Optimization of Mixed-Integer Non-Linear Electricity Generation Expansion Planning Problem Based on Newly Improved Gravitational Search Algorithm

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ABSTRACT: Electricity demand is forecasted to double in 2035, and it is vital to address the economics of electrical energy generation for planning purposes. This study aims to examine the applicability of Gravitational Search Algorithm (GSA) and the newly improved GSA (IGSA) for optimization of the mixed-integer non-linear electricity generation expansion planning (GEP) problem. The performance index of GEP problem is defined as the total cost (TC) based on the sum of costs for investment and maintenance, unserved load, and salvage. In IGSA, the search space is sub-divided for escaping from local minima and decreasing the computation time. Four different GEP case studies are considered to evaluate the performances of GSA and IGSA, and the results are compared with those from implementing particle swarm optimization algorithm. It is found that IGSA results in lower TC by 7.01%, 4.08%, 11.00%, and 6.40%, in comparison with GSA, for the four case studies. Moreover, as compared with GSA, the simulation results show that IGSA requires less computation time, in all cases.

1- Introduction

Electrification plays a critical role in promoting economic growth and social welfare for all economies. Therefore significant resources from governments and international development agencies are allocated to generation expansion [1], which is expected to reach $6.8 trillion in 2030 [2, 3]. Total world primary energy demand grew by 26% from 2000 to 2010 and it is projected to increase by 47% in 2035 [2, 3], mainly due to the expansion of rural electrification programs in countries with developing economies and higher utilization of electric appliances and heating in countries with developed economies [4].

Independent of the type of need for electrification, GEP is expected to resolve the problem of determining the type and the size of new generation units installed over the planning horizon with considering reliability criterion [5, 6].

As the electricity demand increases over the planning horizon, a small error in the planning phase can result in loss of the capital expenditure in addition to the social costs of unmet energy demand. The literature review indicates that there is a continuous interest in the development of more accurate techniques for optimization of the GEP problem. Various mathematical programming methods such as linear programming [7, 8], mixed-integer linear programming [9-13], and non-linear programming [5, 6, 14] have been applied to optimize the GEP problem. For the large-scale mixed-integer non-linear (MINL) programming GEP problem, a number of meta-heuristic optimization methods have been examined [7]. Park et al. applied genetic algorithm (GA) to solve the GEP problem, where an artificial creation scheme for an initial population was developed and a stochastic

crossover technique to overcome some structural problems in the GA was proposed [15]. In that study, the planning horizon was considered as 14 and 24 years for two case studies. The results, as compared with GA, dynamic programming (DP), and tunnel-constrained DP (TCDP) algorithms, showed that improved GA achieved 1.1 and 0.21% less cost than GA and TCDP in one case study and 0.72 and 0.61% in the other one, respectively. Also, J. Sirikum et al. [16] used a GA-based heuristic methodology to solve the GEP problem which was applied to a test system with different planning horizons of 5, 7, 10, 15, 20, 25, and 30 years and the findings were compared with those from LINGO software to demonstrate the ability of the proposed methodology. In a study by B. Alizadeh et al., the Benders decomposition and a novel heuristic reliability algorithm are employed for the optimization of GEP problem [17]. Z. Hejrati et al. applied honey bee mating optimization method to solve a case study with a six-year planning horizon and five types of candidate generation units [18]. In another study, the immune algorithm was improved by using tabu search algorithm to obtain the optimal GEP for a system with four candidate generation units [19]. In that study, the results were compared with those from GA and immune algorithms. Imperialist competitive algorithm (ICA) was used by Hedayatfar and Barjaneh to optimize the GEP problem for two test systems, one with 15 and 5 types of candidate generation units for a 14-year planning period, and the other, a practical long-term system with a 24-year planning period [20]. The results from that study showed that in both case studies, ICA provided a better solution than those of TCDP and GA. Kothari and Kroese developed cross-entropy optimization method to solve the GEP problem for a test system with a 10-year planning horizon [21]. In another study by Kannan et al., the application of particle swarm optimization (PSO) algorithm and its variants to the GEP problem was presented,

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where a novel virtual mapping procedure was introduced to enhance the effectiveness of PSO algorithm [22]. In that study, PSO algorithm and its variants were applied to a synthetic test system of five types of candidate generation units with 6- and 14-year planning horizons. It was determined that PSO technique produced the best result with a lower computation time, when compared with DP. In a study by Jadidoleslam et al., GEP problem was solved by shuffled frog leaping (SFL) algorithm [23]. In that study, to test the proposed SFL algorithm, two case studies were used for planning horizons of 10 and 20 years. Moreover, a modified SFL algorithm is proposed to solve GEP problem which is applied to a test system for two planning horizons of 12 and 24 years [24].

Although various optimization methodologies have been developed for the GEP problem, the complexity of the MINL GEP problem warrants the development of more efficient algorithms for better accuracy and lower computation time. While it has been demonstrated that GSA is comparable with other optimization algorithms [25], it has been applied for the analysis of power system, including unit commitment [26], voltage stability enhancement in optimal reactive power dispatch [27], and optimal power flow [28]. The goal of this study is to examine the applicability of GSA and the newly improved GSA (IGSA) for optimization of the MINL electricity GEP problem. To this end, in this paper, the GEP problem is formulated, and the solution methodology based on GSA and IGSA for four case studies is presented.

