Least-Cost Generation Expansion Planning Using an Imperialist Competitive Algorithm

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Abstract: This paper presents using Imperialist Competitive Algorithm (ICA) and its application to a least-cost Generation expansion planning (GEP) problem. Least-cost GEP problem is concerned with a highly constrained nonlinear dynamic optimization problem that can only be fully solved by complete enumeration, a process which is computationally impossible in a real-world GEP problem. In this paper, Imperialist Competitive algorithm incorporating a stochastic technique and random initial population scheme is developed to provide a faster search mechanism. The main advantage of the ICA approach is that the "curse of dimensionality" and a local optimal trap inherent in mathematical programming methods can be simultaneously overcome. The ICA approach is applied to two test systems, one with 15 existing power plants, 5 types of candidate plants and a 14-year planning period, and the other, a practical long-term system with a 24-year planning period.
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1. Introduction

GENERATION expansion planning (GEP) is one of the most important decision-making activities in electric utilities.

Least-cost GEP is to determine the minimum-cost capacity addition plan (i.e., the type and number of candidate plants) that meets forecasted demand within a prespecified reliability criterion over a planning horizon.

A least-cost GEP problem is a highly constrained nonlinear discrete dynamic optimization problem that can only be fully solved by complete enumeration in its nature [1]–[3]. Therefore, every possible combination of candidate options over a planning horizon must be examined to get the optimal plan, which leads to the computational explosion in a real-world GEP problem.

To solve this complicated problem, a number of salient methods have been successfully applied during the past decades. Masse and Gilbrat [4] applied a linear programming approach that necessitates the linear approximation of an objective function and constraints. Bloom [5] applied a mathematical programming technique using a decomposition method, and solved it in a continuous space. Park et al. [6] applied the Pontryagin's maximum principle whose solution also lies in a continuous space. Although the above-mentioned mathematical programming methods have their own advantages, they possess one or both of the following drawbacks in solving a GEP problem. That is, they treat decision variables in a continuous space. And there is no guarantee to get the global optimum since the problem is not mathematically convex. Dynamic programming (DP) based framework is one of the most widely used algorithms in GEP [1]–[3],[7],[8]. However, so-called "the curse of dimensionality" has interrupted direct application of the conventional full DP in practical GEP problems.

For this reason, WASP [1] and EGEAS [2] use a heuristic tunneling technique in the DP optimization routine where users prespecify states and successively modify tunnels to arrive at a local optimum. David and Zhao developed a heuristic-based DP [7] and applied the fuzzy set theory [8] to reduce the number of states. Recently, Fukuyama and Chiang [9] ,Park et al [10], applied genetic algorithm (GA) to solve sample GEP problems, and showed promising results. Park et al Also Implemented A hybrid GA/DP to same case studies as this paper [11] and S.Kannan and partners Applied some Evolutionary Computation Techniques for GEP problem on also same Case studies as this paper [12]. However, an efficient method for a practical GEP problem that can overcome a local optimal trap and the dimensionality problem simultaneously has not been developed yet.

Imperialist Competitive Algorithm (ICA) is a new socio-politically motivated global search strategy that has recently been introduced for dealing with different optimization tasks [13]. Recently, a global optimization technique using ICA has been successfully applied to various areas of power system such as economic dispatch, Distribution Systems [14], And Transmission Expansion Planning. ICA-based approaches for least-cost GEP have several advantages. Naturally, they can not only treat the discrete variables but also overcome the dimensionality problem. In addition, they have the capability to search for the global optimum or quasi optimums within a reasonable computation time.

In this paper, an imperialist competitive algorithm (IGA), which can overcome the aforementioned problems of the conventional GA to some extents, is developed.

The results of the ICA are compared with those of the genetic algorithm, the full DP, the tunnel-constrained DP employed in WASP, Different Methods of Genetic Algorithm, And Evolutionary Programming.

I. Formulation Of The Least-Cost gep problem

Mathematically, solving a least-cost GEP problem is equivalent to finding a set of optimal decision vectors over a planning horizon that minimizes an objective function under several constraints.

