A New Efficient GA-Benders' Decomposition Method: For Power Generation Expansion Planning With Emission Controls

Jiraporn Sirikum, Anulark Techanitisawad, and Voratas Kachitvichyanukul

***Abstract*—The power generation expansion planning (PGEP) problem is a large-scale mixed integer nonlinear programming (MINLP) problem cited as one of the most complex optimization problems. In this paper, an application of a new efficient methodology for solving the power generation expansion planning problem is presented. A comprehensive planning production simulation model is introduced toward formulating into an MINLP model. The model evaluates the most economical investment planning for additional thermal power generating units of the optimal mix for long-term power generation expansion planning with emission controls, regarding to the incorporated environmental costs, subject to the integrated requirements of power demands, power capacities, loss of load probability (LOLP) levels, locations, and environmental limitations for emission controls. A GA-heuristic-based method called GA-Benders' decomposition (GA-BD) is proposed for solving this complex problem. Finally, an application of the proposed GA-BD method is discussed and concluded.**

***Index Terms*—Benders' decomposition, emission modeling, GA-benders' decomposition, genetic algorithms, mixed integer nonlinear programming, power generation expansion planning.**

NOMENCLATURE

Indices

- d — DSM program $(d = 1, 2, \ldots, \mathrm{D})$.
- $j(n)$ — Types of the generating units $n(j = 1, 2, \ldots, \mathrm{J})$.
- $l(n)$ — Location of the generating units n in grid number $l(l = 1, 2, \ldots, \mathrm{L})$.
- $n, n(j,l)$ — Generating unit n, type j at location $l(\mathrm{n} = 1, 2, \ldots, \mathrm{N})$.
- p — Segments/blocks of load duration curve $(p = 1, 2, \ldots, \mathrm{P})$.
- q — Air pollutants; $q = 1$ is $\mathrm{SO_2}$; $q = 2$ is $\mathrm{PM_{10}}$.
- r — Location of receptors in grid number $r(r = 1, 2, \ldots, \mathrm{R})$.
- t — Time period of year t or year of operation of generating units $(t = 1, 2, \ldots, \mathrm{T})$.

Parameters

- a_{nt} — Availability of generating unit $n(j,l)$ in year t (%).
- b_{qrt} — Background concentrations of pollutant q at receptor in grid r in year $t(\mu\mathrm{g/m^3})$.
- c_{tp} — Big M coefficient for the power purchased cost of each block p in year t ($/MWh).
- d_{dt} — DSM costs for implementing DSM program d in year t ($/year).
- du_p — Duration time of block p (hours).
- e_{ntp} — Environmental costs of the generating unit $n(j,l)$ in year t ($/MWh).
- er_{nq} — Emission rate of the pollutant q emitted by generating unit $n(j,l)$ (g/MWh).
- f_{ntp} — Fuel cost for each unit of energy output from the generating unit $n(j,l)$ of block p in year t ($/MWh).
- g_{qt} — Maximum allowance for emitting pollutant q in year t (kg).
- i_{nt} — Capital cost of capacity of generating unit $n(j,l)$ in year t ($).
- $lolpc_t$ — Level of actual loss-of-load probability in year t.
- $lolps_t$ — Level of loss-of-load probability limit in year t.
- ls — Transmission and distribution losses of the system (%).
- ma_{qrt} — Maximum allowance of pollutant concentrations or Ambient Air Quality Standards for pollutants q at the receptor in grid r in year t $(\mu\mathrm{g/m^3})$.
- mc_n — Maximum annual capacity factor for generating unit $n(j,l)$ in MWh (%).
- m_{lt} — Maximum number of generating units to be constructed at location l in year t.
- n_t — Energy not supplied cost in year t ($/MWh).
- p_{nt} — Power capacity of thermal generating unit $n(j,l)$ and year t (MW).
- q_{tp} — Power demand in block p in year t (MW).

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J. Sirikum is with the Electricity Generating Authority of Thailand, System Planning Division, Bang Krui, Nonthaburi 11130, Thailand (e-mail: jiraporn.s@egat.co.th).

A. Techanitisawad and V. Kachitvichyanukul are with the Industrial Engineering and Management Department, Industrial System Engineering Program, School of Engineering and Technology, Asian Institute of Technology (AIT), Klong Luang, Pathumthani 12120, Thailand (e-mail: anulark@gmail.com; voratas@ait.ac.th).

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rm	Reserve margin (%).
s_{nt}	Salvage values of generating unit $n(j,l)$ in year t ($).
t_{nqr}	Local range transfer coefficient of pollutant q emitted from plant $n(j,l)$ to receptor located in grid number r $(\mathrm{s/m^3})$.
u_t	Unserved energy in year t (MW).
v_{ntp}	Variable O&M cost for each unit of energy output from the generating unit $n(j,l)$ of block p in year t ($/MWh).
w_t	Discount factor (present worth factor).
z_{dtp}	Power saved by the efficient energy under DSM program d in block p, year t (MW).

