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Optimal Generation Expansion Planning Strategy with Carbon Trading

Tung-Sheng Zhan Chih-Cheng Kao Chin-Der Yang Jong-Ian Tsai

***Abstract*—**Fossil fuel-firing power plants dominate electric power generation in Taiwan, which are also the major contributor to Green House gases (GHG). CO2 is the most important greenhouse gas that cause global warming. This paper penetrates the relationship between carbon trading for GHG reduction and power generation expansion planning (GEP) problem for the electrical utility. The Particle Swarm Optimization (PSO) Algorithm is presented to deal with the generation expansion planning strategy of the utility with independent power providers (IPPs). The utility has to take both the IPPs' participation and environment impact into account when a new generation unit is considering expanded from view of supply side.

***Keywords*—**Carbon Trading, CO2 Emission, Generation Expansion Planning (GEP), Green House gases (GHG), Particle Swarm Optimization (PSO).

I. INTRODUCTION

The third United Nations Framework Convention on Climate Change (UNFCC) conference met in Kyoto in December 1997 and produced the Kyoto Protocol, under which 39 of the industrialized countries agreed to imperative reduction of GHG emission. The protocol signed by more than 160 nations has promised to achieve the convention's objective to prevent the Greenhouse effects related to global warming. The agreement calls for industrialized countries to cut their emissions by an average of 5 percent from 1990 levels by 2010. The protocol propose the three flexible mechanisms, namely Emissions trading schemes (ETS), Joint implementation(JI) and Clean development mechanism (CDM), to help countries meet their obligation of emission reduction. ETS underpins the "cap-and-trade" mechanism that was designed to govern CO2 emission from various emission sources of each nation. The "cap" mechanism ensures that emission reduction objective can be met. The "trade" implies that the environment objectives will be achieved at the lowest possible cost. For example, there are two companies, A and B, each year-estimated CO2 emission is 10,000 metric tons and each has been allocated allowances for 9,500 metric tons per year. Thus, each company has emission shortage of 500 metric tons unless some action is taken, either to make the reduction to fit the cap or to purchase credits on the carbon market which currently trading at $10/ton. For company A, the cost to cut 1,000 metric tons is $5/ton, so it decides to make that reduction by diminished production planning. The marginal abatement costs (MACs) of company B is $15/ton, and thus it is cheaper for this company to purchase on the market.

Tung-Sheng Zhan and Chih-Cheng Kao are with the Department of Electrical Engineering, Kao-Yuan University, Kaohsiung 821, Taiwan, R.O.C. (corresponding author to provide phone: 886-7-607-7019; fax: 886-7-607-7009; e-mail: tszhan@cc.kyu.edu.tw).
Chin-Der Yang is with the Department of Electrical Engineering, Yung-Ta Institute of Technology, Ping-Tung 909, Taiwan, R.O.C.
Jong-Ian Tsai is with the Department of Electrical Engineering, Kao-Yuan University, Kaohsiung 821, Taiwan, R.O.C.

The net result is that company A receives $5,000 from the sale of its surplus emission cuts, this revenue covers the cost of its reduction and $2,500 extra profit. For company B, with higher MAC, the cap has been met at a cap credit cost of $5,000, instead of the $7,500 it would have cost to make the required self-reduction.

The Power industry is certainly a major contributor (about 33%) to global CO2 emissions, which traps the heat radiation and increase the temperature of atmosphere. Generating technologies consist of nuclear, coal, gas, and oil fired plants [1]. There are three-types of generators depending upon generation characteristics: the base-type, middle-type, and peak-type. The scheduling order for generations to satisfy the load profile is generally nuclear, coal, oil, and liquefied natural gas (LNG) or gas generations respectively. IPPs want to sell as much electricity as possible for various load profiles. The utilities need to minimize the total cost under operational constraints for all types of generations. It is important to determine what type of generating units to be constructed and when the unit should be on line over a planning horizon to maximize profits or minimize the investment and operation cost while meeting the load demand with a pre-specified reliability criterion. In order to achieve the objective, utilities will perform the generation expansion planning to determine the minimal-cost capacity addition. For better economy and efficiency, they will consider options of either constructing new generating units or purchasing electricity from other utilities or IPPs. Generation expansion planning is an important decision-making activity in a competitive market.

