OPTIMIZING THE FLEXIBILITY OF A PORTFOLIO OF GENERATING PLANTS

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Abstract – The uncertainties resulting from the integration of a large amount of wind threaten the reliability of the power system. While it is generally agreed that coping with this uncertainty will require a more flexible system, not enough work has been done to provide dependable estimates of the amount of "flexibility" needed. This paper proposes a technique to determine the optimal amount of flexibility that a generation portfolio should provide for different levels of wind penetration. Such an optimization must bridge the gap between long-term investment decisions on the plants to be built and short-term operational decisions on how these plants are scheduled. To achieve this goal, the unit commitment problem has been extended to consider not only whether a particular generating unit should be committed at a given time but also whether building this unit would reduce the sum of the operational and investment costs. A proper assessment of the balance between these two costs must consider the seasonal variations in the load profile and must therefore consider an optimization horizon representative of a year. Test results based on the IEEE RTS system are presented and demonstrate how different amounts of wind and reserve requirements affect the need for flexibility.

Keywords: Flexibility, generation mix optimization, integration of wind generation, long-term unit commitment, reserve requirements

1 INTRODUCTION

Renewable energy sources such as wind and solar generation are not only intermittent but also subject to stochastic fluctuations. While significant progress has been made in forecasting techniques, the residual uncertainty will increase as the proportion of generation with limited controllability increases. This could threaten the security and reliability of power systems unless these systems have enough "flexibility" to cope with adverse situations. However, providing flexibility is expensive, whether it comes from agile generating units[1], [2], demand side management [3], energy storage[4] or interconnections with neighboring systems [5]. Before settling on a technology or a mix of technologies, it is thus imperative to determine precisely the optimal amount of flexibility that a given power system needs [2], [6], [7], [8], [9]. As is often the case, finding this optimum means striking a balance between investment and operational costs. Some sources of flexibility (e.g. storage) require very large investments but make possible substantial savings in operations. Others (e.g. demand-side response) carry more modest investments but may entail substantial utilization payments.

This paper focuses on the provision of flexibility using a portfolio of generating units with different dynamic characteristics. In this case one has to balance the cost of building flexible units against the operational benefits that these units provide. Assessing these benefits requires a model that adequately represents the operational constraints of the system (such as the need to follow the load profile while maintaining enough spinning reserve) as well as the operating limits of the generating units (e.g. ramp rate and minimum up- and down-time). Unit Commitment (UC) programs are typically used to enforce these constraints. However, a conventional UC considers only the cost of running the generating units over an optimization horizon ranging from a day to a week. Several extensions are required to transform such a UC program into a tool capable of balancing the long- and short-term costs of providing flexibility:

- The objective function must include not only the operating cost but also the amortized investment cost of each generating unit
- The optimization must be able to decide not only when a particular generating unit is started–up and shutdown, but also whether building that unit is optimal or not
- The optimization horizon must be extended because the need for flexibility varies with the seasonal variations in load level, load profile and renewable generation.

Section 2 describes how these extensions have been implemented. Because it is clear that these enhancements increase very significantly the size of the optimization problem, Section 3 presents the techniques that have been put in place to achieve solutions in a reasonable amount of computing time. Finally, Section 4 demonstrates the effectiveness of the proposed approach using the IEEE RTS 26-unit system.

2 OPTIMIZATION MODEL

2.1 Unit Commitment

The starting point of the optimization model is a conventional unit commitment program implemented using mixed integer linear programming. This program minimizes the sum of the various components of the cost of operating generating units: running cost, no-load cost and startup cost while enforcing the standard unit constraints (minimum and maximum generation, up- and down-time, ramp rates) and system constraints (load/generation balance, reserve requirements). Two types of decision variables are determined in this optimization: binary variable representing the on/off status of each unit at each hour ("commitment" decisions) and continuous variables representing the production of each unit at each hour.

2.2 Variable set of generating units

While a conventional UC optimizes the commitment of a fixed set of available generating units, the proposed model should have the opportunity to add or remove generating units from the available set to model the existence or non-existence of generating units providing flexibility in the commitment. To this end, another binary decision variable is introduced for each possible generating unit. This decision variable models the existence of the generating unit. If it takes the value "1", the generating unit exists and can be committed. On the other hand, if its value is "0", the unit does not exist and cannot be committed at any hour of the horizon.