The remainder of this study is organized as follows. In the next section, GEP problem formulation is given. GSA and the improvements introduced in this study for IGSA are explained in section 3. Results and discussions are presented in section 4. Finally, the conclusions and recommendations are given in section 5.

2- GEP formulation

2- 1- Performance index

The performance index of MINL GEP problem is based on the total cost (TC) which is the sum of the investment cost of candidate generation units (Inv), operation and maintenance cost (including fixed and variable costs) of existing and candidate generation units (OM), energy not served cost (ENS), and salvage costs of candidate generation units (Sal). Mathematically, TC is optimized based on the following formulation [15, 23, 29]:

$$Min \ TC = \sum_{t=1}^{T} \left[Inv(U_t) + OM(X_t) + ENS(X_t) - Sal(U_t) \right] \quad (1)$$

where T is the planning horizon in terms of the number of years and it is divided into several stages, denoted by t, where cost calculation is performed for each stage. U_t and X_t are the capacity addition of all candidate generation units and cumulative capacity of all existing and candidate generation units in the stage t, respectively. X_t is calculated based on

$$X_t = X_{t-1} + U_t \quad (2)$$

In Eq. (1), the cost components of TC are formulated based on consideration for discount rate, i, given by

$$Inv(U_t) = \frac{1}{(1+i)^{t'}} \times \sum_{k=1}^{N} \left[Inv\_C_k \times U_{t,k} \right] \quad (3)$$

$$OM(X_t) = \sum_{y=0}^{S-1} \left[\frac{1}{(1+i)^{t'+0.5+y}} \times \sum_{k=1}^{N} \left[F\_C_k \times X_{t,k} + V\_C_k \times G_{t,k} \right] \right] \quad (4)$$

$$ENS(X_t) = \sum_{y=0}^{S-1} \left[\frac{1}{(1+i)^{t'+0.5+y}} \times EENS_t \times ENS\_C \right] \quad (5)$$

$$Sal(U_t) = \frac{1}{(1+i)^{T'}} \times \sum_{k=1}^{N} \left[\delta_{k,t} \times Inv\_C_k \times U_{t,k} \right] \quad (6)$$

where Inv_C_k, F_C_k, and V_C_k are investment, fixed, and variable operating cost of unit k, respectively. $U_{t,k}$, $X_{t,k}$, and $G_{t,k}$ are the capacity of kth candidate generation unit, cumulative capacity of kth unit, and produced energy by kth unit in the stage t, respectively. The cost of energy expected not served in each stage ($EENS_t$) is represented as ENS_C. In the formulation of TC in Eq. (1), it is assumed that the candidate generation units are added to the power system at the beginning of each stage, where OM and ENS costs are assumed to occur in the middle of each year.

To consider investments with the longer lifetimes than the planning horizon, the sinking fund depreciation method is utilized for the calculation of salvage factor ($\delta_{k,t}$) in each stage [30],

$$\delta_{k,t} = \frac{i}{(1+i)^{L_k} - 1} \times (1+i)^t \quad (7)$$

where L_k is the lifetime of kth unit. Also, t` and T` are defined as

$$t' = t_0 + S \times (t-1) \quad (8)$$

$$T' = t_0 + S \times t \quad (9)$$

where S and t_0 are the number of years in each stage and the number of years between the reference year for discounting and the first year of study, respectively.

2- 2- Constraints

For the optimization of GEP problem, five sets of constraints are considered. Due to physical limitations, the maximum installation units of jth candidate generation units in each stage is limited by

$$0 \le U_{j,t} \le U_{j,t}^{max} \quad (10)$$

and the reserve in each year is bounded by maximum (R_{max}) and minimum (R_{min}) limits

$$(1+R_{min}) \times Load_t \le \sum_{k=1}^{N} X_{t,k} \le (1+R_{max}) \times Load_t \quad (11)$$

The capacity limitations of each candidate generation unit based on its fuel types in each stage are

$$M_{min}^{\ j} \le \frac{X_{t,j}}{\sum_{k=1}^{N} X_{t,k}} \le M_{max}^{\ j} \quad (12)$$

and the loss of load probability (LOLP) reliability criterion is bounded by

$$LOLP(X_t) \le \varepsilon \quad (13)$$

where $U_{j,t}^{max}$ is the maximum available capacity of jth unit in stage t. $Load_t$ denotes the peak demand in the stage t. $M_{min}^{\ j}$ and $M_{max}^{\ j}$ are the lower and upper bounds of jth fuel type in

stage t. Also, LOLP in each stage is limited by ε.

It must be noted that determining the number of candidate generation units in each stage and their capacities pose the GEP problem as a mixed-integer type. In this study, the power capacities of each candidate generation unit are assumed to be dependent on the number of them, which must be treated as an integer in the GEP problem. The power capacities are calculated based on the merit order of each candidate generation unit in each stage. Also, the existence of U_t in the GEP formulation calculated by the products of the number of candidate generation units and their capacities makes the problem non-linear. In the next section, GSA and IGSA are discussed for optimization of the MINL GEP problem.