Decision variables

G_{ntp}	Utilization capacity of generating unit $n(j,l)$ of block p, in year t (MW).
Y_{tp}	Power purchased amount to meet the power demand in block p of year t (MW) (without environmental effects consideration).
X_{nt}	$\begin{cases} 1, & \text{if generating unit n(j,l) is selected at year t or} \\ 0, & \text{otherwise.} \end{cases}$
D_{dt}	$\begin{cases} 1, & \text{if the DSM program d is implemented at year t or} \\ 0, & \text{otherwise.} \end{cases}$

I. Introduction

THE power generation expansion planning (PGEP) problem is a large-scale mixed integer nonlinear programming (MINLP) problem. The main objective is to determine the minimum cost of the capacity expansion subject to power demand, plant availability, environmental and reliability constraints, etc. In the past, many researchers attempted to deal with this problem by using deterministic criteria as well as stochastic ones with uncertainty [1]–[3]. However, there are difficulties in taking into account too many aspects of the problem because of the complexity of the problem.

Known as a combinatorial optimization problem, a mixed integer linear programming (MILP) problem can generally be solved by Branch & Bound (B&B) with LP relaxation proven to be sufficiently efficient in many cases [4], [5]. However, nonlinear programming (NLP) problems cannot be solved in a finite number of steps but only in iteration. It can be said that the MINLP problems are the most difficult optimization problems of all. Up to now, no polynomial algorithm has been created to effectively and efficiently solve general MINLP problems. The MINLP problem requires a special algorithm for a special structure of the problem and that special algorithm allows advanced users to adjust the algorithm to suit the problem at hand.

Genetic algorithm (GA) is an approach for solving the highly nonlinear combinatorial PGEP problem, and it has been demonstrated to be a powerful, efficient, and effective algorithm for solving the PGEP problem [6]. Moreover, there are several successive studies on applying GA for solving the generation expansion planning in several ways with satisfactory results [7]–[10].

In power generation and transmission expansion planning, there are many studies considering the decomposition technique and Benders' decomposition method as a tool for solving those problems [11], [12]. The application of generalized Benders' decomposition (GBD) for the least cost investment planning is presented in [13], and the investment planning in the large hydroelectric in Cameroon based on Benders technique is given in [14]. A comprehensive planning in a mixed integer linear stochastic program of the distributed utility planning problem is given and solved in [15] by using generalized Benders' decomposition.

This paper proposes an innovative technique called "*GA-Benders' Decomposition (GA-BD) method*" (a combination of GA-heuristic-based method and Benders' decomposition method) for solving the PGEP problem. The proposed GA-BD heuristic applies the decomposition structure of Bender to the PGEP problem. Similar to integer programming (IP), the master problem (MP) deals with the integer variables representing the selection of power generating plants but also includes the Benders' cuts as its additional constraints. Given each investment plan prescribed by MP, a linear programming (LP) subproblem is solved for an optimal operational plan. For the proposed GA-BD, instead of solving the MP to optimality, the GA is proposed for solving those MP. In the GA part of the proposed GA-BD, only q best chromosomes are solved for LP optimality. This can shorten the computational runtimes, whereas the pure GA solves all chromosomes for LP optimum taking longer runtimes. This alternative method of the proposed algorithm (GA-BD) is anticipated to be a better method for improving the solution runtimes. To demonstrate the effectiveness and efficiency of the proposed GA-BD algorithm, computational experiments are conducted, and the results are compared with those of the pure GA method proposed by [6].

The remainder of this paper presents problem formulation, a new proposed GA-BD method, the numerical examples, and the experimental results. Finally, the conclusion is given.

II. Problem Formulation

Specifically for this study, the PGEP problem is improved and modified from the formulation of [6] that was formulated as an MINLP model based on the model given in [4]. The model incorporated reliability constraints of [16], DSM programs of [2], environmental requirements, and location constraints of [17] to determine an optimal electricity generation plan that minimizes the expected sum of discounted investment costs and variable costs that comprise of fuel costs, operating costs, and environmental costs of each new generating unit of power generation. Moreover, the model also incorporated the environmental factors related to Thailand location and the environmental cost of Thailand studied by [18].

A. PGEP Problem

The modification of the PGEP problem is considered since the installed capacity sometimes may not be enough to meet the power demand. To ensure that the LP subproblem is always feasible for any integer solution of the problem, artificial variables with large positive costs are added in the problem to represent the amount of the purchased power (Y_{tp}). It will take a big M coefficient (large amount of cost) for the power purchased cost

$(c_{tp},)$, which implies the penalty cost for an infeasible solution, which becomes a less attractive one.