Besides minimizing GEP cost, environmental issues are important and must be taken into account. Thus, the other objective of this paper is to investigate an influence of carbon trading on GEP issue. In recent years, rigid environmental regulations and CO2 emission tax [2]-[4] force utility planners to consider emission as a cost and an important constraint in generation expansion planning. Besides, the plan must satisfy a desired level of reliability generally defined by two indices: loss-of-load probability (LOLP) and the expected energy demand not served (EENS)[5]-[7].

Choosing a generation expansion planning is complicated, especially finding the best strategy in a world of uncertainty. Mathematical methodologies used are linear programming, non-linear programming, dynamic programming, and mix-integer programming techniques with certain simplifications [8]. With the non-linearity and discrete nature considered in generation expansion planning, the problem becomes more difficult to solve. Recently, new algorithms based on the artificial intelligence (AI) have been developed, such as simulated annealing (SA) [9], genetic algorithm (GA) [10]-[12], immune algorithm (IA) [13]-[16]. Solution strategies proposed by most AI algorithms need to consider a large solution space. On the other hand, conventional methods may

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be faster; they are very often limited by the problem structure and may diverge or could lead to a local minimum. Eberhart and Kennedy developed particle swarm optimization (PSO) based on the analogy of swarm of bird and fish school [17]. These researches are called "Swarm Intelligence" [18], [19]. PSO has been found to be robust in solving continuous nonlinear optimization problems [20]–[23]. The PSO technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than other stochastic methods [21]–[23].

In this paper, PSO algorithm was presented to deal with GEP problem which can be formulated as a mixed-integer and non-linear optimization problem. This paper focused on the minimization of cost for a short-term GEP problem subjected to carbon trading, operational constraints and reliability. Numerical examples are also provided to show its effectiveness. Testing results shows that PSO algorithm can offer an efficient way in determining the generation expansion planning.

II. Problem Formulation

When IPP provides a relatively low transaction price for similar types of generation, they will replace the utility generation. The utility needs to minimize the cost consisting of generation expansion and purchasing cost from IPPs while satisfying the load balance and operational constraints. The objective function can be formulated as

$$Min.\ \ Obj\_f = \{Cost_1(\bullet) + Cost_2(\bullet) + Cost_3(\bullet) + CT(\bullet)\} \tag{1}$$

where

$$Cost_1(\bullet) = \sum_{y=1}^{Y}\left[\sum_{n=1}^{T} \mathrm{Nm\_Exi}_n^y \cdot (b_n \cdot QUPG_n)\right]$$

$$Cost_2(\bullet) = \sum_{y=1}^{Y}\left[\sum_{n=1}^{T} \mathrm{Nm\_Exp}_n^y \cdot (\mathrm{a}_n \cdot UPG_n + b_n \cdot QUPG_n))\right]$$

$$Cost_3(\bullet) = \sum_{y=1}^{Y}\sum_{m=1}^{M} BPP_m^y \cdot QIPG_m^y$$

$$CT(\bullet) = \sum_{y=1}^{Y}\sum_{m=1}^{M} BPCO2_m^y \cdot (QCO2\_buy_m^y - QCO2\_Sale_m^y)$$

where Y is number of years in a planning horizon, T is number of utility generation technology (Nuclear, Coal, Oil and Gas are included), M is number of IPP. *a* is the fixed construction cost of n/m-th power plant of utility/IPP (US$/MW), and *b* is variable cost of n/m-th power plant of utility/IPP (US$/MWh). UPG is capacity of generation plant of utility in MW. QUPG and QIPG are annual energy production of power plant of utility and IPPs, respectively. BPP_m is the purchase price for m-th IPP (US$/MWh), and BPCO2 is clear price of carbon spot market (US$/metric-tons). QCO2_buy is carbon purchase quantity and QCO2_sale is carbon sale quantity. Nm_Exi and Nm_Exp are number of cumulative existing and expanding plant for generation technology in planning horizon, respectively. Nm_Exp is will be arranged optimally year-by-year in this research. The constraints considered and trading condition are described as follows.

