Application of Opposition-based Differential Evolution Algorithm to Generation Expansion Planning Problem

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Abstract – 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 pre specified reliability criterion over a planning horizon. In this paper, Differential Evolution (DE), and Opposition-based Differential Evolution (ODE) algorithms have been applied to the GEP problem. The original GEP problem has been modified by incorporating Virtual Mapping Procedure (VMP). The GEP problem of a synthetic test systems for 6-year, 14-year and 24-year planning horizons having five types of candidate units have been considered. The results have been compared with Dynamic Programming (DP) method. The ODE performs well and converges faster than DE.

Keywords: Dynamic programming, Differential evolution, Generation expansion planning, Opposition-based differential evolution, Virtual mapping procedure

1. Introduction

The Generation Expansion Planning (GEP) problem for an electric utility is the problem of determining WHAT generation plants should be constructed, WHERE and WHEN they should be committed over a "long-range" planning horizon [1-2]. GEP is a challenging problem due to its non-linear, large-scale, highly constrained, and discrete nature of the decision variables (unit size and allocation) [2-3].

The basic objective of the GEP is to determine the best investment plan that minimizes present value of the investment and operating costs such that it will meet the load demand. Earlier for finding the solution of the GEP problem, the methods like DP [3], tunnel constrained DP [4], Branch and bound method [5], and Benders-decomposition [6] were applied. Some of the emerging techniques for GEP problem are reviewed in [7].

Genetic Algorithm (GA) and its variants are applied to the GEP in [8-10]. Argyris G. Kagiannas et al have given a comprehensive review of GEP methods applied from monopoly to Competitive markets [11]. Hybrid approaches like GA with Immune algorithm [12] and DP [13] are also applied. Eight meta-heuristic techniques were applied and the results are compared with DP in [14]. The authors

concluded that Differential Evolution (DE) [15] outperformed other meta-heuristic techniques.

The Elitist Non-dominated Sorting Genetic Algorithm version II (NSGA-II) is applied to multi-objective GEP problem [16-17]. The environmental constraints and impact of various incentive mechanisms are considered in [18-20]. Yanyi He et al compared the effectiveness and efficiency of cap-and-trade and carbon tax policies in a GEP framework [21].

The game theory and modified game theory along with Meta-heuristic techniques has been applied to GEP in partially deregulated and Competitive environment in [22-26]. Still in the developing countries, the GEP has been done by the Centralized Electricity Authority. Hence, the least cost GEP model will be very much useful for those countries.

DE has been widely applied in variety of fields [27-28]. Even though it produces better results, the convergence rate of the DE for a particular problem is low. The concept of Opposition-based Learning has been utilized to accelerate the convergence rate of DE in [29]. This new approach has been called as opposition-based differential evolution (ODE) [30].

In this paper, DE, and ODE are applied to the GEP problem and the results are compared with DP. The rest of the paper is organized as follows: Section II describes the GEP problem formulation and Section III describes implementation of the GEP problem. Section IV provides test results, and section V concludes.

2. Generation Expansion Planning (GEP) Problem Formulation

The GEP problem is equivalent to finding a set of best

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decision vectors over a planning horizon that minimizes the investment and operating costs under relevant constraints.

2.1. Cost objective

The cost objective is represented by the following expression

$$\min\ Cost\ =\ \sum_{t=1}^{T}\left[I(U_t)+M(X_t)+O(X_t)-S(U_t)\right] \quad (1)$$

where,

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

$$I(U_t) = (1+d)^{-2t} \sum_{i=1}^{N}\left(CI_i \times U_{t,i}\right) \tag{3}$$

$$S(U_t) = (1+d)^{-T'} \sum_{i=1}^{N}\left(CI_i \times \delta_i \times U_{t,i}\right) \tag{4}$$

$$M(X_t) = \sum_{s'=0}^{1}\left((1+d)^{1.5+t'+s'}\left(\sum(X_t \times FC)+MC\right)\right) \tag{5}$$

$$O(X_t) = EENS \times OC \times \sum_{s'=0}^{1}\left((1+d)^{1.5+t'+s'}\right) \tag{6}$$

The outage cost calculation of (6), used in (1), depends on Expected Energy Not Served (EENS). The equivalent energy function method [1] is used to calculate EENS (and also to calculate loss of load probability, LOLP, used in the constraint objective).

