Abstract - This paper presents an approach for calculating the optimal generation capacity reserve and siting in power systems planning. The proposed methodology is based on a least-cost planning approach which considers, along the planning horizon, the capacity reserve investment costs and the expected operational costs, comprising thermal generation and interruption costs. This problem is solved by using the Benders decomposition technique in which investment and operation subproblems solutions are obtained iteratively and separately. The operation subproblem corresponds to a probabilistic evaluation of the minimum operation cost in composite generation/transmission systems, in which the system states are selected through Monte Carlo simulation or state enumeration and the system performance is analysed by a non-linear optimal power flow solved by an interior point algorithm. The proposed methodology is illustrated in a case study with a modification of the IEEE Reliability Test System (MRTS).

Keywords: Power system planning, generation capacity reserve, probabilistic analysis, optimization, decomposition techniques.

INTRODUCTION

The need for more efficiency in power production and delivery has led to the restructuring of the power sector in several countries. Although the new frameworks are deeply related to the country characteristics, some common features have been emphasized such as industry deverticalization, introduction of competition on energy production and trading [1], and open access of the transmission systems to third parties [2].

As a consequence, a heavier use of the transmission grid as well as a possible decrease on system reserve margins is expected. Therefore, power engineers have been deeply concerned with respect to the impact of the restructuring process on the system reliability levels [3]. This led the reliability management, i.e., the provision of the set of services needed to assure a reliable and secure system operation, to be one of the most important activities in this new competitive environment.

Usually the reliability management can be carried out, at operations level, by the transmission entity (e.g., in the United Kingdom) or by the Independent System Operator (e.g., in Brazil). Among others, generation reserve, including operational reserve and capacity reserve, are of key importance in reliability management. However, especially in countries experiencing high load growth rates, as is the case of Brazil, the definition of capacity reserve requirements can not be only decided at operations level. This definition should take place in advance during the expansion planning phase.

It should be noted that the actual contribution of each generator to system reliability depends not only on equipment capacities but also on transmission limitations. In other words, a generation capacity increase at a site with transmission bottlenecks for power export may bring little or no improvement to system reliability. Hence, in the case of generation reserve, both required capacity and siting should be determined. Additionally, this contribution also depends on equipment forced outages, which are random. Therefore, the best way to analyse the benefits of the possible capacity reserve reinforcements to the system performance is to use probabilistic methods.

This work presents a methodology for calculating the optimal generation capacity reserve and siting in power systems planning. The proposed methodology is based on a least-cost planning approach [4] which considers along the planning horizon, the capacity reserve investment costs and the expected operational costs, comprising thermal generation and interruption costs. This problem is solved by using the Benders decomposition technique [5-7] in which investment and operation subproblems solutions are obtained iteratively and separately thus allowing the use of taylor-made algorithms for each subproblem. The operation subproblem corresponds to a probabilistic evaluation of the minimum operation cost in composite generation/transmission systems, in which the system states are selected through Monte Carlo simulation or state enumeration [9] and the system performance is analysed by a non-linear optimal power flow solved by an interior point algorithm [8,13].

The proposed methodology is illustrated in a case study with a modification of the IEEE Reliability Test System (MRTS).

FORMULATION OF THE GENERATION CAPACITY RESERVE ALLOCATION PROBLEM

In the expansion planning process, the generation capacity reserve problem consists on determining the system buses in which new generation units should be installed in order to provide adequate generation capacity reserve while minimizing the investment and operational costs along the planning horizon. This problem can be seen as a least cost planning problem, where the objective function is associated to the investment and operational costs of the generation reserve candidates, the operational costs of the existing plants and the system interruption costs. In this way, the interaction between generation location and transmission network is taken into account.