(A) Power Bargain Condition

In this paper, the bargain condition is only the purchase price is higher than the average generation cost, That is

$$[(a_m \cdot IPG_m + b_m \cdot QIPG_m)/QIPG_m] \le BP_m \tag{2}$$

(B) CO2 Emission Constraints

$$\sum_n^T UPGCo2_n + \sum_m^M IPGCo2_m \le Total\_Co2 \tag{3}$$

Total_CO2 is the total limit of CO2 emission, then LimCO2 limit CO2 emission limit of each plant. The CO2 emission model is assumed to be a combination of polynomial and exponential term of the form [24]

$$PGCo2_n = \alpha_n + \beta_n \cdot PG_n + \gamma_n \cdot PG_n^{\ 2} + \eta_n \exp(\mu_n \cdot PG_n) \le LimCo2_n \tag{4}$$

(C) Power Balance Constraints

$$\sum_n^T UPG_n + \sum_m^M IPG_m \ge P_D + P_{res} \tag{5}$$

where the P_D and P_{res} are the peak load and reserve power at target year.

(D) Capacity Limit Constraints

$$UPG_n^{\min} \le UPG_n \le UPG_n^{\max} \quad , n \in [1, N]$$

$$IPG_m^{\min} \le IPG_m \le IPG_m^{\max} \quad , m \in [1, M]$$

(E) Reliability Constraints

$$LOLP \le LOLP\_limit$$

$$EENS \le EENS\_limit$$

LOLP_limit is the level of loss of load probability, and *EENS_limit* is the level of expected energy not supplied. In this paper, LOLP and EENS are estimated by using the probabilistic production cost approach [5] and the load curve is expressed as in Fig. 1.

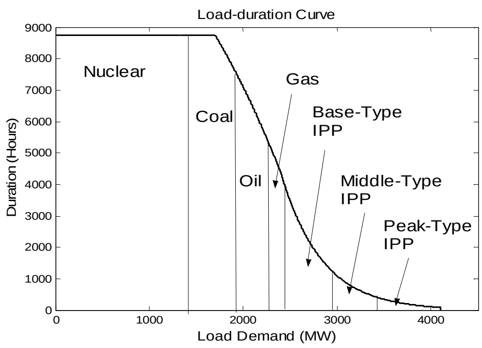

Fig. 1 Load Duration Curve

(F) Carbon Trading Condition

$$
\begin{aligned}
&if \quad \sum_n^N PGCo2_n > Co2\_allow \quad then\\
&\qquad \Delta Co2 = \sum_n^N PGCo2_n - Co2\_allow\\
&\qquad if \quad Co2\_buy\_\cos t < P\_reduce\_\cos t \quad then\\
&\qquad\quad \text{buy deficit of carbon credits.}\\
&\qquad elseif \quad Co2\_buy\_\cos t > P\_reduce\_\cos t \quad then\\
&\qquad\quad \text{reduce generation \& increase power purchase.}\\
&\qquad end\\
&elseif \quad Co2\_allow > \sum_n^N PGCo2_n \quad then\\
&\qquad \text{sell surplus of carbon credits.}\\
&end
\end{aligned}
$$

Co2_allow : CO2 emission allowances, Metric Tons.
Co2_buy_cost : cost of purchased carbon credit.
P_reduce_cost : power reduction cost of utility for more power purchased from IPPs.

III. SOLUTION ALGORITHM

In a PSO system, Birds (particles) flocking optimizes a given objective function. Each agent (pbest) knows its best value so far and its position. This information is analogy of personal experiences of each agent. Moreover, each agent knows the best value (gbest) so far in the group among pbests. This information is analogy of knowledge of how the other agents around them have performed [17].

This modification can be represented by the concept of velocity. Velocity of each agent can be modified by the following equation:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot rand_1 \cdot \left(pbest_i^t - p_i^t \right) + c_2 \cdot rand_2 \cdot \left(gbest^t - p_i^t \right) \tag{6}$$

where
v_i : velocity of agent i at iteration $(t+1)$
w : weighting function
c_1, c_2 : weighting factor
p_i : current position of agent i at iteration t
$pbest_i$: pbest of agent i
$gbest$: gbest of the group
$rand$: random number between 0 and 1,