The primary objective function is to determine an investment schedule to meet the customer power demand and operating reserve levels at the minimal cost (the sum of the present worth of investment and operation cost) and, at the same time, to meet all security constraints imposed on the electricity system for reliability purposes as well as the emission constraints for the environmental control purposes. The PGEP model formulated as an MINLP model can be written as follows:

Objective function : Minimize Z

$$\begin{aligned} Z = &\left(\sum_{t=1}^{T}\sum_{n=1}^{N} w_t \cdot (i_{nt} - s_{nt}) \cdot X_{nt}\right) \\ &+ \left(\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{n=1}^{N} w_t \cdot (f_{ntp} + v_{ntp}) \cdot G_{ntp} \cdot du_p\right) \\ &+ \left(\sum_{t=1}^{T}\sum_{d=1}^{D} w_t \cdot d_{dt} \cdot D_{dt}\right) \\ &+ \left(\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{n=1}^{N} w_t \cdot e_{ntp} \cdot G_{ntp} \cdot du_p\right) \\ &+ \left(\sum_{t=1}^{T} 8760 \cdot n_t \cdot u_t\right) + \left(\sum_{p=1}^{P}\sum_{t=1}^{T} c_{tp} \cdot Y_{tp} \cdot du_p\right) \end{aligned} \tag{1}$$

subject to

- *Power demand constraints*:

$$(1-ls)\cdot\left(\sum_{n=1}^{N} G_{ntp} + Y_{tp}\right) + \sum_{d=1}^{D} z_{dtp}\cdot D_{dt_t} + u_t \geq q_{tp}, \quad \forall t, p. \tag{2}$$

- *Capacity constraints*:

$$G_{ntp} \leq a_{nt} \cdot X_{nt} \cdot p_{nt}, \quad \forall n, t, p. \tag{3}$$

- *Thermal energy availability constraints*:

$$\sum_{p=1}^{P} (G_{ntp} \cdot du_p) \leq 8760 \cdot mc_n \cdot X_{nt} \cdot p_{nt}, \quad \forall t, n(j, l). \tag{4}$$

- *Reliability constraints*:
  a) *Reserve margin constraints*:

$$\begin{aligned} (1-ls)\cdot\left(\sum_{n=1}^{N} a_{nt}\cdot X_{nt}\cdot p_{nt}\right) + (1+rm)\cdot\sum_{d=1}^{D} z_{dtp}\cdot D_{dt} \\ \geq (1+rm)\cdot q_{tp}, \quad \forall t, p^* = \text{peak}. \end{aligned} \tag{5}$$

  b) *LOLP constraints*: $lolpc$ is calculated by using the cumulant method; the formula is extracted from the study of [16], [19], and [20]. In addition, it was also presented in [6, Appendix 1]. This cumulant method is a cause of the nonlinearity of the problem

$$lolpc_t \leq lolps_t, \quad \forall t. \tag{6}$$

- *Emission constraints*:
  a. *Pollution emission constraints*:

$$\sum_{p=1}^{P}\sum_{n=1}^{N} G_{ntp} \cdot du_p \cdot er_{nq} \leq g_{qt}, \quad \forall q, t. \tag{7}$$

  b. *Primary pollutant concentration constraints*:

$$\sum_{p=1}^{P}\sum_{n\in\aleph_l} G_{ntp} \cdot t_{nqr} \cdot er_{nq} + b_{qrt} \leq ma_{qrt}, \quad \forall q, r, t \tag{8}$$

  in which $\aleph_l$ is the set of generating unit n located in grid number l.

- *Location constraints*:

$$\sum_{n\in\aleph_l} X_{nt} \leq m_{lt}, \quad \forall t, l. \tag{9}$$

- *Non-negativity constraints*:

$$G_{ntp} \geq 0 \tag{10}$$

$$Y_{tp} \geq 0 \tag{11}$$

$$X_{nt} \quad \text{Binary} \tag{12}$$

$$D_{dt} \quad \text{Binary.} \tag{13}$$

B. Benders Reformulation of the PGEP Problem

Using the Benders' decomposition method, it solves the PGEP problem by separating the problem into master problem and subproblems, which are then iteratively solved by generation of dual variables from the subproblem to form the Benders' cut and add it into the master problem until the stopping criteria are met.

The mathematical formulation given in Section II-A above could be reduced into two subproblems: investment master problem, in which sequence and timing of the candidate generating unit is selected, and the operation subproblem, where the operation cost of a given investment decision is calculated. The reformulated investment master problem is modeled as an integer nonlinear programming (INLP) problem, and the operation subproblem is modeled as a linear programming (LP) problem as shown below.

C. Operation Subproblem

Given an investment plan (X^*, D^*), the operation subproblem can be solved for the minimum cost of the subproblem. The solutions obtained are the optimum operation (G^*) and the power purchased amount (Y^*) as well as its dual variables supplied to use in the investment master problem, in Section II-D. Then, the primal LP subproblem can be rewritten as the following:

$$\begin{aligned} Z_{LP} = \text{Min.} &\left(\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{n=1}^{N} w_t \cdot (f_{ntp} + v_{ntp}) \cdot G_{ntp} \cdot du_p\right) \\ &+ \left(\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{n=1}^{N} w_t \cdot e_{ntp} \cdot G_{ntp} \cdot du_p\right) \\ &+ \left(\sum_{p=1}^{P}\sum_{t=1}^{T} c_{tp} \cdot Y_{tp} \cdot du_p\right) \end{aligned} \tag{14}$$

subject to

- *Power demand constraints*:

$$(1-ls)\cdot\left(\sum_{n=1}^{N} G_{ntp}+Y_{tp}\right)\geq q_{tp}-u_t-\sum_{d=1}^{D} z_{dtp}\cdot D_{dt_t},\quad \forall t,p. \tag{15}$$