The GEP problem to be considered is formulated as follows :

$$\underset{U_1,U_2,\dots,U_T}{Min} \sum_{t=1}^{T} f_t^{\,1}(U_t)+f_t^{\,2}(X_t)-f_T^{\,3}(U_t) \quad . \qquad (1)$$

$$X_t = X_{t-1}+U_t-S_t \qquad \forall t=1,2,\dots,T \qquad (2)$$

$$LOLP(X_t)\geq \varepsilon \qquad \forall t=1,2,\dots,T \qquad (3)$$

$$\underline{R}\leq R(X_t)\leq \overline{R} \qquad \forall t=1,2,\dots,T \qquad (4)$$

$$\underline{M_t^j}\leq \sum_{i\in\Omega_j} x_t^i \leq \overline{M_t^j} \quad \forall t=1,2,\dots,T \ \ and \ \ \forall j=1,2,\dots,J \qquad (5)$$

$$0\leq U_t \leq \overline{U_t} \qquad \forall t=1,2,\dots,T \qquad (6)$$

Where:

T = number of periods (years) in a planning horizon,

J = number of fuel types,

Ω_j = index set for j th fuel type plant,

X_t = cumulative capacity [MW] vector of plant types in year t,

x_t^i = cumulative capacity [MW] of th plant type in year t

U_t = capacity addition [MW] vector by plant types in year t,

$\overline{U_t}$ = maximum construction capacity [MW] vector by plant types in year t,

x_t^i = capacity addition [MW] of th plant in year t ,

$LOLP(X_t)$ = loss of load probability (LOLP) with X_t, in year t,

$R(X_t)$ = reserve margin with X_t , in year t.

ε = reliability criterion expressed in LOLP,

$\underline{R},\overline{R}$ = lower and Upper bounds of reserve margin,

$\underline{M_t^j},\overline{M_t^j}$ = reserve margin with X_t , in year t.

$f_t^{\,1}(U_t)$ = discounted construction costs [$] associated with capacity addition U_t in year t,

$f_t^{\,2}(X_t)$ = discounted construction costs [$] associated with capacity addition U_t in year t,

$f_T^{\,3}(U_t)$ = discounted construction costs [$] associated with capacity addition U_t in year t,

The objective function is the sum of tripartite discounted costs over a planning horizon. It is composed of discounted investment costs, expected fuel and O&M costs and salvage value.

To consider investments with longer lifetimes than a planning horizon, the linear depreciation option is utilized [1]. In this paper, five types of constraints are considered. Equation (2) implies state equation for dynamic planning problem [6]. Equations (3) and (4) are related with the LOLP reliability criteria and the reserve margin bands, respectively. The capacity mixes by fuel types are considered in (5). Plant types give another physical constraint in (6), which reflects the yearly construction capabilities.

Although the state vector, X_t , and the decision vector, U_t , have dimensions of MW, we can easily convert those into vectors which have information on the number of units in each plant type. This mapping strategy is very useful for ICA implementation of a GEP problem such as encoding and treatment of inequality (6) and illustrated in the following (1) equations:

$$X= (x_t^1 , \dots . x_t^N) T \qquad X_t^{'} = (x_t'^1, \dots, x_t'^N)^T \qquad (7)$$

$$U= (u_t^1 , \dots . u_t^N) ^T \qquad U_t^{'} = (u_t'^1, \dots, u_t'^N)^T \qquad (8)$$

Where :

N = number of plant types including both existing and candidate plants,

X'_t = cumulative number of units by plant types in year t.

U'_t = addition number of units by plant types in year t.

x'^i_t = ith plant type's cumulative number of units in year t ,

u'^i_t = ith plant type's addition number of units in year t.

II. imperialist competitive algorithm

Imperialist Competitive Algorithm (ICA) [13] is a new evolutionary algorithm in the Evolutionary Computation field based on the human's socio-political evolution. The algorithm starts with an initial random population called countries. Some of the best countries in the population selected to be the imperialists and the rest form the colonies of these imperialists. In an N dimensional optimization problem, a country is an 1 x n array. This array defined as below:

$$\text{Country}= [p_1,p_2. \ldots, p_n] \tag{9}$$

The cost of a country is found by evaluating the cost function f at the variables ($p_1,p_2. \ldots, p_n$). Then

$$c_i = F(\text{Country}_i)= F(p_{i1}, p_{i2}, ..., p_{in}) \tag{10}$$

The algorithm starts with N initial countries and the Nimp best of them (countries with minimum cost) chosen as the imperialists. The remaining countries are colonies that each belong to an empire. The initial colonies belong to imperialists in convenience with their powers. To distribute the colonies among imperialists proportionally, the normalized cost of an imperialist is defined as follow

$$Cn= \max \{ci\}- cn \tag{11}$$

Where, c_n is the cost of nth imperialist and C_n is its normalized cost. Each imperialist that has more cost value, will have less normalized cost value. Having the normalized cost, the power of each imperialist is calculated as below and based on that the colonies distributed among the imperialist countries.