3- Proposed optimization algorithms

3- 1- Gravitational search algorithm

GSA is a meta-heuristic optimization method introduced by Rashedi et al. [25] and is based on Newton's law of gravity and mass interactions. GSA is initialized by random objects that are spread in the feasible solution space. The objects considered in GSA are identified based on their masses. Objects move due to the attraction between them by gravitational forces which cause their global movement towards the objects with heavier masses corresponding to the acceptable solutions. Objects with heavier mass impose higher forces on the other objects and move slower than the objects with relatively smaller mass.

Similar to PSO, in GSA, it is assumed that each object is associated with two vectors, namely the position Ψ_i and velocity V_i vectors [31]. Therefore, the ith object's position in the search space can be represented by $\psi_i = \left[x_i^1, x_i^2, ..., x_i^N \right]$ in the N-dimensional space for i=1,...,K, where K is the number of objects and x_i^d represents the position of ith object in the dth dimension. Also, each object has an inertia mass, shown by M_i, which is updated in each iteration of GSA, corresponding to the performance index value of each object, Performance(t).

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{K} m_j(t)} \quad (14)$$

where $m_i(t)$, the normalized value of performance index, is defined as

$$m_i(t) = \frac{Performance_i(t) - worst_i(t)}{best_i(t) - worst_i(t)} \quad (15)$$

where $best_i(t)$ and $worst_i(t)$ are the best and the worst performance index values, respectively, among K objects in each iteration.

The gravitational constant, G(t), is updated in each iteration based on

$$G(t) = G_0 \left(\frac{iteration}{Maximum\ iteration} \right)^{\beta}, \beta < 1 \quad (16)$$

where G_0 is an initial gravitational constant in the first iteration (t_0) and β is a constant parameter.

The forces between each object and the others are determined as

$$F_{ij}^d(t) = G(t) \frac{M_j^a(t)}{R_{ij}(t) + \varepsilon} (x_j^d(t) - x_i^d(t)) \quad d = 1, 2, ..., N \quad (17)$$

$$F_i^d(t) = \sum_{j=1, j \neq i}^{K} rand_j F_{ij}^d(t) \quad d = 1, 2, ..., N \quad (18)$$

where M_j^a denotes the active gravitational mass related to the jth object. ε is a small constant. $R_{ij}(t)$ indicates the distance between object i and j and $rand_j$ is a uniform random variable in the interval [0,1]. $F_{ij}^d(t)$ is the force between i^{th} and j^{th} objects in direction d and $F_i^d(t)$ is the summation of all forces on the ith object.

Based on the law of motion, the acceleration, a_i^d, of the ith object in direction d is given by

$$a_i^d = \frac{F_{ij}^d(t)}{M_i(t)} \quad d = 1, 2, ..., N \quad (19)$$

Then, the velocity and position of ith object are updated by

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \quad d = 1, 2, ..., N \quad (20)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \quad, d = 1, 2, ..., N \quad (21)$$

This process is repeated until the convergence criterion is satisfied. The flowchart of GSA is depicted in Fig. 1.
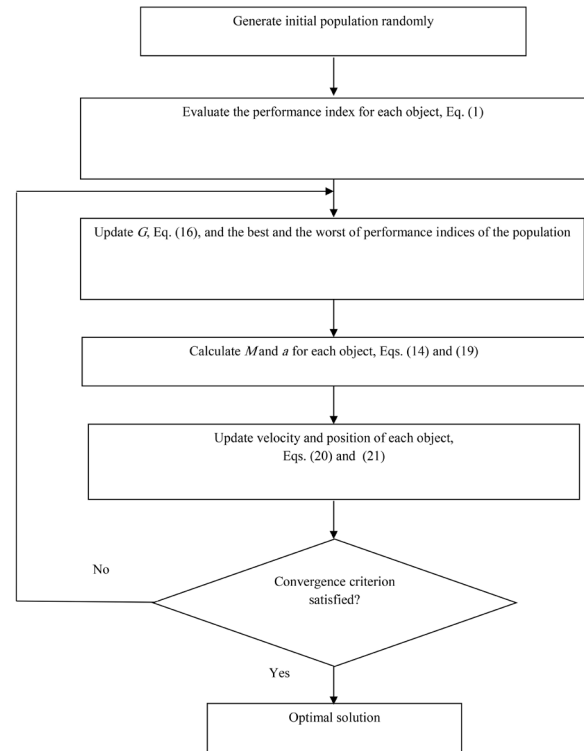
Fig. 1. Flowchart of GSA [25].

3- 2- Proposed IGSA

Improving the performance of GSA has been the subject of several studies. For example, in a study by Rashedi et al., a new version of GSA for binary encoding was introduced [32]. In their study, the probability value for each element of the binary vector corresponded to the calculated forces of each element which determined the zero and the unity values of those elements. Also, a novel moving strategy in the search space of GSA, was introduced and applied for identifying the parameters of hydraulic turbine governing system by Li and Zhou [33].