$$t' = 2(t-1) \text{ and } T' = 2\times T - t' \tag{7}$$

and

Cost	total cost, \$;
U_t	N-dimensional vector of introduced units in the *t*-th stage (1 stage = 2 years);
$U_{t,i}$	the number of introduced units of *i*-th type in *t*-th stage;
X_t	cumulative capacity vector of existing units in *t*-th stage, (MW);
$I(U_t)$	is the investment cost of the introduced unit at the *t*-th stage, \$;
$M(X_t)$	total operation and maintenance cost of existing and the newly introduced units, \$;
s'	variable used to indicate that the maintenance cost is calculated at the middle of each year;
$O(X_t)$	outage cost of the existing and the introduced units, \$;
$S(U_t)$	salvage value of the introduced unit at *t*-th interval, \$;
d	discount rate;
CI_i	capital investment cost of *i*-th unit, \$;
δ_i	salvage factor of *i*-th unit;
T	length of the planning horizon (in stages);

N	total number of different types of units;
FC	fixed operation and maintenance cost of the units, \$/MW;
MC	variable operation and maintenance cost of the units, \$;
$EENS$	Expected energy not served, MWhrs;
OC	value of outage cost constant, \$/ MWhrs

2.2. Constraints

1) Construction limit: Let U_t represent the units to be committed in the expansion plan at stage *t* that must satisfy

$$0 \le U_t \le U_{\max,t} \tag{8}$$

where $U_{\max,t}$ is the maximum construction capacity of the units at stage *t*.

2) Reserve Margin: The selected units must satisfy the minimum and maximum reserve margin.

$$(1+R_{\min})\times D_t \le \sum_{i=1}^{N} X_{t,i} \le (1+R_{\max})\times D_t \tag{9}$$

where

R_{min}	minimum reserve margin;
R_{max}	maximum reserve margin;
D_t	demand at the *t*-th stage in megawatts (MW);
$X_{t,i}$	cumulative capacity of *i*-th unit at stage *t*.

3) Fuel Mix Ratio: The GEP has different types of generating units such as coal, liquefied natural gas (LNG), oil, and nuclear. The selected units along with the existing units of each type must satisfy the fuel mix ratio

$$FM_{\min}^{j} \le X_{t,j}\left/ \sum_{i=1}^{N} X_{t,i}\right. \le FM_{\max}^{j} \quad j=1,2,...,N \tag{10}$$

where

$FM_{\min}^{j}$	minimum fuel mix ratio of *j*-th type;
$FM_{\max}^{j}$	maximum fuel mix ratio of *j*-th type;
j	type of the unit (e.g., oil, LNG, coal, nuclear).

4) Reliability Criterion: The introduced units along with the existing units must satisfy a reliability criterion on loss of load probability (LOLP)

$$LOLP(X_t) \le \varepsilon \tag{11}$$

where ε is the reliability criterion, a fraction, for maximum allowable LOLP. Minimum reserve margin constraint avoids the need for a separate demand constraint.

3. Implementation of the GEP Problem

3.1. Virtual Mapping Procedure (VMP)

To improve the convergence characteristics of the algorithms VMP is introduced in the GEP problem. VMP is concerned with the solution representation; it transforms each combination of candidate units for every year into a dummy decision variable, referred to as the VMP variable [14]. The value of the VMP variable for a specific candidate solution is the rank of that solution when all solutions are sorted in ascending order of capacity.

To illustrate, consider the range of the decision vector lies between [0] and $U_{\max,t}$ as given in [9]. The capacity vector is [200 450 500 1000 700]. Let a candidate solution be U_1= [5 0 1 1 0]; then its corresponding capacity will be 2500 MW ($5\times200 + 0\times450 + 1\times500 + 1\times1000 + 0\times700$). If U_1 changes to [5 0 1 2 0] (via mutation operators), then the capacity is increased from 2500 MW to 3500 MW, a difference of 1000 MW, which is a large deviation.

The solution [5 0 1 1 0] with capacity of 2500 has VMP value of 190. A change (by mutation) to VMP value of 198 would correspond to a solution of [2 1 2 0 1] with capacity of 2550, a relatively small change in capacity. Without VMP, to get a solution with capacity of 2550 MW, all 5 variable values must be changed. This may take a very large number of iterations, and in general, moving from sub-optimal to optimal may take much iteration.