For ease of explanation, let us assume that the planning horizon is only one year. The minimum cost generation capacity reserve allocation problem can be represented by the following optimization problem:
The operating cost $d(y^*)$, where $y^*$ is the optimal solution of Problem (2), can be seen as a function $\alpha(x)$ of the generation capacity reserve decision $x$, that is [6]:

\[
\alpha(x) = \min d(y) \quad \text{s/to} \quad F(y) \geq h - E(x)
\]

The expansion Problem (1) can then be rewritten in terms of the $x$ variables as

\[
\min \quad c(x) + \alpha(x) \quad \text{s/to} \quad A(x) \geq b
\]

Observe that the function $\alpha(x)$ is the solution of Problem (3) for any given $x$. The function $\alpha(x)$ provides information about the “consequences” of the investment decision $x$ in terms of operational costs. If this function is available, the generation capacity reserve problem can be solved without an explicit representation of the operation subproblem.

The Benders decomposition scheme [5] is a technique for building an approximation to $\alpha(x)$, based on the solution of the operation subproblem (2).

In the Benders algorithm, stage 1 and stage 2 problems are iteratively solved as follows:

1. Start with an approximation $\hat{\alpha}(x)$ which is a lower bound to $\alpha(x)$, e.g., $\hat{\alpha}(x) = 0$; set an upper bound to the cost function $z$, i.e., set $\bar{z} = +\infty$.
2. Solve the relaxed problem (5) which is written only in terms of the investment decision variables $x$. This problem is an approximation to the generation capacity reserve expansion problem (4):

\[
\min \quad c(x) + \hat{\alpha}(x) \quad \text{s/to} \quad A(x) \geq b
\]

3. Let $x^*$ be the solution of Problem (5). Calculate a lower bound to the optimal solution of the generation capacity reserve problem (1) as:

\[
\underline{z} = c(x^*) + \hat{\alpha}(x^*)
\]

4. Once the investment decision $x^*$ is known solve the operation problem (7) which is written only in terms of the variables $y$:

\[
\min \quad d(y) \quad \text{s/to} \quad F(y) \geq h - E(x^*)
\]

5. Let $y^*$ be the solution of Problem (7). The pair $(x^*, y^*)$ is a feasible solution of the expansion problem but not necessarily the optimal solution. Therefore one can determine an upper bound to the optimal solution value of the generation capacity reserve expansion problem:

\[
\bar{z} = c(x^*) + d(y^*)
\]

6. If $\underline{z} - \bar{z}$ is smaller than a given tolerance, the problem is solved and the pair $(x^*, y^*)$ is the optimal solution. Otherwise, generate a new approximation $\hat{\alpha}(x^*)$ from the solution of problem (7). This approximation will still be a lower bound to $\alpha(x)$. Go to Step (ii).

One important feature of the Benders decomposition scheme is the availability of upper and lower bounds to the optimal solution at each iteration. These bounds can be used as an effective convergence criterion, as shown in Step (vi).

The critical point in the decomposition scheme is the modification of $\alpha(x)$ from the solution of problem (7). Associated with the solution of the operation subproblem there is a set of Lagrange multipliers which measure the change in system operating costs caused by marginal changes in the trial generation reserve plant capacities. These multipliers are used to form a linear constraint, written in terms of the investment variable $x$. This constraint, known as a Benders cut, is returned to the investment subproblem, which is modified and re-solved to determine a new trial capacity expansion plan. For example, when the operation subproblem is linear, the Benders cut is given by [6]:

\[
\alpha(x^*) + \pi^* x^* - \pi^* E \leq 0
\]
where the vector \( \pi \) are the Simplex multipliers and \( \alpha \) is a scalar. An extension of the Benders decomposition to non-linear programming problems can be found in [7].

It is still possible to apply the Benders decomposition if the planning horizon is greater than one year. In this case, besides determining the amount and location of new generation capacity reserve, the investment subproblem should also decide when those units should be installed. Also, the operational costs should be calculated for each year of the planning horizon.

**Considering Uncertainties in the Operation Subproblem**

As mentioned before, power system operation is essentially stochastic due to the equipment random outages and load fluctuations. It means that it is very important to ensure a feasible and economical operation not only for the base case, but also under contingency situations.

Therefore, the operation subproblem should utilise a probabilistic framework [13] to draw several operational conditions rising from combinations of generator and transmission outages and load variations, and to calculate the expected value of the minimum operational costs.