- *Capacity constraints*:

$$-G_{ntp}\geq -a_{nt}\cdot X_{nt}\cdot p_{nt},\quad \forall n,t,p. \tag{16}$$

- *Thermal energy availability constraints*:

$$-\sum_{p=1}^{P}(G_{ntp}\cdot du_p)\geq -8760\cdot mc_n\cdot X_{nt}\cdot p_{nt},\quad \forall t,n(j,l). \tag{17}$$

- *Emission constraints*:
  a) *Pollution emission constraints*:

$$-\sum_{p=1}^{P}\sum_{n=1}^{N} G_{ntp}\cdot du_p\cdot er_{nq}\geq -g_{qt},\quad \forall q,t. \tag{18}$$

  b) *Primary pollutant concentration constraints*:

$$-\sum_{p=1}^{P}\sum_{n\in\aleph_l} G_{ntp}\cdot t_{nqr}\cdot er_{nq}\geq -ma_{qrt}+b_{qrt},\quad \forall q,r,t. \tag{19}$$

- *Non-negativity constraints*:

$$G_{ntp}\geq 0 \tag{20}$$

$$Y_{tp}\geq 0. \tag{21}$$

D. Investment Master Problem

From the dual variables associated to the optimal solution of X^* and D^* of the proceeding operation subproblem, the Benders cuts (η_B) given for the investment master problem is reformulated as the following [21]:

$$Z_{Mi^*} = \text{Minimize } \eta_B \quad Mi^* \tag{22}$$

subject to

$$\begin{aligned}\eta_B \geq &\left(\sum_{t=1}^{T}\sum_{n=1}^{N} w_t\cdot(i_{nt}-s_{nt})\cdot X_{nt}\right)\\ &+\left(\sum_{t=1}^{T}\sum_{d=1}^{D} w_t\cdot d_{dt}\cdot D_{dt}\right)+\left(\sum_{t=1}^{T} du_1\cdot n_t\cdot u_t\right)\\ &+\sum_{t,p} y1_{t,p}^{i}\cdot\left(q_{tp}-u_t-\sum_{d=1}^{D} z_{dtp}\cdot D_{dt}\right)\\ &+\sum_{n,t,p} y2_{n,t,p}^{i}\cdot(-a_{nt}\cdot X_{nt}\cdot p_{nt})\\ &+\sum_{n,t} y3_{n,t}^{i}\cdot(-8760\cdot mc_n\cdot X_{nt}\cdot p_{nt})\\ &+\sum_{q,t} y4_{q,t}\cdot(-g_{qt})+\sum_{q,r,t} y5_{q,r,t}\\ &\cdot(-ma_{qrt}+b_{qrt})\quad \text{for all cuts}\end{aligned} \tag{23}$$

and constraints (5), (6), (9), (12), and (13).

According to the difficulty for solving the INLP problem, in this study, the developed heuristic procedure of GA [6] is proposed for solving the problem in INLP part (investment master problem), whereas the LP part (operation subproblem) is solved by the LP method provided in the MATLAB package.

III. New GA-BD Method for the PGEP Problem Solving

A. Genetic Algorithm Approach for the Problem

GA: this method is a heuristic search method that mimics the natural evolution process of natural selection and natural genetics for solving large, difficult, and complex optimization problems [22]. In general, GA must have five components: 1) string representation or encoding for potential solution of the problem, 2) creation of an initial population, 3) evaluation or fitness function, rating the solutions in terms of fitness, 4) genetic operators, and 5) termination criteria [23].

Fundamentally, the procedure of the proposed GA for solving the PGEP problem was described in [6]. This proposed GA is a method that decomposes the problem into two parts, namely, combinatorial and continuous LP model. The first combinatorial subproblem is to determine a feasible generation mix (combinatorial solutions) by GA search. Given a combinatorial solution obtained in the first part, the second LP subproblem is to determine an optimum level of power generation (other continuous decision variables) subject to the related constraints.

B. Benders' Decomposition Method Overview

Benders' Decomposition (BD) method is a classical solution approach for handling constraints in the combinatorial optimization problems based on the idea of partition and delayed constraint generation [24]. At first, a mathematical formulation is proposed [24] as a mixed integer programming. The basic idea behind this method is to decompose the problem into two simpler parts: the first part, called master problem, solves an integer part of the problem to optimality by B&B technique to obtain values for a subset of the original variables and associated constraints. The second part, called subproblem, obtains the values for the remaining original variables by any LP method, while keeping the first one fixed, and uses these to generate cuts for the master problem. The master problem and subproblem are solved iteratively until no more cuts can be generated. The conjunction of the variables found in the last master and subproblem iteration is the solution of the original formulation.

Examples of successful applications of this methodology to mixed integer programming problems, particularly in power generation and transmission expansion planning problems, are abundant [13]–[15].