Since five different types of units are assumed to be available for each stage, the size of the decision vector increases by multiples of 5 as the number of stages increases. However, when using VMP, the number of decision variables obtained is a multiple of its number of stages; the size of the decision vector becomes 3 for a 3-stage problem. Thus, a size reduction of 80%, [(15-3)/15, for 3 stages] is realized. Hence, the dimensionality of the problem, in terms of the number of decision variables, is reduced, and computational time and memory requirements reduce accordingly.

3.2. Differential Evolution (DE)

Price and Storn [15] proposed DE. It is a population-based stochastic direct search algorithm like GA but differs from GA with respect to the mechanics of mutation, crossover and selection.

At each iteration J, DE employs the mutation and crossover operations to produce a trail vector $V_{i,J}$ for each individual vector $X_{i,J}$, also called target vector, in the current population.

Based on the mutation rule, the DE has been classified into more than ten different strategies [15]. Few of them are:

i) DE/best/1

$$U_{i,J+1} = X_{best} + F \times (X_{r1,J} - X_{r2,J}) \tag{13}$$

ii) DE/rand/1

$$U_{i,J+1} = X_{r3,J} + F \times (X_{r1,J} - X_{r2,J}) \tag{14}$$

iii) DE/rand-to-best/1

$$U_{i,J+1} = X_{i,J} + F \times (X_{best} - X_{i,J} + X_{r1,J} - X_{r2,J}) \tag{15}$$

iv) DE/best/2

$$U_{i,J+1} = X_{best} + F \times (X_{r1,J} - X_{r2,J} + X_{r3,J} - X_{r4,J}) \tag{16}$$

v) DE/rand/2

$$U_{i,J+1} = X_{r5,J} + F \times (X_{r1,J} - X_{r2,J} + X_{r3,J} - X_{r4,J}) \tag{17}$$

where,

X	is the set of population
$U_{i,J+1}$	is the mutated i-th individual for the next iteration
$X_{i,J}$	is i-th individual of current iteration
X_{best}	is the best individuals among the population X
F	is a constant [0, 2]
J	is the current iteration

$X_{r1,J}$, $X_{r2,J}$, $X_{r3,J}$, $X_{r4,J}$, and $X_{r5,J}$ are the randomly selected populations in the current iteration.

After mutation, the exponential crossover is applied on the individuals by the rule

$$V_{i,J+1} = \begin{cases} U_{k,i,J+1} & \text{if } (\text{rand}_j[0,1] \leq CR) \text{ or } (k = k_{rand}) \\ X_{k,i,J} & \text{otherwise} \end{cases}, \ k = 1,2,...,n \tag{18}$$

where, CR is the crossover rate [0, 1]

The parents for the next iteration are selected based on one-to-one greedy selection scheme for minimization problems such as GEP as follows:

$$X_{i,J+1} = \begin{cases} V_{i,J+1} & \text{if } f(V_{i,J+1}) > f(X_{i,J+1}) \\ X_{i,J+1} & \text{if } f(X_{i,J+1}) > f(V_{i,J+1}) \end{cases} \tag{19}$$

where,

$f(V_{i,J+1})$ is the fitness function value of i-th individual of the population in which the mutation and crossover operators are applied

$f(X_{i,J+1})$ is the fitness function value of i-th individual in the original population

The loss of best individuals in the subsequent iteration is avoided by this selection mechanism, as the best individuals replace the worst individuals.

3.3. Opposition-based Differential Evolution (ODE)

ODE [24] uses opposite numbers during population initialization and also for generating new populations

during the evolutionary process. The main idea behind the opposition is the simultaneous consideration of an estimate and its corresponding opposite estimate (i.e., guess and opposite guess) in order to achieve a better approximation for the current candidate solution. The pseudo code for the ODE [25] is given below