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \tag{12}$$

On the other hand, the normalized power of an imperialist is assessed by its colonies. Then, the initial number of colonies of an empire will be NC_n = rand{$P_n \times N_{col}$} where,

NC_n is initial number of colonies of nth empire and N_{col} is the number of all colonies.

To distribute the colonies among imperialist, NC_n of the colonies is selected randomly and assigned to their imperialist. The imperialist countries absorb the colonies towards them- selves using the absorption policy. The absorption policy shown in Fig .1 makes the main core of this algorithm and causes the countries move towards to their minimum optima. The imperialists absorb these colonies towards themselves with respect to their power that described in (13). The total power of each imperialist is determined by the power of its both pans, the empire power plus percents of its average colonies power.

$$TC_n = \text{cost(imperialist)} + £ \times \text{mean}\{\text{cost [(colonies of empire}_n)\} \tag{13}$$

Where TC_n is total cost of the nth empire and £ is a positive number which is considered to be less than one.

$$x\sim U (0,\beta\times d) \tag{14}$$

In the absorption policy, the colony moves towards the imperialist by x unit. The direction of movement is the vector from colony to imperialist, as shown in Fig. 1, in this figure, the distance between the imperialist and colony shown by d and x is a random variable with uniform distribution. Where β is greater than I and is near to 2. So, a proper choice can be β=2 . In our implementation γ is 45 (deg) respectively.

$$\Theta \sim U(- \gamma, \gamma) \tag{15}$$

In ICA algorithm , to search different points around the imperialist. a random amount of deviation is added to the direction of colony movement towards the imperialist. In Fig, 1, this deflection angle is shown as θ, which is chosen randomly and with a uniform distribution.

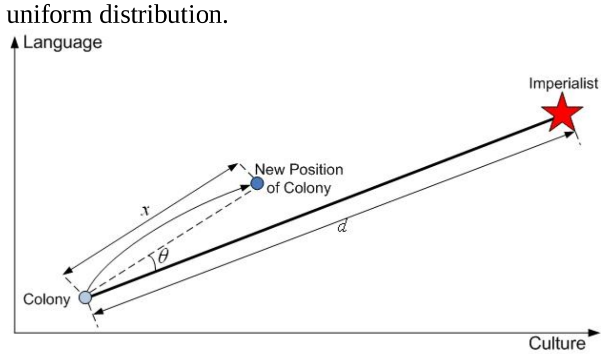

Figure 1. Fig.1. Movement of colonies toward their relevant imperialist in a randomly deviated direction

As shown in Fig.2 While moving toward the imperialist countries, a colony may reach to a better position, so the colony position changes according to position of the imperialist.

In each iteration we select some of the weakest colonies and replace them with new ones, randomly. The replacement rate is named as the revolution rate.

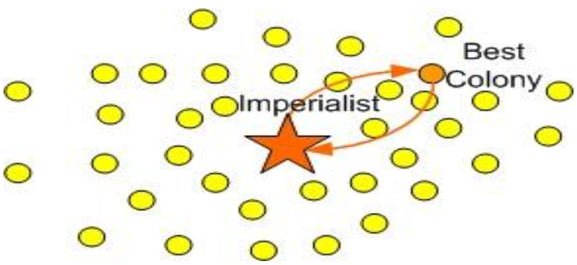

Figure 2. Fig.2. Exchanging the position of a colony and the imperialist

In this algorithm, the imperialistic competition has an importa-nt role. During the imperialistic competition, the weak empires will lose their power and their colonies. To model this compet-etion, firstly we calculate the probability of possessing all the colonies by each empire considering the total cost of empire.

$NTC_n = \max \{TC_i\} - TC_n$
(14)

Where, TC_n is the total cost of nth empire and NTC_n is the normalized total cost of nth empire. Having the normalized total cost, the possession probability of each empire is calculated as below :

$$p_{p_n} = \left| \frac{N.T.C._n}{\sum_{i=1}^{N_{imp}} N.T.C._i} \right| \quad (15)$$

After a while all the empires except the most powerful one will collapse and all the colonies will be under the control of this of this unique. Fig.3 shows the flowchart of this algorithm.

III. CASE STUDIES

ICA was implemented on GEP using Matlab R2012a on PC/Pentium G 6950,2.8 GHZ.

A. Test System Description

The Imperialist Competitive Algorithm methods have been applied in two test systems: Case I for a power system with 15 existing power plants, 5 types of candidate options and a 14-year study period, and Case 2 for a real-scale system with a 24-year study period. The planning horizons of 14 and 24 years are divided into 7 and 12 stages (two-year intervals), respectively. The forecasted peak demand over the study period is given in Table I.