The Benders algorithm is able to handle stochastic problems [10,11] which have the property that the solution of the second stage problem depends on the outcome of random variables. Let assume that the vector \( h \) in Problem (1) is a random variable and can assume \( m \) values each one with probability \( p_k \) \( (p_1 + ... + p_m = 1) \). In this case the objective is to find the strategy that minimizes the expected value of the operation cost:

\[
\begin{align*}
    z &= \text{Min } c(x) + p_1 d(y_1) + ... + p_m d(y_m) \\
    \text{s/to } A(x) + E(x) + F_1(y_1) &\geq b_1 \\
    &\vdots \\
    &E(x) + F_m(y_m) \geq b_m
\end{align*}
\]

The stochastic Problem (10) can also be written as a two-stage decision process: in the first stage a feasible decision \( x^* \) is made. Then, based on that investment decision, \( m \) operation subproblems (11) are solved, as depicted in Figure 2.

\[
\begin{align*}
    \alpha_k(x) &= \text{Min } d_k(y_k) \\
    \text{s/to } F_k(y_k) &\geq h_k - E(x), \quad k = 1, ..., m
\end{align*}
\]

The solutions of Problems (11) are weighted by the probabilities \( p_k \) to obtain the expected operational cost \( \bar{C}(x) \):

\[
\bar{C}(x) = \sum_{k=1}^{m} p_k \alpha_k(x)
\]

The stochastic decision problem (10) can also be rewritten in terms of the \( x \) variables:

\[
\begin{align*}
    \text{Min } c(x) + \alpha(x) \\
    \text{s/to } A(x) \geq b
\end{align*}
\]

Besides the expected operational cost we can also obtain the expected values of the Lagrange multipliers associated to each one of the operation subproblems. These figures are utilized in the Benders algorithm to construct a mean Benders cut, which is returned to the investment subproblem.

If the operation subproblem scenarios are selected by using Monte Carlo simulation, the convergence of the Benders algorithm (step vi) can be based on the confidence interval associated to the mean operation cost upper bound.

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**SOLUTION OF THE FIRST AND SECOND STAGE SUBPROBLEMS**

As we have seen, the investment subproblem (5) and the operation problem (7) are solved separately. In other words, the natural decomposition between investment and operation decisions is mathematically exploited thus allowing the use of taylor-made algorithms as shown next.

**Solution of the Investment Subproblem**

The investment stage of the generation capacity reserve problem was formulated as a mix integer linear programming problem. Several techniques are available to solve problems of this type, including the cut, implicit enumeration, and branch and bound methods [12].

Due to the good performance when applied to energy expansion planning under uncertainty problems [11], the branch and bound method was adopted. The basic idea of this method is to relax the integrality constraints \( x \in \{0,1\} \), thus converting the original investment subproblem into a linear programming problem. If all components of the vector \( x \) are integer in the solution of the linear problem, then the optimal solution of the original problem is obtained. Otherwise, if at least one component of \( x \) is not integer, two new linear problems are developed by setting this component value equal to the nearest integer figures. These two new problems are solved and the integrality of their solutions is checked again. In case of non integer values, this procedure is repeated until the optimal solution is calculated or is concluded to be infeasible.

**Solution of the Operation Subproblem**

For each year of the planning horizon, the operation subproblem corresponds to a probabilistic evaluation of the minimum operation cost in composite generation/transmission systems, comprising generation, losses and interruption costs. For each sampled scenario, the operation subproblem can be stated by the following non-linear optimal power flow:
Min $\sum_{i=1}^{n} c_{gi} P_{gi} + \sum_{i=1}^{n} \theta_{j} c_{Li} P_{Li}$ \hspace{1cm} (14)

s/to
\[ \begin{align*}
(1-\theta_{j})P_{Li} - P_{gi} + P_{i}(x) &= 0, \quad i = 1, \ldots, n \quad (14.1) \\
(1-\theta_{j})Q_{Li} - Q_{gi} + Q_{i}(x) &= 0, \quad i = 1, \ldots, n \quad (14.2) \\
\theta \sum_{i} g_i(x) &= 0, \quad i = 1, \ldots, n \quad (14.3)
\end{align*} \]

where:
- $P_{Li}, Q_{Li}$ are active and reactive loads at bus $i$, $i = 1, \ldots, n$;
- $P_{gi}, Q_{gi}$ are active and reactive generations at bus $i$, $i = 1, \ldots, n$;
- $n$ is the number of buses;
- $\theta$ is a vector which represents the fraction of load curtailed in each bus;
- $x$ is a vector which represents the power flow control and state variables.

