Solving the Single-period Multi-objective Power Generation Expansion Planning Problem

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Abstract

We present a new approach to determine the electricity generation technology options to be added, and where in the grid, they should be constructed for a single period multi-objective generation expansion plan. The proposed approach minimizes simultaneously multiple objectives, such as cost and air emissions. Distributed and central energy generation technologies are both considered as a part of expansion options to explore the benefit of using distributed energy resources. Unmet demand is also considered in the objective function so that the proposed approach considers the reliability of the system. This new approach is used to find the Pareto front for the multi-objective generation expansion planning problem that explicitly considers availability of the system components and operational dispatching decisions. Monte Carlo simulation is used to generate the component availability scenarios, and then, the mixed-integer optimization problem is solved to find optimum solutions considering these scenarios.

Keywords
Generation expansion, generation planning, multi-objective optimization, Monte-Carlo simulation

1. Introduction
The electricity generation expansion planning (GEP) problem is defined as the problem of determining the generation technology options to be added to an existing power generation system, and the time and location where they should be constructed to meet the growing energy demand over a planning time horizon. The GEP problem is a highly studied problem, where many of the studies focus on finding the least cost expansion plan. However, there are many conflicting objectives in the GEP problem such as environmental impact, reliability, imported fuel, safety and so on. Moreover, there are uncertainties associated with the input data such as demand forecasts, water flows to reservoirs, input fuel prices, system component failure and others. Therefore, a multi-objective, stochastic optimization method is desirable to solve the GEP problem.

Kagiannas *et. al.* [1], Zhu and Chow [2], Hobbs [3], and Nara [4] provide a survey of modeling techniques developed for GEP. Malcolm and Zenios [5] propose an optimization model to produce robust power system capacity expansion under uncertain demand. Sirikum and Techanitisawad [6] and Park *et. al.* [7] apply a GA-based heuristic to solve the least cost GEP problem. Bloom [8] and Firmo and Legey [9] apply generalized Benders' decomposition. Antunes *et. al.* [10] models the GEP problem as a multiple objective mixed integer linear programming problem. Meza *et. al.* [11] proposes a model for the multi-period multi-objective GEP problem. Meza *et.al.* [12] presents a framework to determine the set of non-dominated solution for single-period multi-objective mixed integer nonlinear GEP with Kirchoff`s Law. Zerriffi *et. al.* [13] compares the performance of the centralized and distributed generation systems under various levels of stress using Monte-Carlo simulation.

In this study, we describe and solve a single period multi-objective mixed integer GEP problem. We use multi-objective optimization to minimize the cost, and the environmental impact, namely the CO_2 and NO_x emissions. The CO_2 and SO_2 emissions are largely generated from coal burning, and therefore, the SO_2 emission is highly and positively correlated with the CO_2 emission. Therefore, we implicitly consider minimizing the SO_2 emission by minimizing CO_2 emission. The forced outages of the system components are explicitly considered as a part of expansion planning problem. Monte-Carlo simulation is used to generate scenarios based on the uncertainty of availability of the system components. A two-stage stochastic programming model is proposed to solve the GEP problem. Our previous work Tekiner *et.al.*[14] presents a similar model for multi-period GEP problem. Here, we solve single period GEP problem with large number of scenarios and provide a new approach to generate scenarios.

2. Single Period Multi Objective Generation Expansion Planning Problem

The focus of this research is to integrate reliability, generation expansion and dispatching decisions while reducing air emissions, and to consider supplementing the existing centralized system with distributed power generation. Distributed power generation involves the use of smaller generating units located closer to energy users.

The topology for existing central system studied here is the same as in Zerriffi, *et. al.* [13]. The existing system consists of central generation units distributed among ten power groups. These generation units have different technologies. The energy generated in these power groups is transmitted to the distribution system via transmission lines. Some of the generation units use natural gas as fuel. For those, we also consider the same natural gas network presented in Zerriffi, *et. al.* [13]. The transmission pipelines from natural gas storage feed the five power groups which contain natural gas burning generation units. There are 273 independent local load blocks and these load blocks are connected to the area grid by the distribution lines. There is a similar natural gas network as in Zerriffi *et. al.* [13] providing natural gas to these load blocks. The transmission pipelines are used to transmit natural gas from storage areas to 13 city-gates. Each city-gate has three sub-transmission mains, each of which feeds seven micro-grids. The distribution pipelines are used to distribute natural gas from city-gate to sub-transmission mains.