The following weighting function is usually utilized as follow

$$w = w_{\max} - \left[(w_{\max} - w_{\min}) / iter\_time_{\max} \right] \cdot iter \tag{7}$$

where
$iter\_time_{\max}$: maximum iteration number
$iter$: current iteration number
$w_{\max}$: initial weight
$w_{\min}$: final weight

Using the above equation, a certain velocity, which gradually gets close to *pbest* and *gbest* can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$p_i^{t+1} = p_i^t + v_i^{t+1} \tag{8}$$

The execution step of PSO for solving optimal generation expansion planning problem with carbon rrading can be described as follows:

Step. 1 Initial Condition: Generate each agent or particle

Initial searching point p_i^0 and velocities v_i^0 of each agent are usually generated randomly within limited range. The particle coding scheme can be illustrated in Fig. 2, where each particle indicates a combination of number of expanding plant for generation technology and purchase price each year. The current searching point is set to *pbest* for each agent. *pbest* with best fitness value evaluated is set to *gbest* and its index number will be stored.

Step. 2 Evaluation of searching point of each particle

The fitness function or objective function value is calculated for each particle. If the value is better than the current *pbest* of the particle, the *pbest* value is replaced by the current value. If the best value of *pbest* is better than the current *gbest*, *gbest* is replaced by the best value and the particle index number with the best value is stored.

Step. 3 Modification of each searching point

The current searching point of each particle is changed using Eq.(6), Eq.(7) and Eq.(8).

Step. 4 Check the stopping rule

When current iteration number reaches the predetermined maximum iteration number, then exit. Otherwise, go to step 2.

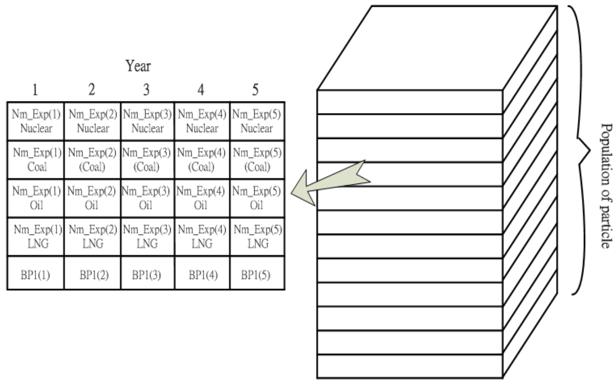

Fig. 2 Particle Coding Scheme

IV. CASE STUDY

The PSO algorithm was implemented using the MATLAB 7 on an IBM PC with Intel Core2 Quad Q6600 2.4GHz CPU and 4GB DRAM.

4.1 Test System Description

The proposed algorithm was applied to a 5-year test system with a power utility and three IPPs. Table 1 and 2 show the fixed cost, variable cost, outage rate and construction capacities of each participant for future additions respectively. Table 3 is the forecasted peak demand over the study period is given and each forecasted demand includes 20% power reserve. By considering the CO2 emission, the emission model can be formulated as Eq. (4). The CO2 Emission Allowances are assigned year-by-year with increasing forecasted carbon price also shown in Table 3. In this paper, the optimal GEP strategy for utility and optimal purchase prices for IPPs on every planning year was determined by the PSO process.

Table 1 5-year test system data for the utility

Unit type of Utility	Fixed Cost (US$/MW)	Variable Cost (US$/MWh)	Capacity (MW)	Existing Number	Expanding Number Considering	Outage Rate (%)
Nuclear	257312.5	6.6	900	2	6	4
Coal	159593.8	15	600	1	6	3.5
Oil	216562.5	27.5	500	1	6	2.5
LNG	76812.5	39.1	350	0	10	2

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Table 2 5-year test system data for IPPs

IPP type	Fixed cost (US$)	Variable cost (US$/MWh)	Max. Available Power (MW)		Outage Rate (%)
			Year 1	Year 2-5	
Peak-type	5.94×10^7	36.3	600	800	2
Middle-type	9.69×10^7	18.8	900	1100	2.5
Base-type	12.8×10^7	9.4	1300	1600	2.1

Table 3 Load forecasting and CO2 trading data of 5-year test system

Year	1	2	3	4	5
Peak(MW)	5200	6200	7300	8500	9400
Assigned CO2 Emission Allowance (Tons)	500	500	600	600	700
Forecasted Carbon Price (US$/Ton)	23.2	28.3	32.5	36.7	40.2

4.2 Generation Combination

Table 4 shows optimal GEP results for each generation technology for test system under carbon trading scheme. It shows the trading scheme force utility to expand low CO2 emission plant, i.e. nuclear, LNG etc., and utility consider purchasing electricity from IPPs to avoid CO2 emission increasing.