C. Proposed GA-Benders' Decomposition Method

This section explains methodology of the proposed GA-Benders' decomposition method (GA-BD) for solving the formulated PGEP nonlinear model. The advantage of GA-BD is that, in terms of GA part, GA is a robust random search method requiring little information to search effectively in a large or poorly understood search space, especially of nonlinear optimization problems. On the other hand, the disadvantage is that

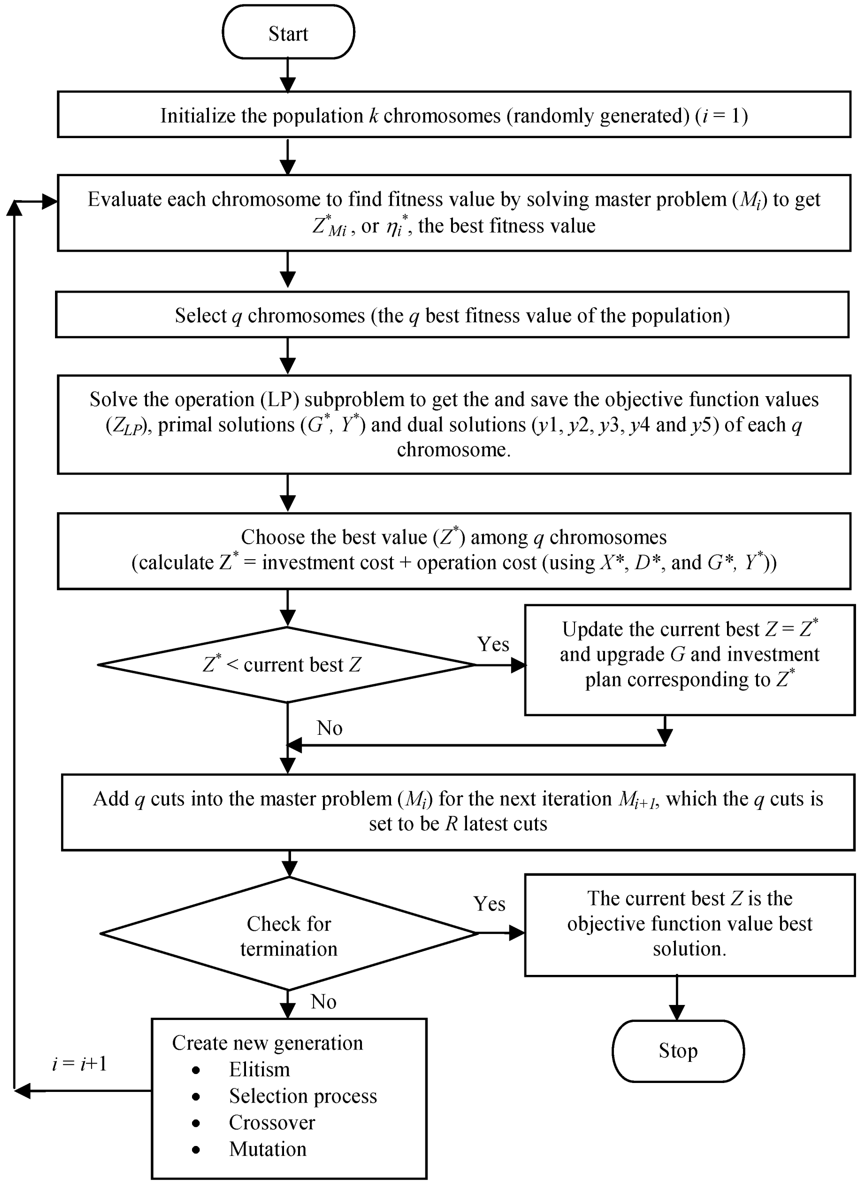

Fig. 1. Solution procedure of GA-Benders' decomposition flowchart.

GA is a heuristic method that cannot guarantee optimality of solutions obtained. For Bender concept, partition, and delayed constraint generation, its advantage is solving the mixed integer programming problem efficiently. Additional advantage is that GA is proposed for solving the master problem (MP) for good solutions that takes shorter runtime, rather than solving MP for optimality, which takes longer runtime.

The proposed GA-Benders' decomposition method called "*GA-BD*" is a combination of GA method and Benders' decomposition method. The structure of the power expansion planning problems presents a decomposition scheme for the Bender approach, the MP deals with the integer variables representing the selection to open the plants, while the LP subproblem works with the continuous variables representing the level of power generation of each plant to meet the power demand. At any iteration, the master solution gives the investment plan for which subproblem finds the optimal level of power generation as well as the optimal cost of generation. Each combined (MP and LP) solution is used to generate the Bender cuts for MP in the next iteration. For the proposed GA-BD, instead of solving the MP to optimality, the GA is proposed for solving those MP. Moreover, in the GA part of the proposed GA-BD, only q best chromosomes are solved for LP optimality. This can shorten the computational runtimes, whereas the pure GA solves all chromosomes for LP optimum taking longer runtimes. Therefore, it would be more efficient for this proposed GA-BD method to solve the PGEP problem. The flowchart of the solution procedure of the proposed GA-BD is shown as Fig. 1.

