristics?

Why to use metaheuristics?

Motivated by underlying problem complexity:

- High dimensional search space (mixed-integer).
- Non-explicitly defined objective functions, differentiation is not possible.
- Nonlinear, non-convex, discontinue and multimodal landscape.

Classical optimization tools cannot be applied
2 Why Metaheuristics?

Classification

Metaheuristics

Population

Evolutionary algorithm

- Genetic algorithm
- Genetic programming
- Evolutionary programming
- Differential evolution
- Scatter search
- MVMO

Particle swarm optimization
- Evolution strategy
- Ant colony optimization algorithms
- Estimation of distribution algorithm
- Simulated annealing

Implicit

Explicit

Direct

No memory

Local search

Trajectory

- Tabu search
- GRASP
- Iterated local search
- Stochastic local search
- Variable neighborhood search
- Guided local search

Dynamic objective function

3 Emerging algorithms

1. Mean-variance mapping optimization (MVMO)
   https://www.uni-due.de/mvmo/download

2. Linearized Biogeography-based Optimization (LBBO)
   http://academic.csuohio.edu/simond/bbo/

3. Fireworks Algorithm (FWA)
   http://www.cil.pku.edu.cn/research/fa/

4. Firefly algorithm, cuckoo search, and bat algorithm
   http://www.mathworks.com/matlabcentral/profile/authors/2652824-xin-she-yang

5. Teaching-Learning-Based Optimization (TLBO)
   https://sites.google.com/site/tlborao
3 Emerging algorithms

The pros and cons...

Advantages of metaheuristic techniques:

- Conceptual simplicity
- Easy adaptability due to open architecture
- Reduced human intervention

Potential drawbacks:

- Different solutions due to stochastic nature
- Optimality could not be guaranteed
- Sensitivity to initialization and parameter tuning
3 Emerging algorithms

MVMO: single parent-offspring scheme

Start

- Initialize algorithm and optimization problem parameters
- Normalize optimization variables in vector $\mathbf{x}$ to range $[0, 1]$.

No

- Fitness evaluation
- $i = i + 1$

Yes

- Local search
- $i = i + \Delta FE$

Termination criteria satisfied?

- Yes
- Stop

- No

- $rand < \gamma_{LS}$

- Solution archive
  - Store n-best population

- Parent assignment
  - The first ranked solution $\mathbf{x}_{best}$ is chosen as parent

- Offspring generation

Hybridization

Search range of all optimization variables normalized to $[0, 1]$. 
3 Emerging algorithms

MVMO-SH: Population based approach

Start

Initialize algorithm parameters
Generation and normalization of initial population
\(i=0\)

\(k=1\)

Fitness evaluation
\(i=i+1\)

Local search
\(i=i+\Delta FE\)

Fill/Update individual archive

Classification of good and bad solutions and parent selection

Bad solution?

Yes

Offspring generation

Single parent crossover based on local best

Mutation through mapping of \(m\) selected dimensions based on local mean and variance

\(k=N_p\)

Yes

\(k=k+1\)

No

Termination criteria satisfied?

Yes

Stop

No

Yes

Multi-parent crossover based on a subset of good solutions

\(rand < \gamma L_S\) No

Yes

\(k=k+1\)
3 Emerging algorithms

MVMO: Some highlights

1. Winner of IEEE competitions on Expensive optimization: CEC-2014 (Beijing, July 2014), and CEC-2015 (Sendai, Japan, May 2015)

2. 3rd out of 13 place in the competition on real-parameter single Objective optimization at CEC-2015, Sendai, Japan, May 2015.

3. 4th out of 17 place in the competition on real-parameter single Objective optimization at CEC-2014, Beijing, PR-China, July 2014.

