Lecture Series on

Intelligent Control

Lecture 23

Improved Genetic Algorithm

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An Improved Genetic Algorithm for Generation Expansion Planning

J.-B. Park, Y.-M. Park, J.-R. Won, and K. Y. Lee
IEEE Transactions on Power Systems, Vol. 15, No. 3, pp. 916-922, August 2000

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1. Introduction

Least-cost Generation Expansion Planning Problem

- determine the minimum-cost capacity addition plan that meets forecasted demand & specified reliability criterion
- highly constrained nonlinear discrete dynamic optimization problem

Conventional Approaches for Least-cost GEP

- LP Approaches: Approximation
- NLP Approaches such as Pontryagin maximum principle: Local Optimal Trap
- DP Approaches: Curse of Dimensionality

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1. Introduction (Cont.)

Commercial Packages such as WASP, EGEAS

a heuristic tunneling technique-based DP to find local solutions

Present Status for GEP Optimization

An efficient method that can overcome a local optimal trap and the dimensionality problem simultaneously has not been developed yet

Recent Researches

Fuzzy Set Theories

Artificial Intelligent Approaches

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1. Introduction (Cont.)

Advantages of GA-based approaches for the least-cost GEP

- Treatment of discrete variables
- Overcome the dimensionality problem
- Possibility to overcome local optimal trap

Contribution of this work

- Development of Improved Genetic Algorithm (IGA)
- and Its Application to GEP
- artificial creation scheme for an initial population
- stochastic crossover strategy

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2. Least-cost GEP Problem

Objective Function

Minimization of discounted investment costs, operating costs, and salvage values

$$\underset{U_1,\ldots,U_T}{Min} \sum_{t=1}^{T} \{f_t^1(U_t) + f_t^2(X_t) - f_T^3(U_t)\}$$

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2. Least-cost GEP Problem (Cont.)

Constraints

State Equation

$$s.t.\quad X_t = X_{t-1} + U_t \quad (t = 1,\cdots,T)$$

LOLP constraint

$$LOLP\ (X_t) < \varepsilon \quad (t = 1,\cdots,T)$$

Reserve Margin constraint

$$\underline{R} \le R(X_t) \le \overline{R} \quad (t = 1,\cdots,T)$$

Fuel Mix constraint

$$\underline{M_t^j} \le \sum_{i\in\Omega_j} x_t^i \le \overline{M_t^j} \quad (t = 1,\cdots,T\ and\ j = 1,\cdots,J)$$

Construction Limits

$$0 \le U_t \le \overline{U_t} \quad (t = 1,\cdots,T)$$

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3. Improved Genetic Algorithm

Encoding Structure

Integer value of added power plants in each year

$$\hat{U}' = \left(u_1'^1, u_2'^1,.., u_T'^1, \cdots, u_1'^n, u_2'^n,.., u_T'^n, \cdots, u_1'^N, u_2'^N,.., u_T'^N\right)^T$$

Fitness Function : inverse of objective function

$$f = \frac{\alpha}{1 + J}$$

Premature Convergence

Duplications among population

Dominance of high-fitness string

Modified Fitness Function

$$f'(i) = \frac{f(i) - f_{\min}}{f_{\max} - f_{\min}}$$

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3. Improved Genetic Algorithm (Cont.)

Creation of an Artificial Initial Population

Objective: create an initial population of strings spread out throughout the whole solution space

Characteristics: Random Generation + Artificial Generation

Procedure of AIP

Step 1. Generate all possible binary seeds of each plant type.

e.g., if *i-th* plant type has an upper limit of 3 units per year, then generate 4 possible binary seeds (*i.e.*, 00,01,10,11).

Step 2. Find the least common multiple (LCM) m from the numbers of the binary seeds of all types, and fill m binary seeds in a look-up table for all plant types and planning years.

e.g., if three plant types have upper limits of 3, 3 and 5 units per year, respectively, then the numbers of binary seeds are 4, 4, and 6, and m becomes 12.

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3. Improved Genetic Algorithm (Cont.)

Procedure of AIP (Cont.)

Step 3. Select an integer within [1, m] at random *for each element (plant type)* of a string. Fill the string with the corresponding binary digits and delete it from the look-up table. Repeat until m different strings are generated.

Step 4. Check the constraints. If a string satisfies all constraints for all years, then it becomes a member of the initial population. Otherwise, only parts of the string that violate the constraints in year t are generated at random until they satisfy the constraints. Go to Step 3 n times for $n \cdot m$ less than P, where P is the number of strings in a population and n is an arbitrary positive integer.

Step 5. The remaining (P - $n \cdot m$) strings are created using *uniform* random variables with binary number {0,1}. Go to Step 4 to check constraints and generate them if necessary. This process is repeated until all (P) strings, which satisfy the constraints, are generated.

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3. Improved Genetic Algorithm (Cont.)