IV. Numerical Examples and Experimental Results

The computer program of the proposed GA-BD method for solving the problem is developed in MATLAB. The implementation of the proposed GA part is adapted from the computer program of [25] and the Optimization Toolbox of MATLAB, which is modified for the Benders part. The test of the algorithm

TABLE I
SUMMARY OF GA PARAMETERS RECOMMENDED FOR THE PROPOSED GA-BD METHOD

GA Parameters	Both Small and Medium problems
Number of cuts:	1
Remaining cuts:	25 (for small), 10 (for medium)
Population size:	10
Crossover method:	Mixed heuristic & simple crossover
Crossover rate:	80%
Mutation method:	Uniform mutation
Mutation rate:	0.5%
Selection procedure:	Roulette wheel selection
Termination criteria:	
- Max. no. of generations	1000
- Non-improving generations	30% of max. no. of generations

with sample data and the real data will be carried out. The experiments of the study are run on the Notebook with Pentium-M (1.3 GHz) processor with 256 MB of DDR-RAM.

A. Problem Descriptions

The extension of the generation expansion planning model as described in Section II has been implemented for the case study of Thailand. We use the scaled down version of the Thailand generation system, while the data used in this study were arbitrarily selected from the real data related to Thailand generation system. In fact, the shares of power plant types in Thailand as of the year 2004 comprise of 12.7% hydro power plants, 32.4% thermal, 48.7% combined cycle, 4.5% gas turbine and diesel, 0.5% renewable energy, and 1.2% linked from neighboring countries.

The thermal power plants considered consist of four different plant types—oil-fired, gas-fired, lignite-fired, and coal-fired plants—of 21 generating units, comprising of five existing units and 16 candidate generating units. We consider the two DSM options with initial costs of US$0.29 million and US$0.31 million and with power save of 40 MW and 15 MW, respectively. Three different planning periods are considered and divided into three blocks of duration. Peak load demand for the first year is 1600 MW and assumed to increase by 10% per year. There are several parameters given for the PGEP problem, i.e., discount rate set at 10% per year. Reserve margin and system losses are set at 15% and 5% of peak load, respectively. Each location is assumed to have limited area for installation of generating units within the requirement of emission limits. Data and parameters for the analysis are given in Tables III–VI. Seven cases are used as the test problems in this study by varying the number of variables (330, 462, 660, 990, 1320, 1650, and 1980) presenting in the length of planning horizon (5, 7, 10, 15, 20, 25, and 30).

B. GA Parameters for the Proposed GA-BD Application

Since the GA parameters have significant effects on the quality of solutions, they must be evaluated and predetermined for the suitable GA parameters before commencing of the experiments. Those GA parameters are the problem specifics. For this study, the suitable GA parameters recommended for the proposed GA-BD method of the small and medium problems are as shown in Table I.

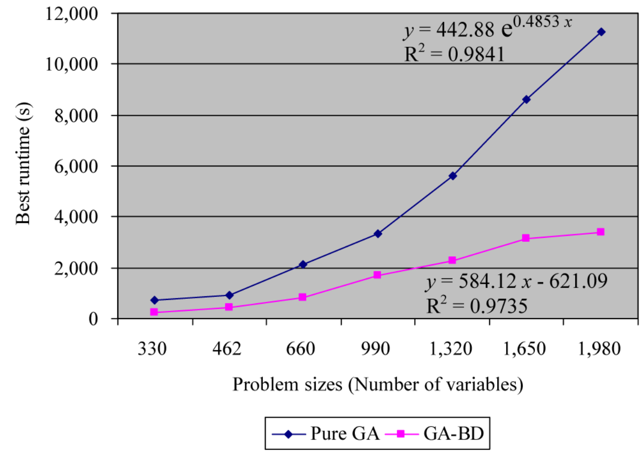

Fig. 2. Relations between the problem size and the best runtimes.

C. Numerical Results

Since the proposed GA-BD method and the pure GA method are random-based methods, each run may yield different solution. Each case of a problem is run for five runs and recorded significant statistics as reported in Table II. The proposed GA-BD method generally yields comparable solution quality to the pure GA, while the best GA-BD solutions of all cases in both small and medium problems show different levels of improvement in the objective function values as well as in the runtime.

Although the proposed GA-BD and the pure GA could not guarantee to find the global solution, all proposed GA-BD cases have provided better solution than the pure GA. Furthermore, by the experience of the study in [6], particularly in small cases, it has been proven that the pure GA method is more efficient than the branch and bound method provided in a conventional optimization software package (LINGO), which implies that the proposed GA-BD can find the local optimum faster. However, it should be noted that, since the proposed model is a nonlinear model, LINGO also cannot guarantee global optimal solutions, although a local optimum may be found.

Throughout the experiments, for small problems, the best GA-BD can achieve better results at an attractive rate of improvement in runtimes. Specifically, in Case 1, both the proposed GA-BD and the pure GA give the same best solution, while in Cases 2–4, the best as well as the average solutions of the proposed GA-BD are better and the convergence rate is also faster. Moreover, when considering the medium cases (Cases 5–7), the proposed GA-BD and the pure GA can heuristically solve these large cases, the best GA-BD can significantly improve the solution quality over those of the pure GA on average. In addition, for the runtimes improvement (as shown in Fig. 2), the runtime of the proposed GA-BD method is obviously improved over the pure GA in all cases; it was reduced by more than half of the pure GA runtimes because the LP is solved only for the best chromosome in the investment master problem.