Table 4 Accumulated unit number for each generation technology

Year \ Gen. Type	Nuclear (Existing Number:2)	Coal (Existing Number:1)	Oil (Existing Number:1)	LNG (Existing Number:0)	Total Capacity of Utility (MW) initial: 2900MW
1	2	2	1	1	3850
2	3	2	1	1	4750
3	3	3	1	4	6400
4	3	4	1	4	7000
5	3	4	1	4	7000

Fig. 3 shows the percentage of utility and IPPs' energy participation. In year 3 and 4, utility has more plant been expanded, so IPPs' participation was reduced. Fig. 4 shows generation percentage of each generation technology and IPPs for study period. The number marked near the bar is the generation quantity (in MWatt.) of each participant.

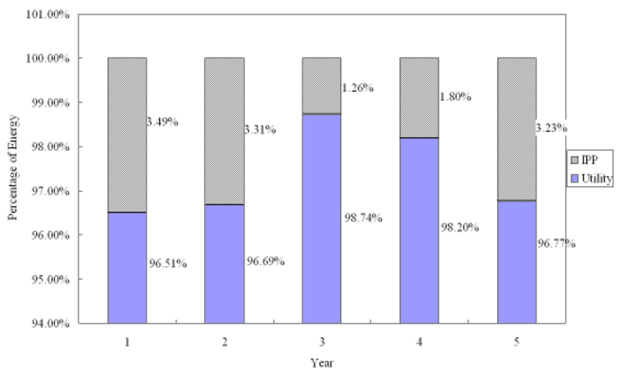

Fig. 3 Energy percentage of utility and IPPs

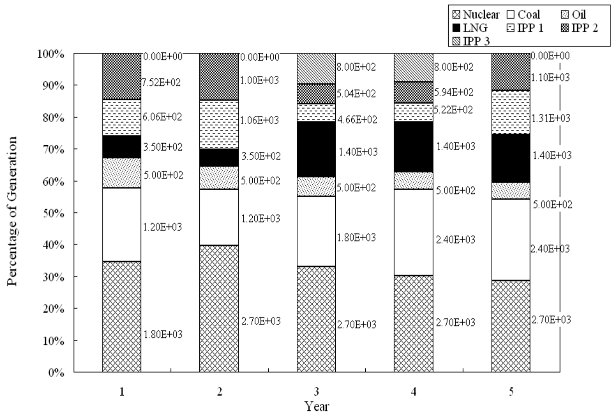

Fig. 4 Percentage of generation capacity combination

4.3 Cost Analysis and CO2 Emission Comparison

Table 5 is the simulation results of proposed test system including purchase price for three IPPs, cost of purchase electricity, generation & expansion cost and cost of purchase emission credits. The annual cost is sum up all of cost mentioned above and it is shown in the last row of Table 5. It is shown that if the emission is strongly limited in the market, the total cost will raise for the utility.

Table 5 Total cost analysis

Year	1	2	3	4	5
Purchase Price (US$/MWh)	33.5069	23.1863	40.7467	37.4185	20.5549
Cost of Purchase Electricity (Billion US$)	31.7236	24.8167	19.5842	29.9063	32.5137
Generation & Expansion Cost (Billion US$)	1092.08	1327.43	1630.39	1829.52	1931.70
Cost of Purchase Emission Credits (US$)	22201.1	17955.4	44257.3	78337.5	102876.4
Annual Cost (Billion US$)	1123.83	1352.27	1650.02	1859.50	1964.32

Fig. 5 shows CO2 Emission of the Utility for GEP problem without considering the CO2 limitation, CO2 trading scheme and IPPs' participations. The number marked near the bar is the CO2 emission quantity (in Tons.) of each participant. Inversely, CO2 Emission of the Utility with considering all issues mentioned above is demonstrated in Fig. 6. It is proved that all the GHG produced from generation technologies can be suppressed and governed effectively by taking consideration of carbon trading and power transaction.