In GSA searching procedure, one object direction is calculated based on the overall force exerted by other objects and, as a result, the required computations are increased which consequently reduce the processing speed of the algorithm. To enhance the performance of GSA, Rashedi et al. hypothesized that considering a percentage of objects to calculate the forces of each object in each iteration can be effective to reduce the needed computations in each iteration, and, consequently, the processing speed of GSA was improved [32].
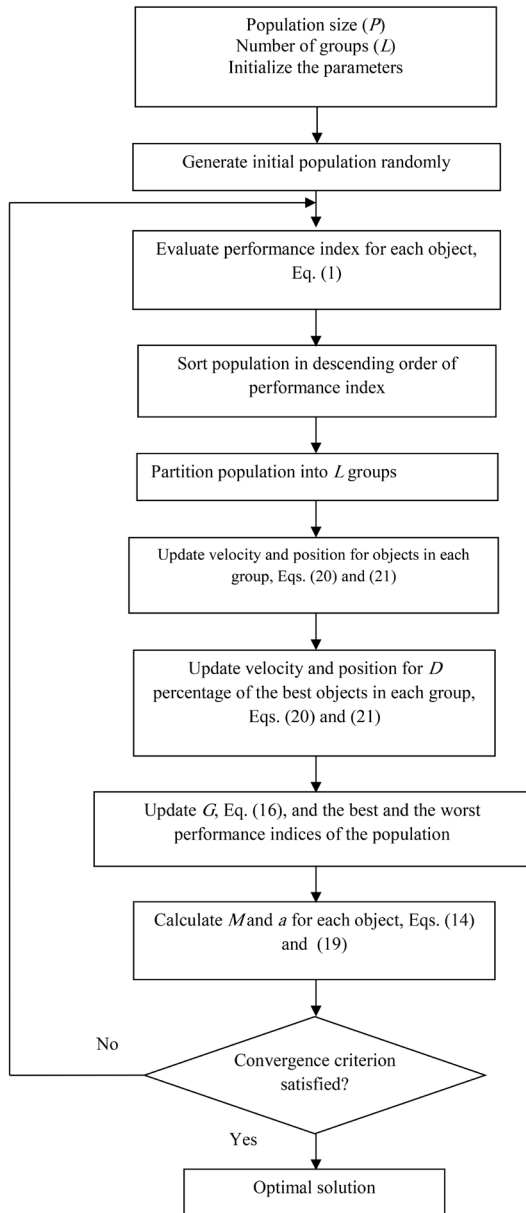

Fig. 2. Flowchart of IGSA developed in this study.

To formulate IGSA in this study, it is proposed to divide up the search space, similar to parallelization process in SFL algorithm [34], to accommodate for utilizing the strategy of considering a percentage of objects for calculating the forces in GSA. Therefore, the entire population of objects is divided into L groups where each group consists of μ objects that conduct local exploration of feasible space.
In each iteration of IGSA, to categorize the objects, their

performance indices are calculated based on Eq. (1) and then the objects are sorted in a descending order according to their performance index values. Then, the first object is assigned to the first group and the second object is assigned to the second group, and so on until $(L \times \mu)^{th}$ object is assigned to the Lth group. For each group, the movement of all objects is calculated. The heaviest objects in each group can be candidates for local minima solutions. To find a better solution, the intra effect of objects in each group is considered. Next, based on parameter D, that is the percentage of the heaviest objects selected from each group, the movements of objects are calculated. Then, all objects are gathered and the next iteration begins. As shown in the flowchart of IGSA in Fig. 2, this process continues until a specified convergence criterion is satisfied.
As the force calculation functions were described by equations (17) and (18), they are extensively time-consuming in GSA. The number of calls to the noted equations is reduced by

$$ U = (m \times L - 1)^{(m \times L - 1)} - [(\frac{D}{100} \times m \times L - 1)^{(\frac{D}{100} \times m \times L - 1)} + L \times (m - 1)^{(m-1)}] \quad (22) $$

in each iteration of IGSA which is expected to result in considerably lower convergence time. The first term of (22) represents all the calls in GSA (for calculation of the forces of each object on another). Also, the second and third terms in the brackets adjust the calls in extra and intra-groups in IGSA, respectively. In IGSA, the forces on each object stem from the objects in its own group while only the D percentage of objects of each group affects the D percentage of objects of the other groups.

3- 3- Applying GSA and IGSA
To apply GSA and IGSA to GEP problem, each object is defined as a 1×F vector where F is the product of time period (T) and candidate generation unit types (N). Figure 3 shows the model for objects used in GSA and IGSA where each element is an integer variable that corresponds to the number of each unit type in each stage.
Each element of the object is initialized randomly with considering equation (10). Also, the constant parameters G_0 and β in GSA and IGSA are assumed to be 100 and 0.5, respectively. It must be noted that to satisfy the constraints of GEP problem, equation (10) is modeled as a hard constraint and the remaining expressed by equations (11) to (13) are assumed as soft constraints modeled by penalty factors. If the soft constraints are not satisfied, an additional cost corresponding to the penalty factor is added to TC of Eq. (1).