Additionally, even though the data used in this study are extracted from the real data related to Thailand's generation system, the results obtained from the proposed GA-BD are similar to those from the pure GA that gives the generation

TABLE II
RESULT COMPARISONS BETWEEN THE PROPOSED GA-BD AND THE PURE GA IN MINLP PROBLEM

MINLP Problem			Problem Size (No. of Variables)	Results															
				Pure GA						GA-BD						GA-BD Improved			
				Fitness Values (M$)			Runtime (s)			Fitness Values (M$)			Runtime (s)			Fitness Values (%)		Runtime (%)	
Cases				Best	Avg.	Stdev.	Best	Avg.	Stdev.	Best	Avg.	Stdev.	Best	Avg.	Stdev.	Best	Avg.	Best	Avg.
Small	1	T=5	330	2,296	2,296	-	733	806	105	2,296	2,300	8	251	288	41	0.0%	-0.2%	65.8%	64.3%
Small	2	T=7	462	3,149	3,234	162	942	1,122	182	3,011	3,159	138	415	523	71	4.4%	2.3%	55.9%	53.4%
Small	3	T=10	660	4,779	5,255	288	2,137	2,688	336	4,361	4,634	248	819	1,189	267	8.7%	11.8%	61.6%	55.8%
Small	4	T=15	990	7,291	7,858	342	3,318	3,798	624	6,647	7,082	283	1,699	2,622	522	8.8%	9.9%	48.8%	31.0%
Medium	5	T=20	1,320	8,996	9,459	511	6,208	11,220	3,619	8,943	9,107	164	2,290	3,067	549	0.6%	3.7%	63.1%	72.7%
Medium	6	T=25	1,650	12,555	14,552	1,251	8,593	11,135	1,694	10,904	11,155	263	3,125	4,042	663	13.2%	23.3%	63.6%	63.7%
Medium	7	T=30	1,980	15,126	17,542	3,536	11,296	13,892	4,255	13,233	15,123	1,112	3,406	5,569	1,929	12.5%	13.8%	69.8%	59.9%

TABLE III
DATA OF THE EXISTING GENERATING UNITS

Plant Type	Unit Cap. (MW)	Av. (%)	FOR (%)	Fuel cost ($/MWh)	Emission Rate (kg/MWh) SO_2	PM
E1. Existing gas fired(CC)	650	94	6	34.9343	0.00	29.18
E2. Existing gas fired(CC)	650	94	6	34.9343	0.00	29.18
E3. Existing gas fired(CC)	380	94	6	36.3168	0.00	30.29
E4. Existing oil fired	310	94	6	60.4723	1,044.23	48.73
E5. Existing oil fired	310	94	6	54.4554	1,044.23	48.73

Notes: Availability (Av.) is the capacity of generating unit.
FOR = Force Outage Rate, CC = Combined Cycle plant

TABLE IV
DEMAND SIDE MANAGEMENT PROGRAMS

Programs	Power Saved (MW)	DSM Cost (M$)
D1	40	0.29
D2	15	0.31

TABLE V
EMISSION REQUIREMENTS

Pollutant	Emission limits (Tons/yr.)	Ambient air standard ($\mu g/m^3$)
SO_2	1200	780
PM	1700	120

Note: SO_2 = sulfur dioxidePM = particulate matters

plans not only with less or lowest total costs but also with less environmental impacts.

For instance, in all cases, the plans of each case obtained from the proposed GA-BD are dominated by the gas-fired (combined cycle) units, while the clean coal-fired, oil-fired, and lignite-fired are later alternatives.

In the power plant selection, it is generally known to depend on many factors, e.g., power demand, investment and operation costs, environmental cost, power plant sizes, and number of planning periods. In this study, for the short-term plan, the gas-fired units are most interesting to be added into the system because of their combined advantages of these factors over other alternatives. For the long-term plan, since the total power demand is much more than that in the short term, the large power plant size with low environmental costs and low investment costs as environmental controls of clean coal-fired units are selected. However, the gas-fired units still dominate others in the long-term plan in terms of cost and environmental impacts. Although the clean coal-fired units and the lignite-fired units running with flue gas desulphurization system are also considered, their investment costs are quite high. They are, therefore, less attractive and less economic, than the gas-fired.

V. CONCLUSIONS

This paper addressed the development of a new efficient GA-BD method as an alternative method to solve the PGEP problems that is formulated as a mixed integer nonlinear model, MINLP problem, with environmental cost and constraints. It could be concluded that the proposed GA-BD method is an efficient heuristic method for solving the PGEP problems. There is a tendency, however, that for a larger instance, the proposed GA-BD method would be able to yield improved solutions at a significant rate. In terms of runtimes, the proposed GA-BD could also achieve an order of magnitude of improvement, especially in larger instances of the PGEP problems.