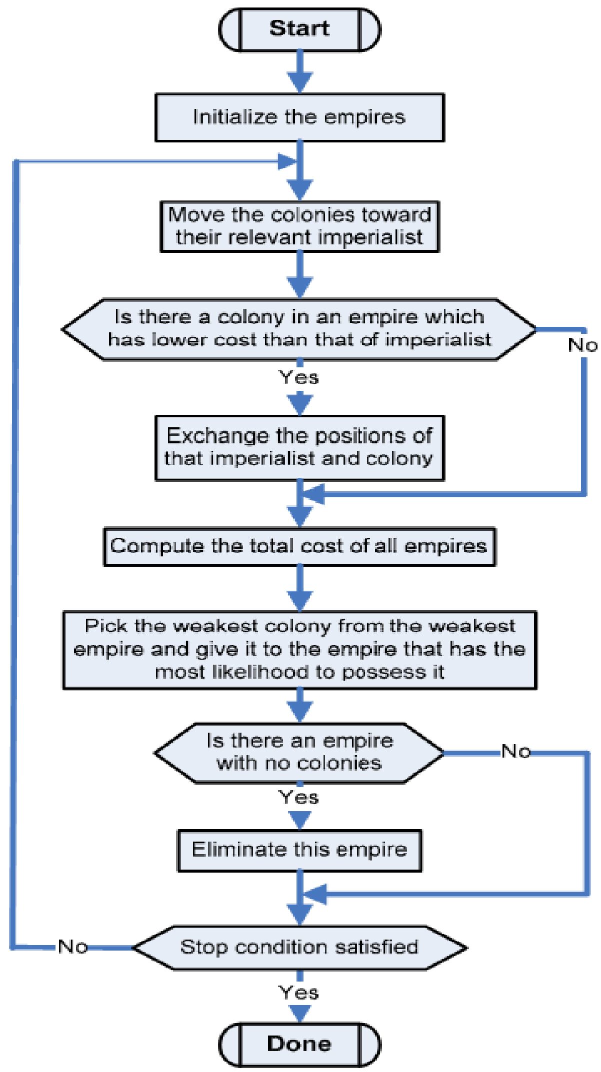

Figure 3. Fig.3. Flowchart of the proposed algorithm

Table 1. Forcasted Peak Demand

Stage (Year)	0 (2012)	1 (2014)	2 (2016)	3 (2018)	4 (2020)	5 (2022)	6 (2024)

Peak (MW)	5000	7000	9000	10000	12000	13000	14000
Stage (Year)	- -	7 (2026)	8 (2028)	9 (2030)	10 (2032)	11 (2034)	12 (2036)
Peak (MW)		15000	17000	18000	20000	22000	24000

B. Parameters for GEP and ICA

There are several parameters to be pre-determined, which are related to the GEP problem and ICA-based programs. In this paper, we use 8.5% as a discount rate, 0.01 as LOLP criteria, and 15% and 60% as the lower and upper bounds for reserve margin, respectively. The considered lower and upper bounds of capacity mix are 0% and 30% for oil-fired power plants, 0% and 40% for LNG-fired, 20% and 60% for coal-fired, and 30% and 60% for nuclear, respectively. Parameters for ICA are selected through experiments. Especially number of initial empires and revolution rate.

Table 2. Parameters for ICA Impelementation

Initial countries	300
Initial Imperialist	30
Number of Colonies	300-30=270
β	2
γ	45(deg)

Table 3. Technical and Economic Data of Candidate Plants

Name (Fuel Type)	No.of Units	Unit Capacity (MW)	FOR (%)	Operating Cost ($/KWh)	Fixed O&M Cost ($/Kwh-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\T #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	1000	9.0	0.005	4.94
Nuclear #2 (PWR)	1	1000	8.8	0.005	4.63

Table 4. Technical and Economic data of candidate Plants

Candidate Type	Const-ruction Upper Limit	Capa-city (MW)	FOR (%)	Opera-ting Cost ($/K-Wh)	Fix-ed O&M Cost	Capital Cost ($/KW)	Life Time (yrs)
Oil	5	200	7.0	0.021	2.2	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	1000	9.0	0.004	4.6	1625.0	25
Nuc. (PHWR)	3	700	7.0	0.003	5.5	1750.0	25

C. Numerical Results

The developed ICA was applied to two test systems, and compared with the results of DP, TCD ,WASP-DP, Different Methods of Genetic Algorithm ,And Other Evolutionary Computation Methods. Throughout the tests, the solution of the conventional DP is regarded as the global optimum and that of TCDP as a local optimum. Both the global and a local solution can be obtained in Case 1; however, only a local solution can be obtained by using TCDP in Case 2 since the "curse of dimensionality" prevent the use of the conventional DP. Table VIII summarizes costs of the best solution obtained by each solution method. In Case 1, the solution obtained by ICA is within 0.07% of the global solution costs while the solutions IGA3 is within 0.18% and SGA and TCDP are within 1.3% and 0.4%, respectively. In Case 1 and Case 2, ICA has achieved a 0.32% and 0.30% improvement of costs over TCDP, respectively. Although SGA and IGA's have failed in finding the global solution, ICA have provided better solution than GA. Furthermore, solutions of ICA are better than that of TCDP in both cases, which implies that it can overcome a local optimal trap in a practical long-term GEP.