4- Results and discussions
For the purpose of verification of simulation results and comparing the performances of GSA and IGSA, PSO algorithm is also used for optimization of the MINL GEP problem for four different case studies (Tables 1 to 4)), as discussed in this section. The single-line diagram for all
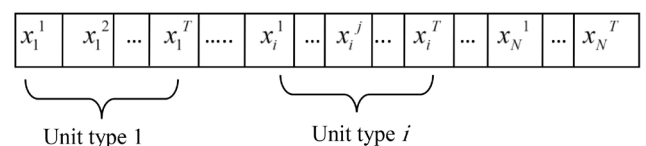

Fig. 3. A model for objects used in GSA and IGSA.

case studies is shown in Fig. 4. Also, comparison survey on other studies on the optimization of MINL GEP problem are provided in Table 5.

For modeling purposes, the peak load in each step is considered as the load model which must be met by adding power plants in the planning horizon. This technique has been used in the most of GEP problems [23]. Moreover, it must be noted that the constraints of this study are divided into hard and soft constraints. The hard constraints are those that must be met without any penalty, which is associated with the maximum installation of each candidate generation units type in each stage (the equation (10)). The soft constraints are those that are penalized in the objective function (see (11) to (13)). It is noted that the penalty cost value affects the values by which the constraints are satisfied. f the penalty cost value is lower than TC, the search algorithm prefers to ignore these constraints as they have small effects on the TC value and the corresponding penalty cost is paid. Thus, in this study, to assure that the soft constraints are met, the penalty cost value is chosen close to TC value.

4- 1- Case Study 1

A system with 15 existing and five types of candidate generation units [15, 23] is examined in Case Study 1. Technical and economic data of existing and candidate generation units are shown in Tables 1 (a) and (b) respectively. Moreover, the forecasted peak load for the planning horizon of 20 years is given in Table 1 (c).
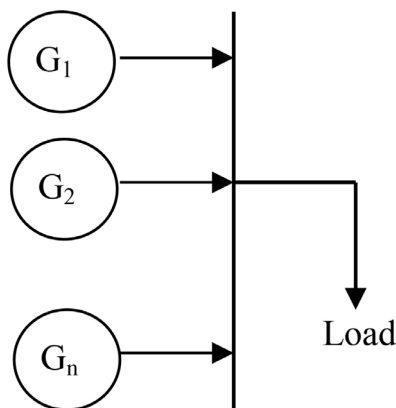

Fig. 4. Single line diagram for all case studies.

The discount rate, LOLP criteria, and the lower and upper bounds for the reserve limit are assumed to be 8.5%, 0.0027, 20%, and 50%, respectively. Lower and upper bounds of capacity limitations of each candidate generation units are considered as 0 and 30% for oil-fired units, 0 and 40% for liquid natural gas (LNG)-fired, 20 and 60% for coal-fired, and 30 and 60% for nuclear, respectively. Also, EENS cost is assumed to be 0.05 $/kWh [23].

For Case Study 1, the planning horizon of 20 years is composed of 10 two-year stages. Moreover, it is assumed that there is a two-year interval between the reference date of the cost calculations and the first year of study.

For PSO, GSA, and IGSA, the initial population size and the maximum number of iterations are 500 and 400 in each algorithm, respectively. To validate the results of GSA and IGSA, the results from application of SFL algorithm and GA for

Case Study 1, examined by Jadidoleslam et al. [23], are used. The optimal solutions obtained from PSO, GSA, and IGSA applied to Case Study 1 are reported in Table 1 (d), and, it is found that IGSA achieves the lowest TC of $19163.31×10⁶. It is determined that GA, SFL, PSO, and GSA result in a higher TC by 2.90, 2.75, 10.61 and 7.01%, respectively. Also, based on the results, the runtime of IGSA is less than GSA but higher than PSO algorithm.
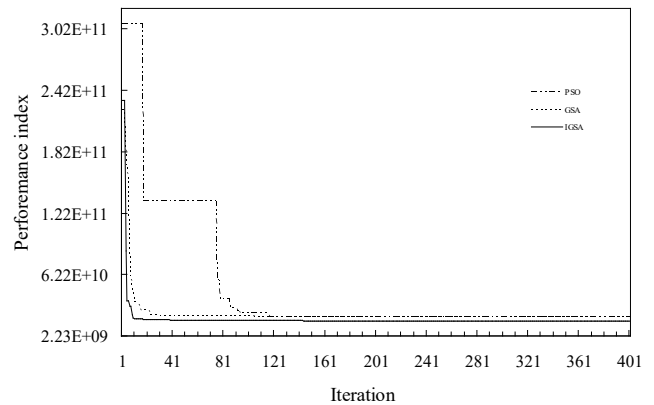
Fig. 5. Case Study 1: convergences of PSO, GSA, and IGSA used for optimization of GEP problem.

For IGSA, all objects are divided into five groups and parameter D is assumed as 30%. The convergence curves of PSO, GSA, and IGSA for optimization of the GEP problem are shown in Fig. 5.