1: Generate uniformly distributed random population X_o
   /*Opposition-based Population Initialization*/
2: for $i = 0$ to NP do
3: for $j = 0$ to D do
4: $OX_{0i, j} \leftarrow X_{min, j} + X_{max, j} - X_{0i, j}$
5: end for
6: end for
7: Select NP fittest individuals from set the $\{X_0, OX_0\}$ as initial population X_0
   /*Opposition-based Population Initialization*/
8: while ($J<J_{max}$ and $NFE<MAX_{NFE}$) do /*NFE number of function evaluations*/
9: **DE's Evolution steps**
   /*Opposition-based Generation Jumping*/
10: if *rand (0, 1)* $<Z_r$(Jumping rate) then
11: for $i = 0$ to NP do
12: for $j = 0$ to D do
13: $OX_{i, j} \leftarrow MIN_j^p + MAX_j^p - X_{i,j}$
14: end for
15: end for
16: Select NP fittest individuals from set the $\{X, OX\}$ as current population X
17: end if
   /*Opposition-based Generation Jumping*/
18: end while

4. Test Results

All the algorithms DE, ODE, and DP were implemented using MATLAB version 7.2, on a desktop PC with Intel Core i5 processor having 3.10GHz speed and 4 GB RAM.

4.1. Test system description

The forecasted peak demand and other technical data are taken from [9]. The test system with 15 existing power plants and 5 types of candidate options is considered for a 6-years, 14-years and 24-years planning horizon. The planning horizon comprises of stages with 2-year intervals.

4.2. Parameters for GEP

The lower and upper bounds for reserve margin are set at 20% and 40% respectively. The salvage factor (δ) for oil, LNG, coal, PWR, and PHWR are taken as 0.1, 0.1, 0.15, 0.2 and 0.2, respectively. Cost of EENS is set at 0.05 $/kWh. The discount rate is 8.5%. It is assumed that the

date of availability of new generation is two years beyond the current date. The year k investment cost is assumed to incur in the beginning of year k; the year k maintenance cost is assumed to incur in the middle of year k and is calculated by using the equivalent energy function method [1]. The year k salvage cost is estimated at the end of the planning horizon.

4.3. Parameters for DE, and ODE

The best parameters for the algorithms DE, and ODE are chosen through 50 independent test runs. Their values for the entire planning horizon are tabulated in Table 1. These values are taken for all the experiments conducted; a change is mentioned in a parameter when we want to study the impact of that particular parameter on GEP problem.

Table 1. Best Parameters for DE and ODE

Sl. No	Parameter	Algorithm	
		DE	ODE
1	Number of Populations NP	$20\times n^*$	$20\times n$
2	Maximum no. of function evaluations	$10000\times n$	$10000\times n$
3	Mutation Strategy	DE/rand/1/bin	DE/rand/1/bin
4	Scaling Factor F	0.5	0.5
5	Crossover rate CR	0.5	0.5
6	Jumping rateZ_r	-	0.3

*where **n** is the number of VMP decision variable

4.3. Results and discussion

The effect of population size, mutation strategy, jumping rate, virtual mapping procedure and selection mechanism are investigated and results for all the planning horizons are presented in this section.

1. Effect of Population Size

In order to investigate the effect of the population size, experiments with various population sizes are done and the results are reported in Table 2. The 6-year planning horizon is considered, since it consumes lesser computational time rather than higher planning horizon. Here the DE and ODE

Table 2. Effect of Population Size

Population size	Algorithm	Cost x 10^{10} \$		Error (%)	SR (%)
		Best	Worst		
20×n (60)	DE	1.2009	1.2009	0	100
	ODE	1.2009	1.2009	0	100
15×n (45)	DE	1.2009	1.2010	0-0.08	80
	ODE	1.2009	1.2012	0-0.025	90
10×n (30)	DE	1.2009	1.2014	0-0.04	70
	ODE	1.2009	1.2012	0-0.025	70
3×n (9)	DE	1.2009	1.2024	0-0.12	30
	ODE	1.2009	1.2014	0-0.04	50
-	DP	1.2009	-	0	100

are considered with VMP.

The solution obtained by the DP is the optimal solution and it is taken as the reference for calculating the error percentage. The Success Rate (SR) is the ratio of the number of times the optimal solution found to the number of test runs. According to the results, the ODE performs better than DE. For larger population size 60, both the DE and ODE produces the better results i.e., 100% SR.

2. Effect of Various Mutation Strategies

There are more than ten mutation strategies are available for the DE. Many of the works reported in [15, 27, 28], utilizes the standard one, DE/rand/1/bin. We also utilized the same strategy for our GEP problem. In order to validate our choice we did some experiments with three other well known mutation strategies, DE/rand/1/exp, DE/rand/2/exp, and DE/rand/2/bin. The results are presented in Table 3.