Table 5. Summary of the Best Results Obtained By Each Solution Methods

Solution Method		Cumulative Discounted Cost (10^6 $)	
		Case1 (14-yearStudy Period)	**Case2 (24-yearStudy 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
WASP-DP		11207.7	16746.7
RGA	RGA1	11238.3	16759.2
	RGA2	11222.0	16751.8
	RGA3	11202.5	16723.7
HGA		11711.9	16635.7
IES		14483	-
IEP		14555	-
ICA		11171.9	16695.2

Fig. 4 illustrates the convergence characteristics of various GA-based methods in Case 1.

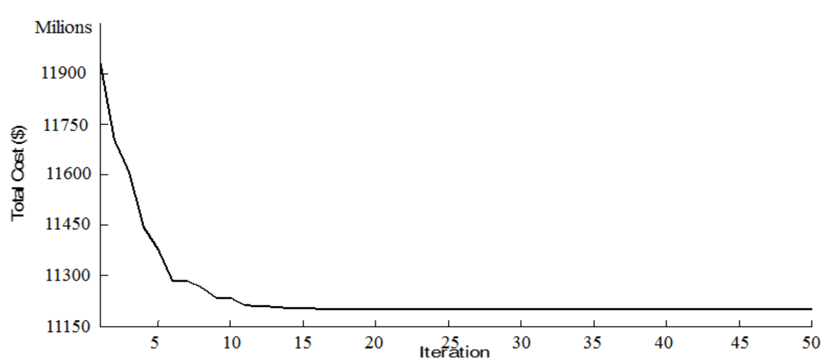

Figure 4. Convergence characteristic of ICA method in Case 1 system

Table IX summarizes generation expansion plans of Case 2 obtained by IGA3.

Table 6. Cumulitve Number of Newly Introduced Plants in case 2 by iga3

Type / Year	Oil (200-MW)	LNG C\C (450-MW)	Coal (500-MW)	PWR (1000-MW)	PWR (1000-MW)
2012	2	0	0	3	2
2014	2	0	0	6	2
2016	2	0	0	6	2
2018	2	0	2	9	2
2020	2	0	2	9	2
2022	2	0	2	9	3
2024	2	0	2	9	4
2026	7	0	2	9	7
2028	9	3	2	9	7
2030	9	6	5	9	7
2032	9	6	5	12	7
2034	14	6	5	12	7

The execution time of GA-based methods is much shorter than that of TCDP and IGA.That is,IGA requires approximately 3.7 and 6 times of execution time in Case 1 and Case 2, respectively .In the system with 11 stages, it takes over 9 days for DP, and requires about 1.2 millions of array memories to obtain the optimal solution while it takes only 1 hour by ICA to get the near optimum.

The proposed method definitely provides quasi optimums in a long-term GEP within a reasonable computation time. Also, the results of the proposed ICA method are better than those of TCDP employed in the WASP, which is viewed as a very powerful and computationally feasible model for a practical long-term GEP problem. Since a long-range GEP problem deals with a large amount of investment, a slight improvement by the proposed IGA method can result in substantial cost savings for electric utilities.

IV. Conclusion

This paper developed an Imperialist Competitive Algorithm [11] (ICA) for a long-term least-cost generation expansion planning (GEP) problem. The proposed ICA is a new evolutionary algorithm in the Evolutionary Computation field based on the human's socio-political evolution

The ICA has been successfully applied to long-term GEP problems with 2 different planning period(14 and 24 Years). It provided better solutions than the conventional GA. Moreover, ICA was found to be robust in providing quasi optimums within a reasonable computation time and yield better solutions compared to the TCDP employed in WASP. Contrary to the DP, computation time of the proposed ICA is linearly proportional to the number of stages.

The developed ICA method can simultaneously overcome the “curse of dimensionality” and a local optimum trap inherent in GEP problems. Therefore, the proposed ICA approach can be used as a practical planning tool for a real-system scale long-term generation expansion planning.

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