As shown in Tables 1 (e) and (f), IGSA performance is affected by the number of groups and values of D, respectively. It is observed that increasing the number of groups can improve the search ability of IGSA and, therefore, decrease TC. However, this decrease in TC continues for a specific number of groups and, thereafter, TC is increased. It is therefore determined that the number of groups must be tuned for applying IGSA.

Moreover, IGSA is applied for 10 runs for different values of D, where the positions of objects in each group change the optimal TCs (Table 1 (f)).

Table 1 (a): Case Study 1: technical and economic data of existing units [15, 23].

Fuel type	No. of units	Unit capacity (MW)	FOR (%)	Operating cost ($/kWh)	Fixed OM cost ($/kW-Mon)
Oil #1	1	200	7.0	0.024	2.25
Oil #2	1	200	6.8	0.027	2.25
Oil #3	1	150	6.0	0.030	2.13
LNG #1	3	50	3.0	0.043	4.53
LNG #2	1	400	10.0	0.038	1.63
LNG #3	1	400	10.0	0.040	1.63
LNG #4	1	450	11.0	0.035	2.00
Coal #1	2	250	15.0	0.023	6.65
Coal #2	1	500	9.0	0.019	2.81
Coal #3	1	500	8.5	0.015	2.81
Nuclear #1	1	1000	9.0	0.005	4.94
Nuclear #2	1	1000	8.8	0.005	4.63

Table 1 (b): Case Study 1: Technical and economic data of candidate generation units [15, 23].

Candidate generation type	Availability upper limit	Unit capacity (MW)	FOR (%)	Operating cost ($/kWh)	Fixed OM cost ($/kW-Mon)	Capital Cost ($/kW)	Lifetime (yr)
Oil	5	200	7.0	0.021	2.20	812.5	25
LNG #2	4	450	10.0	0.035	0.90	500.0	20
Coal	3	500	9.5	0.014	2.75	1062.5	25
Nuclear #1	3	1000	9.0	0.004	4.60	1625.0	25
Nuclear #2	3	700	7.0	0.003	5.50	1750.0	25

Table 1 (c): Case Study 1: forecasted peak load for the planning horizon of 20 years [23].

Stage (two years)	0	1	2	3	4	5	6	7	8	9	10
Year	2010	2012	2014	2016	2018	2020	2022	2024	2026	2028	2030
Peak load(MW)	5000	7000	9000	10000	12000	13000	14000	15000	17000	18000	20000

Table 1 (d): Case Study 1: performances of GA, SFL, PSO, GSA, and IGSA.

Algorithm	TC (M$)	TC difference with optimal answer (%)	Runtime (s)	Iteration
GA [23]	19719.50	2.90	*	*
SFL [23]	19689.87	2.75	*	*
PSO	21196.30	10.61	308.23	137
GSA	20508.39	7.01	725.86	167
IGSA	19163.31	-	426.55	295

*: These data were not available.

Table 1 (e): Case Study 1: effects of a number of groups on optimal TC computed by IGSA (D = 30%).

TC (M$)	Number of groups
20150.23	2
20029.82	4
19163.31	5
20040.45	10
20720.45	20

Table 1 (f): Case Study 1: effect of variation of parameter D on optimal TC computed by IGSA with 5 groups.

TC (M$)	D (%)
19571.68	10
20134.16	15
19884.79	20
19964.90	25
19163.31	30
20170.61	35

Table 1 (g): Case Study 1: optimal number of candidate generation units in each stage of GEP problem, based on IGSA.

Unit types	Number of candidate generation unit types									
	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Stage 8	Stage 9	Stage 10
Oil	3	4	3	3	2	0	2	3	0	1
LNG #2	0	0	0	0	0	1	0	1	0	1
Coal	2	2	1	1	1	1	1	1	1	0
Nuclear #1	2	0	0	1	0	0	0	0	0	1
Nuclear #2	1	0	0	0	0	1	1	0	1	1

Table 2 (a): Case Study 2: technical and economic data of existing units [21].

Name (fuel type)	No. of units	Unit capacity (MW)	FOR (%)	Operating cost ($/kWh)	Fixed OM cost ($/kW-Mon)
Coal	1	1000	6.0	0.00421	1.0
Oil #1	1	300	8.0	0.01130	1.0
Oil #2	1	700	6.0	0.00924	1.0
LNG	1	300	8.0	0.00988	1.0
Gas	1	300	6.0	0.01216	1.0

Table 2 (b): Case Study 2: technical and economic data of candidate generation units [21].

Candidate type	Availability upper limit	Unit capacity (MW)	FOR (%)	Operating cost ($/kWh)	Fixed OM cost ($/kW-Mon)	Capital Cost ($/kW)	Lifetime (yr)
Coal	1	1000	6.0	0.00421	1.0	735	25
Oil #1	2	300	8.0	0.01130	1.0	341	25
Oil #2	2	700	6.0	0.00924	1.0	390	25
LNG	5	300	8.0	0.00988	1.0	400	20
Gas	2	300	6.0	0.01216	1.0	152	25

Table 2 (c): Case Study 2: forecasted peak load for the planning horizon of 10 years [21].