4. 6th out of 21 place in the real-parameter single Objective optimization at CEC-2013, Cancun, Mexicom June 2013.
4 Applications

Working Group on Modern Heuristic Optimization (WGMHO)
http://sites.ieee.org/psace-mho/

Optimization test beds

Operation
- Optimal power flow
- Optimal control
- Optimal reconfiguration
- Optimal scheduling and pricing

Planning
- Addition of distributed generators and storage devices
- Optimal network expansion
- Model Identification
- Location and tuning of controllers
4 Applications

1. Allocation and sizing of dynamic Var sources
2. Identification of dynamic equivalent
4 Applications

Allocation and sizing of dynamic Var sources

Upper boundary $T_{upp}(t)$

Lower boundary $T_{low}(t)$

Voltage $v(t)$

TVI: Trajectory Violation Integral

$$CSI = \frac{1}{N_b} \sum_{i=1}^{N_b} TVI_i$$
4 Applications

Allocation and sizing of dynamic Var sources

Minimize

\[ C = \sum_{i=1}^{N_{cl}} IC(S_i) \cdot S_i \quad \text{Total installation cost} \]

subject to

\[ \dot{x} = f(x, y, u, S) \]

\[ 0 = g(x, y, u, S) \]

\[ b(x_0, y_0) = 0 \quad \text{Solvability of DAE} \]

\[ S_{\text{min}} \leq S \leq S_{\text{max}} \quad \text{Physical Mvar rating} \]

\[ \sum_{k=1}^{N_c} TVI_{\text{tot}}^k = 0 \quad \text{TVI for all contingencies} \]
4 Applications

Allocation and sizing of dynamic Var sources

Start

MVMO proposal
STATCOM
locations and sizes

Investment cost calculation

Better than worst
known solution?

yes

Select first
contingency

Time domain
simulation
TVI

Feasible?

yes

Beneficial
STATCOM
allocation
to archive

no

Select next
contingency

no

All contingencies
passed?

no

+ 1

yes

Intervention I

Intervention II

Set of ranked contingencies and candidate locations

Potentially beneficial STATCOM allocation

no

yes
4 Applications

Allocation and sizing of dynamic Var sources

7 candidate locations
4 Applications

Allocation and sizing of dynamic Var sources
4 Applications

Allocation and sizing of dynamic Var sources

Intervention II related to contingency #:
22 (Line 16-19) – ranked second
24 (Line 16-24) – ranked first

Bus 19
Bus 21
4 Applications

Allocation and sizing of dynamic Var sources

Average Duration of performed Function Evaluations, i.e. Time-Domain Simulations: 4.95 (sec)
4 Applications

Identification of dynamic equivalent

Ecuador-Colombia interconnected system

Ecuador (study area)
- 320 buses -- 64 generators
- 3.23 GW installed capacity
- 2.66 GW peak load

Colombia (external area)
- 1729 buses -- 109 generators
- 11.08 GW installed capacity
- 8.78 GW peak load

Opt. problem
- 22 dimensions (reactances, gains, time constants)
4 Applications

Dynamic equivalent for Colombia

- Sixth order generator model
- AVR model
- Governor model

Optimization problem
27 dimensions
4 Applications

Optimization & Dynamic simulation

- Reference signals from PMUs
- New parameters $X_j$
- Iteration: Optimization + Dynamic simulation
- Dynamic equivalent
- Selected signals
- Study zone with $u$, $p + jq$
Identification problem statement

Minimize

\[ \text{OF} = \sum_{n_p=1}^{p} \alpha_{n_p} \int_{0}^{\tau} \left[ w_1 (y_1 - y_{1\text{ref}})^2 + \ldots + w_n (y_n - y_{n\text{ref}})^2 \right] dt \] (17)

subject to

\[ x_{j\text{min}} \leq x_j \leq x_{j\text{max}} \] (18)

System with component model to be identified

From PMU or simulations

Parameters of the model
4 Applications

DE for Colombia: comparison of metaheuristics

![Graph showing the comparison of objective function values for different algorithms against the number of function evaluations. The graph includes lines for MVMO-SM, MVMO, JADE-vPS, CLPSO, GA-MPC, DE-ACO, LBBO, and CMA-ES. The x-axis represents the number of function evaluations, while the y-axis represents the objective function values.]
4 Applications

**DE for Colombia: comparison of dynamic responses**

- **Fault 1**
- **Fault 2**
4 Applications

DE for Colombia: Sensitivity of MVMO-SH parameters
Thanks for your attention!

Questions?