In problem (14), equations (14.1), (14.2) represent the active and reactive power flow balance equations at bus $i$, $i = 1, \ldots, n$, and (14.3), bounds on variables. For instance, each component of $\theta$ should be greater or equal to zero and less or equal to one. Note that if for a given vector of active/reactive loads the power flow is solvable, in the optimal solution of problem (14) $\theta_{i} = 0$, $i = 1, \ldots, n$.

**Solution Algorithm**

Letting $z=(\theta, x, y)$, problem (14) can be stated in a more general form as:

\[ \begin{align*}
\text{Min} \quad & g(z) \\
\text{s/to} \quad & h(z) = 0 \\
& a \leq z \leq b
\end{align*} \]

where:
- $g(z)$ = objective function in (14);
- $h(z) = 0$ represents constraints (14.1) and (14.2);

The general problem (15) will be solved by a direct interior point method based on the primal-dual logarithm barrier algorithm [8,13]. This approach consists in applying the interior point method to the original nonlinear programming problem, which is the OPF, and it does not depend on the convergence of any load flow algorithm - in its iterative scheme the power flow equations are only required to be attained at the optimal solution. Also, numerical experiences have shown that direct interior point methods are very effective in dealing with large scale ill-conditioned and voltage problem networks [13].

The first step in the application of the primal-dual algorithm to problem (15) is to incorporate constraints (15.2) to a logarithmic barrier function:

\[ \begin{align*}
\text{Min} \quad & \left\{ g(z) - \mu \sum_{j} \log(z_{j} + a_{j}) - \mu \sum_{j} \log(b_{j} - z_{j}) \right\} \\
\text{s/to} \quad & h(z) = 0
\end{align*} \]

where $\mu$ is the barrier parameter.

The basic idea of the algorithm is to solve approximately problem (16) for each value of $\mu$ and force $\mu$ go to zero; at the limit, the optimal solution of problem (15) is obtained. For each value of $\mu$ one iteration of the Newton-Raphson algorithm is applied to the nonlinear system of equations derived from the optimality conditions of problem (16).

**APPLICATION OF THE METHODOLOGY**

The described approach was implemented in a computational model by taking advantage of the modularity and flexibility of the Benders decomposition scheme. In this way the computational model is composed by two separate modules, related to the first and second stage decisions, which were based on two existing models developed by CEPEL. The solution of the generation capacity reserve investment subproblem was based on the branch and bound algorithm utilized by the MDRPIN program - generation expansion planning under uncertainty [11]. In turn, the solution of the operation subproblem was derived from the NH2 program – composite generation/transmission reliability evaluation [9,13] by modifying the objective function from a minimum load shedding to a minimum operational cost as described in the previous section.

**The MRTS System**

The proposed methodology will be illustrated in a case study with a 24-bus system corresponding to a modification of the IEEE Reliability Test System – RTS’79 [14], which will be denoted as the MRTS. It was assumed a static configuration, i.e., the system load and fuel costs were kept constant along the planning horizon. Only the peak load condition was analysed in the operation subproblem and the Monte Carlo method was used to draw the system operating states. The MRTS was derived from the IEEE-RTS’79 including changes on the total system load (2972 MW) and generation (3207 MW) as well as the number of generating units. This system has 24 buses, 38 circuits and 9 power plants and 31 generating units, as depicted in Figure 3. An interruption cost of US$500/MWh was adopted for all system buses. The generation operating costs ranged from US$10/MWh to US$18/MWh.