Stage (one year)	0	1	2	3	4	5	6	7	8	9	10
Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Peak load (MW)	1600	1760	1936	2129.6	2342.6	2576.9	2834.6	3118.1	3429.9	3772.9	4150.2

Table 2 (d): Case Study 2: comparison of performances of PSO, GSA, and IGSA.

Algorithm	TC (M$)	TC difference with optimal answer (%)	Runtime (s)	Iteration
PSO	1537.87	13.45	248.17	113
GSA	1410.81	4.08	691.03	169
IGSA	1355.45	-	392.57	64

Table 2 (e): Case Study 2: optimal number of candidate generation units in each stage of GEP problem, based on IGSA.

Unit types	Number of candidate generation unit type									
	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Stage 8	Stage 9	Stage 10
Coal	0	0	0	0	0	0	0	0	0	1
Oil #1	0	0	0	0	0	0	0	0	0	0
Oil #2	0	0	0	0	0	0	0	0	0	0
LNG	0	0	0	0	1	4	0	0	0	0
Gas	0	0	2	0	0	0	0	0	0	0

Table 3 (a): Case Study 3: technical and economic data of existing units [35].

Name (fuel type)	No. of units	Unit capacity (MW)	FOR (%)	Operating cost ($/kWh)	Fixed OM cost ($/kW-Mon)
Oil	1	350	2.0	0.02	0
Coal	2	650	4.0	0.01	0
Hydro	2	300	1.0	0.0013	0
Gas	2	100	1.0	0.026	0

Table 3 (b): Case Study 3: technical and economic data of candidate generation units [35].

Candidate type	Availability upper limit	Unit capacity (MW)	FOR (%)	Operating cost ($/kWh)	Fixed OM cost ($/kW-Mon)	Capital Cost ($/kW)	Lifetime (yr)
Oil	2	350	2.0	0.02	0	500	25
Coal	3	650	4.0	0.01	0	650	25
Hydro #1	2	300	1.0	0.013	0	750	30
Hydro #2	2	600	1.5	0.002	0	900	30
Gas	6	100	1.0	0.026	0	250	25
Nuclear	2	900	5.0	0.004	0	1500	25

Table 3 (c): Case Study 3: forecasted peak load for the planning horizon of 20 years [35].

Stage (five years)	0	1	2	3	4
Year	1990	1995	2000	2005	2010
Peak load (MW)	2000	3000	4200	5500	7000

Table 3 (d): Case Study 3: performance comparison of PSO, GSA, and IGSA.

Algorithm	TC (M$)	TC difference with optimal answer (%)	Runtime (s)	Iteration
PSO	2737.14	8.17	168.57	93
GSA	2808.78	11.00	418.76	110
IGSA	2530.43	-	215.02	134

Table 3 (e): Case Study 3: optimal number of candidate generation units in each stage of GEP problem, based on IGSA.

Unit types	Number of candidate generation unit type			
	Stage 1	Stage 2	Stage 3	Stage 4
Oil	0	0	0	0
Coal	0	0	2	1
Hydro #1	0	0	0	0
Hydro #2	0	0	0	1
Gas	0	4	0	3
Nuclear	2	1	0	0

Table 4 (b): Case Study 4: performance comparison for PSO, GSA, and IGSA.

Algorithm	TC (M$)	TC difference with optimal answer (%)	Runtime (s)	Iteration
PSO	4821.24	14.16	295.61	78
GSA	4481.52	6.40	752.55	127
IGSA	4211.96	-	417.9	170

Table 4 (a): Case Study 4: forecasted peak load for the planning horizon of 20 years.

Stage (two years)	0	1	2	3	4	5	6	7	8	9	10
Year	1990	1992	1994	1996	1998	2000	2002	2004	2006	2008	2010
Peak load(MW)	2000	3000	3400	3750	4300	4670	5100	5630	6180	6590	7000

Table 4 (c): Case Study 4: Optimal number of candidate generation units in each stage of GEP problem, based on IGSA.

Unit types	Number of candidate generation unit types									
	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Stage 8	Stage 9	Stage 10
Oil	0	0	0	0	0	0	0	0	1	1
Coal	0	0	0	1	0	0	0	0	0	0
Hydro #1	0	0	1	0	0	1	0	0	0	1
Hydro #2	0	0	0	0	1	0	0	0	0	0
Gas	0	0	1	0	2	2	0	5	2	1
Nuclear	2	0	0	0	0	0	1	0	0	0

Table 5: Summary of studies for solving MINL GEP problem optimized based on different algorithms.

Ref.	GEP horizon (yr)	Generation system type	Optimization algorithm
[15]	14, 24	15 existing and 5 types of candidate generation units	Improved GA
[16]	5, 7, 10, 15, 20, 25, 30	5 existing and 16 types of candidate generation units	GA
[18]	6	12 existing and 5 types of candidate generation units	Honey bee mating
[18]	-	4 types of candidate generation units	Improved immune algorithm
[20]	14, 24	15 existing and 5 types of candidate generation units	ICA
[21]	10	12 existing and 5 types of candidate generation units	Cross entropy
[22]	6, 14	5 existing and 18 and 36 types of candidate generation units for two case studies	Improved PSO
[23]	10, 20	15 existing and 5 types of candidate generation units	SFL
This study	20	12 existing and 5 types of candidate generation units	PSO, GSA, and IGSA
	10	5 existing and 12 types of candidate generation units	
	20	4 existing and 6 types of candidate generation units	
	20	4 existing and 6 types of candidate generation units	

Based on IGSA resulting in lowest TC, the optimal number of candidate generation units for the GEP problem of Case Study 1 is shown in Table 1 (g).