TABLE I. EXAMPLE OF LOOK-UP TABLE WITH 3 PLANT TYPES FOR 3 PLANNING YEARS

	Type 1 (Upper Limit: 3 Units/Year)			Type 2 (Upper Limit: 3 Units/Year)			Type 3 (Upper Limit: 5 Units/Year)		
m	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3	Year 1	Year 2	Year 3
1	00	00	00	00	00	00	000	000	000
2	01	01	01	01	01	01	001	001	001
3	10	10	10	10	10	10	010	010	010
4	11	11	11	11	11	11	011	011	011
5	00	00	00	00	00	00	100	100	100
6	01	01	01	01	01	01	101	101	101
7	10	10	10	10	10	10	000	000	000
8	11	11	11	11	11	11	001	001	001
9	00	00	00	00	00	00	010	010	010
10	01	01	01	01	01	01	011	011	011
11	10	10	10	10	10	10	100	100	100
12	11	11	11	11	11	11	101	101	101
Generated String 1 : 011100101011000101010									

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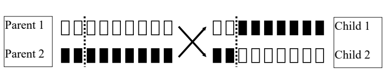
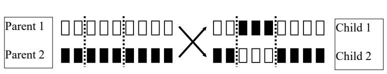
3. Improved Genetic Algorithm (Cont.)

Stochastic Crossover & Elitism

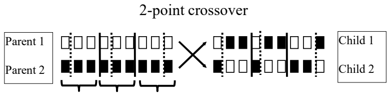
Stochastic Crossover : Random Selection of a Crossover Method among 3 Techniques



1-point crossover



2-point crossover



1-point crossover by plant types

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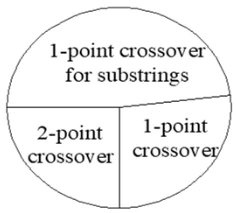
3. Improved Genetic Algorithm (Cont.)

Stochastic Crossover



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4. Case Studies

Solution Methods

- IGA
- SGA
- Tunnel-constrained dynamic programming (TCDP) employed in WASP
- Full dynamic programming (DP)

Test Systems

Case 1 : a power system with 15 existing power plants, 5 types of candidate options and a 14-year study period

Case 2 : a power system with 15 existing power plants, 5 types of candidate options and a 24-year study period

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4. Case Studies (Cont.)

Forecasted Peak Demand

1 stage: 12 years

Stage (Year)	0 (1996)	1 (1998)	2 (2000)	3 (2002)	4 (2004)	5 (2006)	6 (2008)
Peak (MW)	5000	7000	9000	10000	12000	13000	14000
Stage (Year)	-	7 (2010)	8 (2012)	9 (2014)	10 (2016)	11 (2018)	12 (2020)
Peak (MW)	-	15000	17000	18000	20000	22000	24000

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4. Case Studies (Cont.)

Technical and Economic Data of Existing System

Name (Fuel Type)	No. of Units	Unit Capacity (MW)	FOR (%)	Operating Cost ($/kWh)	Fixed O&M Cost ($/kW-Mon)
Oil #1 (Heavy Oil)	1	200	7.0	0.024	2.25
Oil #2 (Heavy Oil)	1	200	6.8	0.027	2.25
Oil #3 (Heavy Oil)	1	150	6.0	0.030	2.13
LNG G/T #1 (LNG)	3	50	3.0	0.043	4.52
LNG C/C #1 (LNG)	1	400	10.0	0.038	1.63
LNG C/C #2 (LNG)	1	400	10.0	0.040	1.63
LNG C/C #3 (LNG)	1	450	11.0	0.035	2.00
Coal #1 (Anthracite)	2	250	15.0	0.023	6.65
Coal #2 (Bituminous)	1	500	9.0	0.019	2.81
Coal #3 (Bituminous)	1	500	8.5	0.015	2.81
Nuclear #1 (PWR)	1	1,000	9.0	0.005	4.94
Nuclear #2 (PWR)	1	1,000	8.8	0.005	4.63

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4. Case Studies (Cont.)

Technical and Economic Data of Candidate Plants

Candidate Type	Construction Upper Limit	Capacity (MW)	FOR (%)	Operating Cost ($/kWh)	Fixed O&M Cost	Capital Cost ($/kW)	Life Time (yrs)
Oil	5	200	7.0	0.021	2.20	812.5	25
LNG C/C	4	450	10.0	0.035	0.90	500.0	20
Coal (Bitum.)	3	500	9.5	0.014	2.75	1062.5	25
Nuc. (PWR)	3	1,000	9.0	0.004	4.60	1625.0	25
Nuc.(PHWR)	3	700	7.0	0.003	5.50	1750.0	25

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4. Case Studies (Cont.)

Parameters for IGA Implementation

Parameters	Value
• Population Size	300
• Maximum Generation	300
• Probabilities of Crossover and Mutation	0.6, 0.01
• Number of Elite Strings	3 (1%)
• Weights of 1-point, 2-point, and 1-point substring	0.15:0.15:0.70

Weights for stochastic crossover techniques are determined empirically with a 6-year planning horizon

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4. Case Studies (Cont.)