4.4 Convergence Test

Table 6 shows the convergence result of three optimal algorithms, it shows maximum, minimum, and average optimized cost of 100 trials. The population size of each trial is 200. Fig. 7 illustrates the convergence characteristics of GA, IA and PSO for 5-year test system. Although the solution trend is subtle, it did show the capability of PSO in exploring a more likely global optimum.

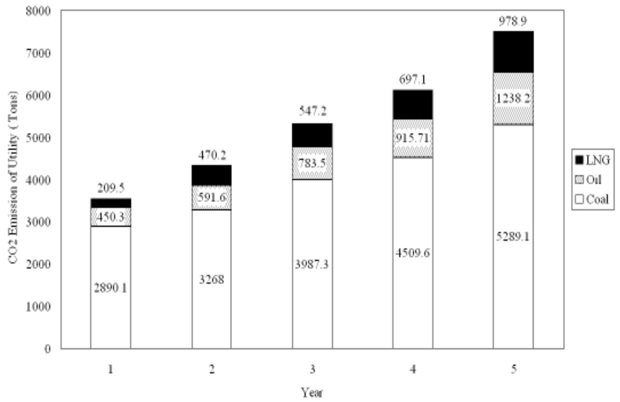

Fig. 5 CO2 Emission without considering the CO2 trading scheme and IPPs' participations

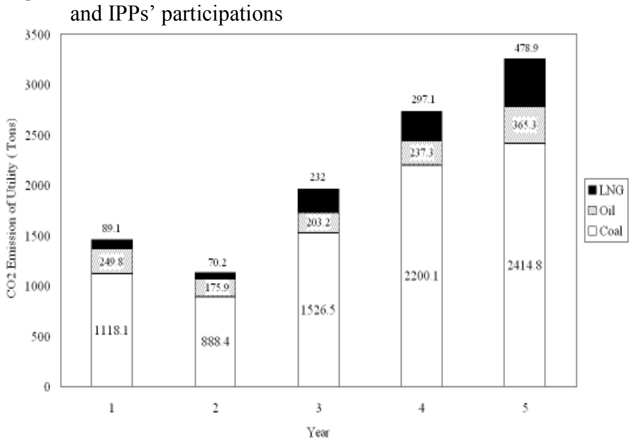

Fig. 6 CO2 Emission for the GEP with considering the CO2 trading scheme and IPPs' participations

Table 6 The total cost analysis of various conditions

5-year total Cost / Algorithm	Max. Converged Cost (Billion US$)	Min. Converged Cost (Billion US$)	Average Converged Cost (Billion US$)
GA	8202.1649	8074.9637	8159.4975
IA	8203.1678	8001.1646	8130.3479
PSO	8003.9176	7949.9312	7950.4972

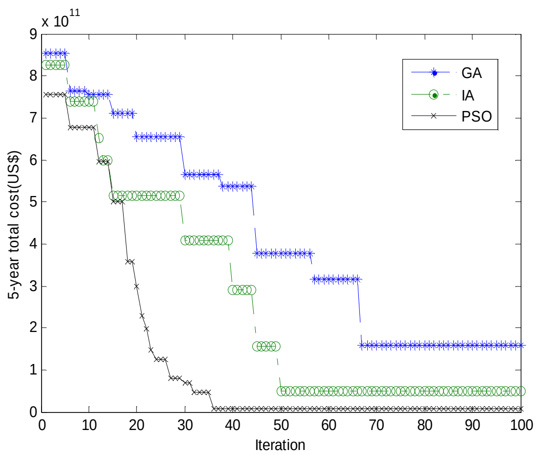

Fig. 7 The comparison of GA, IA and PSO methods

V. Conclusion

In this paper, it is shown that strongly emission limit result in the total cost raise by a carbon trading scheme for the utility. PSO was proposed to determine the generation expansion plan in the electricity market. With the advantages of PSO, it supersedes the conventional ideals in threefold: the complicated problem is solvable, with a better performance than other AI algorithms, and the more likelihood to get a global optimum than heuristic methods. The effectiveness of PSO has been demonstrated by numerical examples. PSO has great potential to be further applied to many ill-conditioned problems in power system planning and operations.

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