According to the results in Table 3, the best mutation strategy for the both DE and ODE is DE/rand/1/bin.

3. Effect of Jumping Rate (Z_r)

In ODE, there is a new parameter called Jumping rate Z_r, that has to be fixed for the entire planning horizon. Obviously, the performance of the ODE will vary according to this parameter. If Z_r=0, means that there is no jumping at all, on the other hand if Z_r=1 in all the iterations jumping will take place and hence the number of function evaluations will increase. According to [29, 30] larger jumping rate more than 0.6 will lead the algorithm to premature convergence for most of the problem. The various values are taken for the comparison and the results are given in Table 4.

The other parameters, namely maximum number of function evaluations, cross over rate (*CR*) and scaling factor (*F*) are shown in Table 1 is also calculated based on the same type of experiments. The maximum number of function evaluations in ODE includes the extra evaluations required for the opposite points both at population initialization and generation jumping.

4. Effect of Virtual Mapping Procedure (VMP)

The results for the 6 year planning horizon for DE and ODE with and without VMP are presented in Table 5. The performance of the DE and ODE without VMP is poor, since it is not able to produce the 100% SR. Both DE and ODE with VMP are performing better, and hence it is very clear that inclusion of VMP improves the SR and also the performance of the algorithms. The convergence characteristics of DE and ODE with VMP are shown in Fig. 1(only 150 iterations are shown for better clarity). The ODE converges faster than DE and also variations in cost during iterations are lower in ODE than DE. The results of the GA and PSO [14] have also been given in Table 5 for comparison purpose. The DE and ODE results are better than GA and PSO, in terms of error and SR.

5. Effect of Selection Mechanism

In ODE algorithm, the best individuals based on the fitness value (objective function value) are selected during the population initialization and generation jumping. Since GEP is constrained problem; the best fit individual may have the constraint violation. Hence, in our study tournament selection with the pair-wise comparison is used. The individuals are selected based on the following procedure

i. when both individual and its opposite are feasible, the one with better objective function value is chosen,

ii. when individual is feasible and its opposite is infeasible, the feasible solution is chosen, and vice- versa

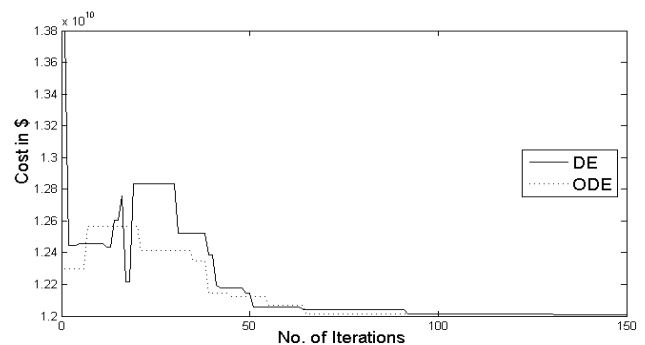iii. when both individual and its opposite are infeasible, the one with smaller constraint violation is chosen.

Table 3. Effect of Various Mutation Strategies

Mutation Strategy	Algorithm	Cost x 10^10 $		Error (%)	SR (%)
		Best	Worst		
DE/rand/1/bin	DE	1.2009	1.2009	0	100
	ODE	1.2009	1.2009	0	100
DE/rand/1/exp	DE	1.2009	1.2012	0-0.025	80
	ODE	1.2009	1.2014	0-0.04	80
DE/rand/2/exp	DE	1.2009	1.2024	0-0.12	50
	ODE	1.2009	1.2012	0-0.025	60
DE/rand/2/bin	DE	1.2009	1.2032	0-0.19	40
	ODE	1.2009	1.2024	0-0.12	30
-	DP	1.2009	-	0	100

Table 4. Effect of Jumping rate (Z_r)

Jumping rate (Z_r)	Cost x 10^10 $		Error (%)	SR (%)
	Best	Worst		
0.1	1.2009	1.2012	0-0.025	80
0.3	1.2009	1.2009	0	100
0.5	1.2009	1.2012	0-0.025	70
0.7	1.2009	1.2012	0-0.025	70
0.9	1.2009	1.2012	0-0.025	60

Fig. 1. Convergence Characteristics of DE and ODE for 6-year planning horizon

For the 6-year planning horizon, both the selection mechanism produces the 100% SR, hence the results for the 14-year planning horizon is taken for comparison purpose and presented in Table 6.