3. Monte Carlo Simulation

The study objective is to integrate reliability analysis with expansion planning and dispatching decisions. Therefore, we propose a simulation based optimization approach. We generate numerous scenarios considering the availability of the system components. Since reliability is an important issue when the demand is high, we are more interested in the unit availabilities in those hours. Therefore, we divided the load duration curve into subperiods and assign the highest demand in that interval as a scenario demand with corresponding probability. We use the highest demand to account implicitly for reserve margin constraints for the system. For that demand, the system can be in any availability status. We generate M_p number of availability scenarios for each selected demand interval and assign a probability for each scenario obtained by dividing demand probability by the number of availability scenarios generated. Then, we calculate the adjustment factor defining the number of hours represented by each scenario by multiplying the probability of each scenario by the total number of hours in the planning horizon. The higher the demand, the more availability scenarios are generated. This is an improved scenario generation method compared to that presented in Tekiner *et. al.* [14].

The system components whose failures are considered are generation units, transmission lines, distribution lines, transmission pipelines providing natural gas to centralized units, transmission pipelines providing natural gas to city gates, and sub-transmission pipelines delivering natural gas to sub-mains. We assume that the backbone of the transmission and distribution grids and the micro-grids, which transfer natural gas from sub-transmission mains to local load blocks, are always available, similar to Zerriffi *et. al.* [13].

Some of the parameters used in mathematical model are scenario based; and they are obtained from Monte-Carlo simulation. In each scenario, uniform distributed random numbers between 0 and 1 are selected for each component. If the chosen number is smaller than the unavailability of the corresponding component, this component is assumed unavailable for that scenario. The parameters and their definitions are presented below.

$\boldsymbol{\Psi_n}$: Satisfiable demand in scenario n calculated as $\sum_{l=1}^{L} D_{nl} \times I_n(l)$ where D_{nl} is demand selected for local load block l in scenario n; and $I_n(l)$ equals 1 if distribution line of load block l is working in scenario n, 0 otherwise.

$\boldsymbol{\Phi_{nl}}$: Locally satisfiable demand at load block l in scenario n calculated by $D_{nl} \times (1 - I_n(l))$ for each load block in the set of □ which represent the load blocks where distributed generation unit can be located.

$\boldsymbol{\gamma_{nk}}$: Available capacity of central unit k in scenario n calculated by $\lambda_k \times Z_n(k) \times R_n(gr_k) \times Y_n(gr_k)$ if unit k uses natural gas and by $\lambda_k \times Z_n(k) \times R_n(gr_k)$ if not where λ_k is capacity of central unit k; gr_k is power group number where unit k is located; $Z_n(k)$ equals 1 if generation unit k is working in scenario n, 0 otherwise; $R_n(gr_k)$ equals 1 if transmission line from power group gr_k is working in scenario n, 0 otherwise; and $Y_n(gr_k)$ equals 1 if natural gas transmission pipe to power group gr_k is working in scenario n, 0 otherwise.

$\boldsymbol{W_{nlj}}$: Available capacity of distributed unit j located at load block l in scenario n which can be used to meet satisfiable demand calculated by $\mu_{l_j} \times Q_{nl}(j) \times H_n(t_l) \times K_n(d_l) \times I_n(l)$ for each distributed unit in the set □ if unit uses natural gas, by $\mu_{l_j} \times Q_{nl}(j) \times I_n(l)$ if not, where μ_{lj} is capacity of distributed unit j located at load block l; Q_{nl} equals 1 if distributed generation unit j located at load block l is working in scenario n, 0 otherwise; $H_n(t_l)$ equals 1 if natural gas transmission pipe serving load block l is working in scenario n, 0 otherwise; and $K_n(d_l)$ equals 1 if natural gas sub-main transmission pipe serving load block l is working in scenario n, 0 otherwise.

$\boldsymbol{F_{nlj}}$: Available capacity of distributed unit j located at load block l in scenario n which can be used to satisfy only local demand calculated by $\mu_{l_j} \times Q_{nl}(j) \times H_n(t_l) \times K_n(d_l) \times (1 - I_n(l))$ for each distributed unit in the set □ if unit uses natural gas, by $\mu_{l_j} \times Q_{nl}(j) \times (1 - I_n(l))$ if not.

4. Mathematical Model

The problem is to determine an optimal expansion plan given the objectives of minimizing cost and minimizing undesirable air emissions. The individual objectives are scaled and combined so that a single objective function problem can be solved. The weights to combine the individual objective functions are varied to determine a Pareto front. This is an effective approach if the Pareto front is convex. In this manner the trade-offs involved can be explicitly considered, such as the relative increase in cost corresponds to a decrease in greenhouse gas emissions.