**Probabilistic Analysis of the MRTS System**

Tables 1 and 2 present the system (composite) reliability indices and the expected operational costs for the MRTS before adding capacity reserve units. The results were obtained by using a sample size of 20,000 states in the Monte Carlo method, leading to a coefficient of variation of 1.3% and 1.6% for the Loss of Load Probability (LOLP) and Expected Energy Not Supplied (EENS) indices, respectively.

Table 1 also presents the generation capacity and transmission reliability assessment results. From this Table we observe that the reliability indices are high and that the major contribution to the system unreliability comes from the insufficient generation scenarios. These results indicate the implementation of generation capacity reserve would benefit the system.

Table 2 also presents the contribution of the generation costs and interruption (reliability) costs to the total
expected operational costs (US$ millions), disaggregated for the system areas. We can see that these contributions are roughly the same for Area 1 whereas the interruption costs represent 16% and 31% of the total costs for Area 2 and for the entire system, respectively.

![Fig. 3 – The MRTS System](image)

**TABLE 1 – RELIABILITY INDICES BEFORE UNITS ADDITION**

<table>
<thead>
<tr>
<th>Index</th>
<th>System</th>
<th>Generation</th>
<th>Transmission</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOLP</td>
<td>0.2341</td>
<td>0.2047</td>
<td>0.0295</td>
</tr>
<tr>
<td>EENS</td>
<td>310,260.5</td>
<td>240,537.8</td>
<td>69,722.73</td>
</tr>
</tbody>
</table>

**TABLE 2 – EXPECTED OPERATIONAL COSTS BEFORE UNITS ADDITION (US$ MILLIONS)**

<table>
<thead>
<tr>
<th>Areas</th>
<th>Operational Costs</th>
<th>Generation Costs</th>
<th>Interruption Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>212.04</td>
<td>100.87</td>
<td>111.17</td>
</tr>
<tr>
<td>2</td>
<td>282.46</td>
<td>238.50</td>
<td>43.96</td>
</tr>
<tr>
<td>System</td>
<td>494.5</td>
<td>339.37</td>
<td>155.13</td>
</tr>
</tbody>
</table>

**Generation Capacity Reserve Candidates**

For this system, 8 buses were considered as candidates to have generation capacity reserve unit installation: buses 4, 5, 6 and 8 in the Area 1, and buses 17, 18, 19 and 20 in the Area 2. This leads to a total of 2^8=256 investment alternatives. Also, it was assumed that when deciding the installation of capacity reserve in a specific bus it will consist on 75 MW. The adopted investment cost is US$ 52.5 millions (US$700/kW) which leads to an annualized cost of US$ 8.39 millions (20 years, 15% per year).

**Benders Decomposition Scheme Results**

Here the Monte Carlo method was also applied to estimate the expected operation costs and Benders cuts in the operation subproblem by using a sample size of 20,000 states. The allocation of generation capacity reserve solved by the Benders algorithm converged in 4 iterations.

The results obtained in the iterative procedure of the Benders algorithm are shown in Table 3 and in Figure 4. In this Figure, the dashed lines correspond to the lower and upper limits associated to the 95% confidence interval of the total cost upper bound (z), while the continuous line represents the total cost lower bound (z). Observe that in the fourth iteration the lower bound z lies inside the 95% confidence interval of z, which is the adopted convergence criterion.

![Fig. 4 – Iterations of the Benders Algorithm](image)

**TABLE 3 – CONVERGENCE OF THE BENDERS METHOD (US$ MILLIONS)**

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Result</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.00</td>
<td>67.12</td>
<td>25.17</td>
<td>25.17</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>0.00</td>
<td>71.87</td>
<td>355.50</td>
<td>378.46</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.00</td>
<td>138.99</td>
<td>380.67</td>
<td>403.63</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>494.50</td>
<td>355.50</td>
<td>378.89</td>
<td>378.71</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>494.50</td>
<td>422.62</td>
<td>404.06</td>
<td>403.88</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>≤ z ≤</td>
<td>489.58</td>
<td>422.07</td>
<td>401.94</td>
<td>405.99</td>
</tr>
</tbody>
</table>

A = investment cost
B = expected operational cost (estimated)
C = lower bound of the total operational cost (z)
D = expected operational cost (calculated)
E = A+D = upper bound of the total operational cost (z)
F = 95% confidence interval of the total operational cost upper bound (z)

Table 4 presents the selected buses chosen by the algorithm to install new reserve units in each iteration. The optimal solution consists on install a total of 225 MW of capacity in the buses 6, 8 and 19, i.e., 75 MW in each one. The annualized total cost obtained was US$ 403.9 millions, in which US$ 25.2 millions corresponds to the investment cost and US$ 378.7 millions to the operational cost.