2.3 Objective function

Because the optimization considers not only whether a generating unit should be committed but also whether it should be built, the objective function must be modified to include not only the operating cost but also the investment cost of all the existing generating units, amortized over the optimization horizon. Equation (1) shows the form of this modified objective function:

$$\min\left(\sum_{i=1}^{N}\sum_{t=1}^{T}OC(i,t)+\sum_{i=1}^{N}IC(i)\right) \tag{1}$$

where $OC(i,t)$ is the operating cost of unit i at time t and $IC(i)$ is the investment cost of unit i amortized over the optimization horizon. N is the number of generating units and T is the number of periods in the optimization horizon. The operating cost is defined as follows:

$$OC(i,t)=u_{i,t}\left(nlc_i+\sum_{j=1}^{M}\left(inc_{i,j}\,p_{i,t,j}\right)+(1-u_{i,t-1})sc_{i,t}\right) \tag{2}$$

where:

- $u_{i,t}$ is the binary decision variable associated with the commitment of unit i at optimization period t.
- nlc_i is the no-load cost of unit i.
- M is the number of piecewise linear segments used to represent the cost function of unit i
- $inc_{i,j}$ is the incremental cost of segment j of the cost curve of unit i
- $p_{i,t,j}$ is the continuous decision variable representing the amount of power produced by unit i at period t on segment j of its cost curve
- $sc_{i,t}$ is the cost of starting up unit i at period t.

Equation (3) defines the investment cost:

$$IC(i)=\sum_{i=1}^{N}\frac{e_i\,C_i^{MW}P_i^{\max}}{L_i} \tag{3}$$

where:

- e_i is the binary decision variable associated with the existence of generating unit i
- C_i^{MW} is the cost per MW of building a unit of the type of unit i
- $P_i^{\max}$ is the capacity of unit i in MW
- L_i is the expected lifetime of unit i.

The investment cost of a generating unit is taken into consideration only if this unit has been built and is thus available for commitment. The optimization ensures that a unit is built only if it reduces the operating by an amount greater or equal than its amortized investment cost.

2.4 Optimization horizon

The optimization horizon of a conventional UC ranges from one day to a week or slightly more. Such an horizon is not suitable for assessing investment decisions because the chosen week is unlikely to be representative of all the operating conditions that the system is likely to face. In particular, when considering the needs for flexibility, one should take into account the variations in demand level, demand profile and wind generation that occur naturally over the course of a year. Running the proposed optimization algorithm over a whole year with the one-hour resolution needed to model the flexibility needs would require an excessive amount of computing time [10]. Instead, four weeks are used to represent a year. The load profile of each of these weeks is the average of the load profiles of all the weeks of a season. The load profiles of these four representative weeks are linked together to make up the 672 hours optimization horizon shown in Figure 1. Two aspects of this linkage must be emphasized. First, the existence decision variables should obviously run through all weeks otherwise a decision might be made to invest in a unit only for the winter. Second, as will be discussed below, the initialization of the commitment variables at the beginning of each week must be done carefully.

In the objective function, the operating cost of each week is weighed by the number of weeks in the season. On this basis, the results of the optimization problem indicate how many generating units of each type are needed to minimize the total cost for an average year.