Comparison of Crossover Methods

TABLE VI. RESULTS OBTAINED BY EACH CROSSOVER METHOD

Crossover Method	Objective Function in Million Dollars (Errors against Optimal Solution, %)		
	PC = 0.6	PC = 0.7	PC = 0.8
One-point Crossover	5035.53 (0.59%)	5013.50 (0.15%)	5057.30 (1.02%)
Two-point Crossover	5034.89 (0.57%)	5032.98 (0.54%)	5034.89 (0.57%)
One-point Substring Crossover	5012.53 (0.13%)	5012.46 (0.13%)	5010.63 (0.09%)
DP	5006.19		

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4. Case Studies (Cont.)

Stochastic Crossover

TABLE VII.
RESULTS OBTAINED BY STOCHASTIC CROSSOVER METHOD

Weights	Objective Function in Million Dollars (Errors against Optimal Solution, %)		
	PC = 0.6	PC = 0.7	PC = 0.8
0.05 : 0.05 : 0.90	5007.40* (0.02%)	5010.63 (0.09%)	5007.40 (0.02%)
0.10 : 0.10 : 0.80	**5006.19 (0.00%)**	5010.63 (0.09%)	5012.37 (0.12%)
0.15 : 0.15 : 0.70	5007.40 (0.02%)	**5006.19 (0.00%)**	**5006.19 (0.00%)**
0.20 : 0.20 : 0.60	**5006.19 (0.00%)**	**5006.19 (0.00%)**	5011.79 (0.11%)
0.25 : 0.25 : 0.50	**5006.19 (0.00%)**	5007.40 (0.02%)	5018.37 (0.24%)
0.30 : 0.30 : 0.40	**5006.19 (0.00%)**	5012.46 (0.13%)	5007.40 (0.02%)

* The solution with objective function as 5007.40 million dollars is the second best solution found by dynamic programming.

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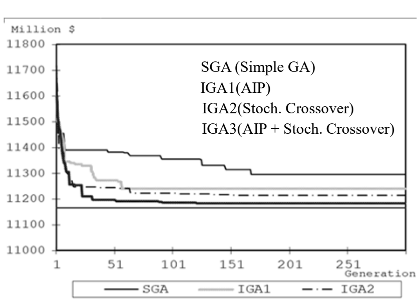
4. Case Studies (Cont.)

Convergence Characteristics of GA Methods in Case 1



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4. Case Studies (Cont.)

Performance Comparison

SGA < IGA1 (AIP) < IGA2 (Stochastic Crossover) < IGA3 (AIP + Stochastic Crossover)

IGA1, IGA2, IGA3: Modified Fitness Function + Elitism

Comparison of best solutions by each method

Solution Method		Cumulative Discounted Cost (10^6 \$) Case 1 (14-year Study Period)	Case 2 (24-year Study Period)
DP		11164.2	unknown
TCDP		11207.7	16746.7
SGA		11310.5	16765.9
IGA	IGA1	11238.3	16759.2
	IGA2	11214.1	16739.2
	IGA3	11184.2	16644.7

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4. Case Studies (Cont.)

Cumulative Number of New Plants

Type / Year	Oil (200MW)	LNG C/C (450MW)	Coal (500MW)	PWR (1000MW)	PHWR (700MW)
1998	3 (5)[1]	2 (1)	2 (3)	0 (1)	2 (0)
2000	5 (6)	3 (1)	5 (6)	0 (1)	4 (1)
2002	5 (7)	3 (1)	5 (6)	0 (2)	4 (1)
2004	8 (10)	7 (3)	6 (7)	0 (2)	4 (1)
2006	10 (12)	10 (3)	6 (7)	0 (2)	6 (2)
2008	10 (13)	10 (3)	6 (9)	0 (2)	6 (2)
2010	10 (13)	10 (3)	6 (9)	0 (2)	6 (4)
2012	14	11	8	1	7
2014	17	14	8	1	7
2016	19	15	10	1	9
2018	19	17	10	3	9
2020	20	18	12	3	9

1. The figures within parenthesis denote the results of IGA3 in Case 1.

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4. Case Studies (Cont.)

Computation Time

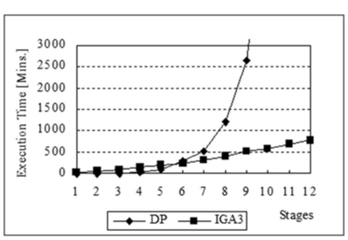

Fig. 5. Observed execution time for the number of stages.

At Stage 11:
DP: 9 days,
IGA3: 11 hrs.

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5. Conclusions

Development of an Improved Genetic Algorithm and Its Application to Least-cost GEP

- Stochastic Crossover
- Modified Fitness Function
- AIP
- Elitism

Better Solutions by IGA than SGA, TCDP of WASP

Application to Practical Large-scale GEP Optimization Problems

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