4.1 Multiple Objective Functions

The first objective is to minimize the total cost (O_1) consisting of investment cost, fixed O&M cost, generation cost, unmet demand cost and revenue from the steam.

$$
\begin{aligned}
O_1 = &\left(\sum_{q=1}^{Q} s_q a_q + \sum_{l \in \Lambda} \sum_{j=1}^{J_l} w_{lj} b_{lj} \right) + \left(\sum_{k=1}^{K} g_k + \sum_{q=1}^{Q} s_q h_q + \sum_{l \in \Lambda} \sum_{j=1}^{J_l} w_{l_j} m_{lj} \right) + \\
&\left(\sum_{n=1}^{N} \sum_{k=1}^{K} pr(n) x_{nk} c_k + \sum_{n=1}^{N} \sum_{q=1}^{Q} pr(n) u_{nq} e_q + \sum_{n=1}^{N} \sum_{l \in \Lambda} \sum_{j=1}^{J_l} pr(n)(y_{nlj} + z_{nlj}) d_j \right) \\
&+ \left(\sum_{n=1}^{N} pr(n) v_n f + \sum_{n=1}^{N} \sum_{l \in \Lambda} pr(n) \pi_{nl} f \right) - \left(\sum_{n=1}^{N} \sum_{l \in \Lambda} \sum_{j \in R} pr(n)(y_{nlj} + z_{nlj}) pr \right)
\end{aligned} \tag{1}
$$

s_q, a_q, and h_q; w_{lj}, b_{lj} and m_{lj}; are the investment decision, investment cost and fixed O&M cost of a central unit type q and of a distributed unit j located at load block l respectively. g_k is the fixed O&M cost for existing central unit k. Q is the total number of centralized generation investment options, J_l is the total number of distributed generation investment options available at local load block l and K is the total number of centralized units in existing system. x_{nk} is the generation amount of existing central unit type k in scenario n. u_{nq} is the generation amount (MW) of new central unit type q in scenario n. y_{nlj} is the generation amount (MW) of distributed unit type j located at load block l to meet satisfiable demand. z_{nlj} is the generation amount (MW) of distributed unit type j located at load block l to meet local demand. c_{tk}, e_{tq} and d_{tj} are the generation costs ($/MW) of existing central unit type k, new central unit type q and distributed unit type j respectively. v_n and π_{nl} are the unmet satisfiable demand (MW) in scenario n and unmet local demand at load block l in scenario n respectively. f is the cost of not satisfying the demand ($/MW). R is the set of distributed generation units with co-generation capabilities. p is the proportion of generated energy can be used to receive benefit and r is the revenue obtained from the usage of steam ($/MW). $pr(n)$ represents the adjustment factor for scenario n.

The second (O_2) and third objectives (O_3) are to minimize the amount of CO_2 emissions and NO_x emissions respectively. They are determined as follows.

$$
O_2 = \sum_{n=1}^{N} \sum_{k=1}^{K} pr(n) x_{nk} C_k + \sum_{n=1}^{N} \sum_{q=1}^{Q} pr(n) u_{nq} E_q + \sum_{n=1}^{N} \sum_{l \in \Lambda} \sum_{j=1}^{J_l} pr(n)(y_{nlj} + z_{nlj}) D_j \tag{2}
$$

$$O_3 = \sum_{n=1}^{N}\sum_{k=1}^{K} pr(n)x_{nk}F_k + \sum_{n=1}^{N}\sum_{q=1}^{Q} pr(n)u_{nq}G_q + \sum_{n=1}^{N}\sum_{l\in\Lambda}\sum_{j=1}^{J_l} pr(n)(y_{nlj} + z_{nlj})H_j \quad (3)$$

C_k, E_q and D_j are the amounts (lbs) of CO_2 per MW generated by existing central unit type *k*, new central unit type *q* and distributed unit type *j* respectively. F_k, G_q and H_j are the amounts (lbs) of NO_x per MW generated by existing central unit type *k*, new central unit type *q* and distributed unit type *j* respectively.

The three individual objective functions have different units and scaling. Next, the objective functions are linearly scaled between 0 and 1. Then, they can be combined into a composite objective function. w_i represents the relative weight assigned to each objective function. The weights can be varied to reflect any different decision maker preferences or to explore the possible trade-offs between different plans and preferences.