4- 2- Case Study 2

This case is based on a test system with five existing and twelve types of candidate generation units, as described in Tables 2 (a) and (b) [21]. The peak load is 1600MW in the base year, 2010, with a 10% annual rise [21], as specified in Table 2 (c). The LOLP limit is assumed as 0.01 and the reserve margin in the lower and upper bounds are 15% and 50% of the peak load, respectively. Also, the lower and upper bounds of capacity limitations of each candidate generation units are set 0% and 40% for oil-fired, LNG-fired, and gas-fired units and 20% and 60% for coal-fired, respectively. Other economic data are assumed to be the same as the test system in Case Study 1.

The planning horizon is set 10 years which consists of one-year stages. Also, the interval between the reference date of the cost calculations and the first year of this case study is one year.

For Case Study 2, the number of groups is 5 and the value of D is set at 19% for IGSA. Table 2 (d) shows that the TC calculated based on IGSA is lower than that of PSO and GSA by 13.45% and 4.08%, respectively, which demonstrates the superiority of IGSA to optimize the GEP problem. Table 2 (e) gives the optimal results of IGSA obtained with lowest TC, for Case Study 2.

4- 3- Case Study 3

For Case Study 3, the system consists of four existing and six types of candidate generation units, as shown in Tables 3 (a) and (b) [35]. The planning horizon extends over 20 years and it is divided into four stages. Moreover, there is a 5-year interval between the reference date of the cost calculations and the first year of this case study.

The forecasted peak load for these stages is given in Table 3 (c). Some data such as the lifetime of candidate generation units and the limitation values, unavailable in Case Study 3, are assumed similar to those of Case Study 1. Also, the fixed operation and maintenance cost of units are included in operating cost, thus the corresponding values in Table 3 (a) are shown as zero.

The lower and upper bounds of capacity limitations of each candidate generation units are set 0% and 40% for oil-fired units, 20% and 60% for coal-fired, 0% and 40% for hydro, 0% and 40% for Gas-fired, and 20% and 50% for nuclear, respectively.

For Case Study 3, the results for TCs based on the application of PSO, GSA, and IGSA for solving GEP problem for 10 runs are reported in Table 3 (d). In this case study, IGSA achieves the best solution and the optimal number of candidate generation units in each stage is listed in Table 3 (e). It must be noted that in this case study, for IGSA, the number of groups is 5 and the value of D is set at 35%.

4- 4- Case Study 4

In this case study, the system is similar to Case study 3 with

the difference that the number of planning stages is assumed to be 10 instead of 4. The peak load of each stage is shown in Table 4 (a). The GEP problem is optimized and the best TCs for GSA and IGSA are listed in Table 4 (b). The results show that IGSA achieves lower TC by 14.16 and 6.4% as compared with PSO and GSA, respectively, and the optimal combinations of candidate generation units are listed in Table 4 (c). IGSA in this case study consists of two groups and the value of D is set at 23%.

Based on the simulation results for four case studies, it is determined that IGSA reaches lower TC value as compared to those of other algorithms due to the improved search ability of the algorithm in the feasible space. Moreover, the results show that by tuning the parameters of the percentage of D and the number of groups, IGSA can achieve a better optimal solution than GSA.

5- Conclusions and recommendations

In this study, GSA is examined to solve MINL GEP problem. Also, GSA is improved and IGSA is introduced and implemented successfully. To validate the performance of GSA and IGSA for the optimization of MINL GEP problem, PSO algorithm is adopted four different case studies. It is determined that GSA and IGSA produce more accurate results than PSO algorithm and also, the improvements of GSA are effective and IGSA achieves the lowest TCs. The results show that IGSA, which is two times faster than GSA on average, achieves a better performance, compared with GSA by 7.01, 4.08, 11.00, and 6.40% in the four case studies examined. It is concluded that the main advantage of IGSA, i.e. a specific grouping of objects and selecting a percentage of them in each group, results in a more accurate and faster performance.

For future works, applying of GSA and IGSA in the formulation of MINL GEP problem with considerations for the penetration of renewable energy resources such as wind power generation is suggested. Also, IGSA can be considered to solve other MINL optimization problems.

List of Acronyms

DP	Dynamic programming
EENS	Energy expected not served
ENS	Energy not served
FOR	Forced outage rate
GA	Genetic algorithm
GEP	Generation expansion planning
GSA	Gravitational search algorithm
ICA	Imperialist competitive algorithm
IGSA	Improved gravitational search algorithm
LNG	Liquid natural gas
LOLP	Loss of load probability
MINL	Mixed-integer non-linear
PSO	Particle swarm optimization
OM	Operating and maintenance
SFL	Shuffled frog leaping
TC	Total cost
TCDP	Tunnel-constrained dynamic programming

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