The error rate for ODE is lesser than the DE both in best cost and worst cost values. That means ODE better converges to the near optimal solution rather than DE. If we replace the selection with tournament selection, the number of times getting the best value is increases. Obviously the mean execution time is increased for the extra computational time required for the comparison.

6. Results for the 24 Year Planning Horizon

The optimal solution (through DP) for the 24 year planning horizon is unknown; it is very difficult to calculate the value due the high time complexity of the problem. The time required to solve the GEP problem increases exponentially with increase in planning period. It is clear from the Table 5 and Table 6 that the mean execution time required for the 14 year planning horizon through DP is 282.81 times higher than mean execution time required for the 6 year planning horizon. Projecting the same for 24 year planning horizon, it may be required to run the DP program continuously for 6 days (approximate), which is impractical.

In [14], it is given that for 24-year planning horizon the best cost value is 2.9206×10^{10}. ODE provides better result than that with lesser computational time.

Table 5. Results for 6-year Planning Horizon

Algorithm	Cost x 10^{10} \$		Error (%)	SR (%)	Mean Execution Time (in Seconds)
	Best	Worst			
DE (without VMP)	1.2057	1.3357	0.398-10.09	0	123.36
DE (with VMP)	1.2009	1.2009	0	100	42.29
ODE (without VMP)	1.2036	1.336	0.22-10.11	0	135.6
ODE (with VMP)	1.2009	1.2009	0	100	62.31
GA[14]	1.2009	1.2024	0-0.12	72	-
PSO[14]	1.2009	1.2014	0-0.14	68	-
DP	1.2009		0	100	6.1

Table 6. Results for 14- year Planning Horizon

Algorithm	Cost x 10^{10} \$		No. of times getting best value	Error (%)	SR (%)	Mean Execution Time (in Seconds)
	Best	Worst				
DE	2.1812	2.1943	1	0.068-0.665	0	512.5
ODE	2.1808	2.1848	3	0.018-0.23	0	493.67
ODE + Tournament Selection	2.1808	2.1923	7	0.018-0.57	0	623.35
GA[14]	2.1834	2.1979	-	0.2-0.8	0	-
PSO[14]	2.1859	2.1987	-	0.3-0.9	0	-
DP	2.1797		-	0	100	1725.2

Table 7. Results for 24- year Planning Horizon

Algorithm	Cost x 10^{10} \$		No. of times getting best value	Error (%)	SR (%)	Mean Execution Time (in Seconds)
	Best	Worst				
DE	2.925	2.9527	1	0.28-1.216	-	1867
ODE	2.9168	2.938	1	0-0.722	-	1932
ODE + Tournament Selection	2.9168	2.947	3	0-1.025	-	2155
GA[14]	2.9356	2.9970	-	0.5-2.6	-	-
PSO[14]	2.9279	2.9608	-	0.2-1.4	-	-
DP	Unknown		-	-	-	Unknown

* 2.9168×10^{10} have been considered as the best and error has been calculated.

5. Conclusion

The Differential Evolution (DE) and Opposition-based Differential Evolution (ODE) have been applied to solve the GEP problem. The optimal solution or near optimal solution is obtained by incorporating VMP. The results were validated with DP. The performance of the DE and ODE are compared in terms of their success rate and error percentage. For the shorter planning horizon (6-year), both DE and ODE are able to find the optimal solution. For the longer planning horizon (14-year), and very long planning horizon (24- year), ODE performs very well and produces better results than DE. The effects of population size, Mutation Strategies, VMP, Jumping rate and Selection Mechanism are also studied on the performance of DE and ODE algorithms. The results are also compared with GA and PSO results which are available in the literature.

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Appendix

Table A1. Forecasted Peak Demand [9]

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

Table A2. Technical and Economic Data of Existing Plants [9]

Name (Fuel Type)	No. of Units	Unit Capacity (MW)	FOR (%)	Operating Cost ($/KWh)	FixedO& M Cost ($/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

Table A3. Technical and Economic Data of Candidate Plants [9]

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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