**TABLE 4 – SELECTED CANDIDATE BUSES IN EACH ITERATION**

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Buses</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>None</td>
</tr>
<tr>
<td>2</td>
<td>4, 5, 6, 8, 17, 18, 19, 20</td>
</tr>
<tr>
<td>3</td>
<td>5, 6, 8</td>
</tr>
<tr>
<td>4</td>
<td>6, 8, 19</td>
</tr>
</tbody>
</table>

Table 5 shows the new reliability indices associated to the solution of the generation capacity reserve allocation problem. Observe that there is no need to perform an additional reliability evaluation run once these indices are a by-product of the operation subproblem solved in each Benders iteration. Therefore the figures presented in Table 5 are associated with the fourth iteration of the Benders algorithm. Comparing Table 1 and Table 5 figures we can observe a drastic improvement on the system reliability indices: the LOLP and EENS indices before the addition of capacity reserve units are respectively 3.6 and 5.8
higher than those obtained after their introduction into the system.

| Table 5 – Reliability Indices for the MRTS After Installing Capacity Reserve |
|---------------------------------|----------------|----------------|----------------|
| Index                           | System        | Generation     | Transmission   |
| LOLP (MWh)                      | 0.0652        | 0.0422         | 0.0230         |
| EENS (MWh)                      | 53.481.6      | 36.607.9       | 16.873.7       |

Table 6 shows the contribution of the generation and interruption (reliability) costs to the annualized expected total operational costs after installing the new generation reserve units. These values are presented for the entire system as well as disaggregated by system areas (US$ millions). We can note that the total operational cost is now US$116 millions less than the US$ 494.5 millions obtained previously (see Table 2). In turn, there was a tremendous decrease of the interruption costs, from US$ 155.3 millions to US$ 26.7 millions. Besides this decrease we observe that now the interruption costs in both system areas are now levelized contrasting with the situation before the units addition where the interruption costs in Area 1 were 2.5 higher than those in Area 2. The Area EENS indices also followed this pattern. In turn, the introduction of new generation capacity reserve units lead to an increase on the expected generating costs, from US$ 339.4 millions to US$ 351.9 millions. However this increase was compensated by the decrease of the interruption costs.

| Table 6 – Expected Operational Costs After Installing Capacity Reserve (US$ Millions) |
|--------------------------------|----------------|----------------|----------------|
| Areas                          | Operational Costs | Generation Costs | Interruption Costs |
| 1                              | 124.46          | 109.47         | 14.99          |
| 2                              | 254.25          | 242.50         | 11.75          |
| System                         | 378.71          | 351.97         | 26.74          |

**CONCLUSIONS**

This paper described a methodology for calculating the optimal generation capacity reserve amount and siting in power systems planning. The proposed methodology is based on a least-cost planning approach which considers along the planning horizon, the capacity reserve investment costs and the expected operational costs, comprising thermal generation and interruption (reliability) costs.

This problem is solved by using the Benders decomposition technique in which investment and operation subproblems solutions are obtained iteratively and separately thus allowing the use of taylor-made algorithms for each subproblem. The operation subproblem corresponds to a probabilistic evaluation of the minimum operation cost in composite generation/transmission systems, in which the system states were selected through Monte Carlo simulation and the system performance was evaluated by a non-linear optimal power flow solved by an interior point algorithm.

The methodology was then applied to a modification of the IEEE Reliability Test System (MRTS). The algorithm converged in only 4 iterations, which can be considered as a small number when compared to other Benders decomposition applications in power system planning studies. This led to a very reasonable computational performance thus encouraging its application to large systems.

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**REFERENCES**