4.2 Problem Formulation

The mathematical formulation is presented below. The objective is to minimize the weighted summation of three scaled objective functions over nine sets of constraints. The first set of constraints is for satisfiable demand constraints. For each scenario, the total generation and unmet demand should be at least as much as the satisfiable demand for the corresponding scenario. The second set of constraints is for locally satisfiable demand. From third to sixth, the constraints limit the generation from the existing generation units, new central units and distributed limit by the corresponding available capacities. The remaining constraints are for nonnegativity and binary variables.

$$\begin{aligned}
&\min z = w_1\bar{O}_1 + w_2\bar{O}_2 + w_3\bar{O}_3 \\
&\text{s.t.} \\
&\quad \sum_{k=1}^{K} x_{nk} + \sum_{q=1}^{Q} u_{nq} + \sum_{l\in\Lambda}\sum_{j=1}^{J_l} y_{nlj} + v_n \ge \Psi_n && \forall n \\
&\quad \sum_{j=1}^{J_l} z_{nlj} + \pi_{nl} \ge \Phi_{nl} && \forall n, \forall l \in \Lambda \\
&\quad x_{nk} \le \gamma_{nk} && \forall n, k \\
&\quad u_{nq} \le \gamma_{nq} s_q && \forall n, q \\
&\quad y_{nlj} \le W_{nlj} w_{l_j} && \forall n, \forall l \in \Lambda, \forall j \in J_l \\
&\quad z_{nlj} \le F_{nlj} w_{l_j} && \forall n, \forall l \in \Lambda, \forall j \in J_l \\
&\quad s_q \in \{0,1\} \quad \forall q,\ w_{lj} \in \{0,1\} \quad \forall l \in \Lambda, \forall j \in J_l \\
&\quad x_{nk} \ge 0 \quad \forall n,k, \quad u_{nq} \ge 0 \quad \forall n,q && v_n \ge 0 \quad \forall n \\
&\quad y_{nlj} \ge 0, z_{nlj} \ge 0 \quad \forall n, \forall l \in \Lambda, \forall j \in J_l && \pi_{nl} \ge 0 \quad \forall n, \forall l \in \Lambda
\end{aligned}$$

5. Numerical Example

To demonstrate the model, we solve an example problem for a single decision period followed by 15 years of operation. In the example system, there are 50 load blocks where the distributed units can be located. We considered internal combustion (IC) engines (0.5 MW each) as distributed generation units. The engines use natural gas as fuel and have cogeneration capabilities. In order to minimize the binary decision variables, we consider building 25 IC engines together and consider the capacity of the distributed generation as binomial variables. The technologies available to add to power groups are Oil/Steam (197 MW), Coal/Steam (155 MW), Wind Turbines (50 MW), Nuclear (400 MW), Combined Cycle Gas Turbines (CCGT/76 MW). The existing system consists of 32 generation units consisting of Oil/CT, Oil/Steam, Coal/Steam, CCGT and nuclear. Total existing capacity is 3405MW. We use the same capacity, unavailability, cost and emission characteristics for each generation units as in Tekiner *et. al*. [14]. We assume that 30% of wind generation capacity can be used to generate electricity [15]. In this study, we assume that the system has sufficient transmission line capacity. However, installation of wind turbines may require adding new transmission lines to the system. As a result, we increase the capital investment cost for the wind turbine by 30%.

The load model presented as the IEEE Reliability Test System is used. We divide the load model into demand intervals and calculate the probabilities for each interval. Table 1, the demand intervals, corresponding probabilities, number of scenarios generated, and adjustment factor are presented.

Table 1: Demand interval and corresponding probabilities

Demand Intervals in terms of % of peak load demand	Interval Prob.	# of Scenarios	Adjustment Factor	Demand Intervals in terms of % of peak load	Interval Prob.	# of Scenarios	Adjustment Factor
1.00	0.01	600	2.19	(0.60,0.70)	0.23	150	201.48
(0.95, 0.99)	0.01	450	2.92	(0.50,0.60)	0.21	75	367.92
(0.90, 0.95)	0.02	375	7.008	(0.40,0.50)	0.22	45	642.4
(0.80,0.90)	0.11	300	48.18	(0.33,0.40)	0.03	30	131.4
(0.70,0.80)	0.16	225	93.44				

Demand for each scenario is determined by multiplying peak load demand with the highest percentage in the interval. The peak load demand in this problem is 2850 MW and we also assume that demand increases 1% in each year. The cost of not satisfying demand is assumed as 10,000 $/MW. We also consider that 50% of energy produced by distributed generation units can be used to gain benefits from the steam, and in our model, the profit per MW by using steam is approximately 60% of energy generation cost from IC, i.e., 15.91 $/MW. Since the period consists of 15 years, the cost parameters for fixed operation and maintenance cost are adjusted accordingly.