In conclusion, for small and medium problems, the results showed that the proposed GA-BD could yield better solution quality effectively and efficiently when compared to that of the pure GA. On the other hand, it could be said that the proposed GA-BD was a better method over the pure GA. According to the successful solutions of the proposed GA-BD to the small and medium cases (scaled-down data of Thailand power system), the proposed GA-BD could further be adapted to large cases for the real case studies on Thailand power system planning. The results from the case studies also suggested more economical and less environmental impacts of gas-fired power plants than those of any other types of plants. For example, the plans of each case obtained from the proposed GA-BD were dominated by the gas-fired (combined cycle) units, while the clean coal-fired, oil-fired, and lignite-fired were later alternatives.

Finally, since a long-range planning of the PGEP problem dealt with a large amount of investment and long computational runtime, an improvement by the proposed GA-BD could help

TABLE VI
DATA OF THE CANDIDATE GENERATING UNITS

Plant Type	Unit Cap.	Av.	FOR	Capital Cost	Fuel Cost	Envi. Cost /4	Emission Rate	
	(MW)	(%)	(%)	(M$/kW)	($/MWh)	(cent/kWh)	SO_2	PM
C1: Candidate oil fired	300	94	6	710	56.3563	0.022	1,079.04	50.36
C2: Candidate lignite fired /1	300	92	8	930	15.4632	0.0506	1,801.74	864.8
C3: Candidate lignite fired	300	92	8	930	15.4632	0.0506	1,801.74	864.8
C4: Candidate oil fired	700	94	6	595	47.2152	0.022	874.85	40.83
C5: Candidate oil fired	700	94	6	595	47.2152	0.022	874.85	40.83
C6: Candidate oil fired	700	94	6	595	47.2152	0.022	874.85	40.83
C7: Candidate gas fired (CC) /2	700	94	6	401	25.1928	0.0112	0	24.41
C8: Candidate gas fired (CC)	700	94	6	417	25.1928	0.0112	0	20.92
C9: Candidate gas fired (CC)	700	94	6	401	25.1928	0.0112	0	24.41
C10: Candidate coal fired /3	1000	94	6	576	20.0636	0.0064	918.86	42.88
C11: Candidate coal fired	1000	94	6	654	13.86	0.0064	490.06	152.7
C12: Candidate lignite fired	300	92	8	930	12.8424	0.0506	1,801.74	864.8
C13: Candidate lignite fired	300	92	8	930	12.8424	0.0506	1,801.74	864.8
C14: Candidate gas fired (CC)	300	94	6	417	34.6824	0.0112	0	48.82
C15: Candidate gas fired (CC)	300	94	6	462	34.6824	0.0112	0	24.41
C16: Candidate gas fired (CC)	300	94	6	462	34.6824	0.0112	0	24.41

Notes:
/1 = Lignite fired (with FGD)
/2 = Gas fired (Combined cycle)
/3 = Coal fired (Low Sulfur content, with FGD)
/4 =Environmental cost estimated.
Av. is availability.
Envi. Cost = Environmental cost
FGD = Flue Gas Desulphurization

the utility planners, who needed to facilitate their works on the studies of the effects of conditions or situations changed in PGEP problems. It will provide faster solutions when the executives require additional information or solutions for decision making with time constraints.

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Jiraporn Sirikum received the B.Eng. degree in industrial engineering from Khon Kaen University, Khon Kaen, Thailand, in 1988 and the M.Eng. degree in energy planning and policy and the D.Eng. degree in industrial engineering and management from the Asian Institute of Technology, Pathumthani, Thailand, in 1995 and 2006, respectively.

She is currently with the Electricity Generating Authority of Thailand (EGAT), Nonthaburi, Thailand, which is the state enterprise responsible for generating and transmitting the power for Thailand and neighboring countries.

Anulark Techanitisawad received the B.Eng. degree from Kasetsart University, Bangkok, Thailand, in 1984, the M.B.A. degree from Eastern Michigan University, Ypsilanti, in 1986, and the Ph.D. degree in industrial engineering from Texas A&M University, College Station, in 1994.

She is an adjunct faculty member in the Industrial Engineering and Management Department, School of Engineering and Technology, Asian Institute of Technology (AIT), Pathumthani, Thailand. Her specialization and research interests include discrete and combinatorial optimization; mathematical programming/optimization; logistics/transportation (vehicle-routing and its applications; location-routing; container loading/selection problem); supply chain management/reversed supply chain; and revenue management.

Voratas Kachitvichyanukul received the Ph.D. degree from the School of Industrial Engineering, Purdue University, West Lafayette, IN, in 1982.

He is an Associate Professor in the Industrial Engineering and Management Department, School of Engineering and Technology, Asian Institute of Technology (AIT), Pathumthani, Thailand. He has extensive experience in simulation modeling of manufacturing systems. His industrial experiences include full-time technical positions in FORTUNE 500 Companies such as Compaq Computer Corporation and Motorola Incorporated in the USA. He has also worked for SEMATECH as a Technical Coordinator of the Future Factory Program in the early 1990s. He also held teaching position at The University of Iowa, Iowa City, prior to taking a position in industry. His teaching and research interests include planning and scheduling, simulation, enterprise resource planning, supply chain modeling, high-performance computing, and applied operations research, with special emphasis on industrial systems.