The Monte-Carlo simulation is coded by using C++, Microsoft Visual Studio 2005. GAMS/CPLEX is used to solve the mathematical model. The problem was solved considering 26 different weight combinations as presented in Table 2. In case 26, the problem is solved only to minimize the total cost. In other scenarios, the weight for cost is at least 0.5. Also, we assume that only one nuclear power plant can be built over the 15 year planning horizon. The objective function values for the Pareto-front solutions and expansion plan are presented in Table 3. Decision makers can choose the solution that is the most appropriate given their preferences. Our analysis is providing the trade-offs between each objective function.

Table 2: Case numbers and corresponding weight combinations

#	Cost	CO_2	NO_x	#	Cost	CO_2	NO_x	#	Cost	CO_2	NO_x	#	Cost	CO_2	NO_x	#	Cost	CO_2	NO_x
1	0.5	0	0.5	6	0.6	0	0.4	11	0.7	0	0.3	16	0.8	0	0.2	21	0.9	0	0.1
2	0.5	0.125	0.375	7	0.6	0.1	0.3	12	0.7	0.075	0.225	17	0.8	0.05	0.15	22	0.9	0.025	0.075
3	0.5	0.25	0.25	8	0.6	0.2	0.2	13	0.7	0.15	0.15	18	0.8	0.1	0.1	23	0.9	0.05	0.05
4	0.5	0.375	0.125	9	0.6	0.3	0.1	14	0.7	0.225	0.075	19	0.8	0.15	0.05	24	0.9	0.075	0.025
5	0.5	0.5	0	10	0.6	0.4	0	15	0.7	0.3	0	20	0.8	0.2	0	25	0.9	0.1	0

Table 3: Objective function solutions for Pareto-front for GEP solutions and expansion plan

Cases	Cost (in billions $)	CO_2 (thousands	NO_x (thousands	SO_2 (thousands	Numbers of Units Added to System			
					Nuclear	Wind	CCGT	DU
1,6,7,11,12,13,14	18.24	89,600	85	179			10	50×25
2,3,9	22.02	62,200	53	95	1		10	50×25
4,8	22.01	61,600	52	92	1		10	50×25
5	24.01	50,800	66	40	1	9	10	50×25
10	22.01	59,100	87	48	1		10	50×25
15	18.24	84,000	170	84			10	50×25
16	18.09	91,700	91	201			9	50×25
17	17.72	94,900	107	297			9	50×25
18	17.91	92,500	99	264			10	50×25
19	17.33	100,500	125	372			7	50×25
20	17.63	90,200	255	128			6	50×25
21,22,23,24	16.78	125,900	209	698				50×25
25	16.78	122,800	254	645				50×25
26	16.65	138,500	302	861				50×25

The investment decisions are changed based on relative weights on cost, CO_2 and NO_x. When the relative weight on cost is high, there is no central unit investment. When the weight on cost keeps decreasing, the system starts choosing to build CCGT. When the relative weight on CO_2 emission is high, the expansion plan includes building nuclear plants and when the weight on CO_2 is at its highest value, wind turbines also become a part of expansion. When the objective includes only cost and NO_x emission, the investments are only made in CCGTs. The dispatching decisions also change with the Pareto solutions. Distributed generation units (IC engines) are used to meet satisfiable demand when NO_x emission is not part of the objective function. Since Oil/Steam units have the second lowest NO_x emissions, for the combination where the objective function includes NO_x, Oil/Steam units are used to satisfy the demand despite their high variable costs. Nuclear plants and wind turbines are both economically and environmentally beneficial (in terms of air emissions), and therefore, they are used to their capacity limits when they are available. Coal burning units have low variable cost; therefore when the objective is only to minimize the cost; they are used as much as possible. However, they have the highest CO_2 emissions and relatively high NO_x emission. Therefore, the usage of coal burning units is lower while the relative importance of the gas emissions is increased. CCGT usage increases with an increase in the importance of reduction in gas emissions and its highest usage occurs when the objective is to minimize cost and NO_x and the cost has its lowest level of importance.

6. Conclusion

In this study, we solve the GEP problem as a two-stage stochastic programming problem to integrate reliability analysis with the expansion planning and dispatching problems. We use multi-objective optimization and apply the model to solve a problem to present the trade-offs between the cost and environmental impacts. The expansion and dispatching decision changes are based on the relative importance of the objectives. The results show that when the importance of reducing gas emission is increased, the technologies with lower gas emissions are built. There are numerous possible extensions of this work. Decomposition methods can be applied to solve multi-period problems with a larger number of scenarios. Uncertainties and risk measures can also be included into the extended model.

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