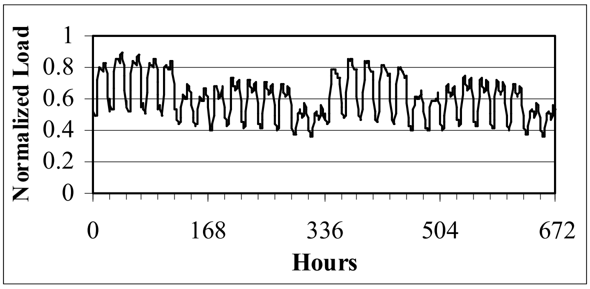


Figure 1: Load profile with four seasonal representative weeks

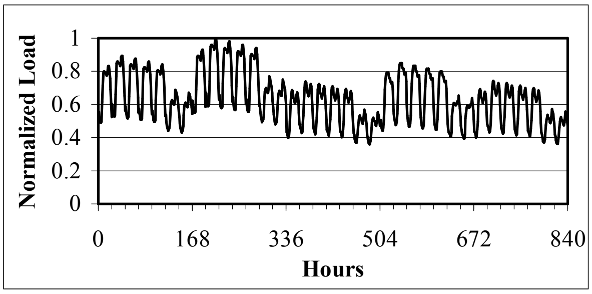


Figure 2: Load profile with four seasonal representative weeks and one extreme winter week.

However, one must consider the possibility that every few years there might be a week with extreme variations in load and renewable intermittent generation. The optimal amount of flexibility calculated on the basis of average representative weeks might not be sufficient to handle effectively such a situation. To take such a possibility into account, the optimization can be performed using a composite load profile consisting of the four average representative weeks plus one or more weeks representing extreme conditions. Figure 2 illustrates such a load profile with an extreme week inserted between the average winter week and the average spring week. The relative weighting given in the objective function to these extreme weeks should reflect their rarity. For example, Table 1 shows the weightings that should be applied to the weekly operating costs if we assume that an extreme winter week happens every four years.

Week	Weighting
Average winter	16.75
Extreme winter	0.25
Average spring	9
Average summer	12
Average autumn	13

Table 1: Typical weighting factors for representative weeks

2.5 Initialization

The number of hours that each unit has been on or off, and their output during the period preceding the optimization interval define the initial state of the system. This initial state affects the optimal solution through the startup costs, the minimum up- and down-time constraints and the ramp rate constraints. In a conventional UC, this initial state is part of the input data [11], [12]. In this problem, however, this information is not available. Moreover, the final state of a week representing a season is usually not the initial state of the week representing the next season. An incorrect initialization could therefore bias the calculation of the optimal amount of flexibility. The initial state for each week should be representative of the initial state for that season. Since each of these weeks represents an average of all the weeks of a particular season, one can make the assumption that it is followed by a similar week. The final state of each representative week should thus be equal to its initial state, as illustrated in Figure 3. This approach is implemented by not assuming any initial status in the mixed integer linear programming approach. Instead new decision variables are introduced to represent the initial state of each generating unit. The value of these decision variables is determined as part of the optimization process, subject to constraints enforcing the equality of the initial and final state of each week. Costs associated with "startups' taking place between representative weeks are not considered because it is assumed that these additional startups take place gradually as the seasons change and are thus amortized gradually over the year.

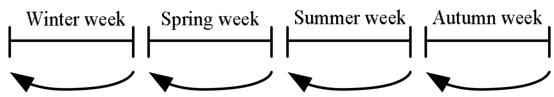


Figure 3: Linkage of four representative weeks

3 IMPROVING COMPUTATIONAL EFFICIENCY

The extended optimization horizon and the introduction of "existence" decision variables make the size of the optimization problem described in the previous section considerably larger than the size of a conventional UC problem with a similar number of generating units. This could lead to a problem whose solution would require an excessive amount of computing time. However, this difficulty can be alleviated through a reduction in the number of binary decision variables and a limitation of the solution space. Both types of approaches have been implemented and are described in the following paragraphs.

3.1 Reduction in the number of decision variables

It is unlikely that an assessment of the amount of flexibility required would be done for a completely unconstrained system. In most cases, a significant proportion of the generating units will already exist and have a substantial residual life. In such cases, the optimization of the amount of flexibility will affect the additional generating units. The number of decision variables (and hence the size of the solution space to be explored) can thus be significantly reduced if the existence of some generating units is posited and thus removed from consideration.

3.2 Heuristic constraints: reasonably adapted system

Optimization problems that involve binary or integer variables reach a solution by essentially searching through the space of possible solutions. It is well known that the size of this space grows exponentially with the number of decision variables. To be able to find a solution in a reasonable amount of time, the search space must be limited by constraints. Some of these constraints arise naturally from the problem definition and structure. Additional constraints of a heuristic nature can further reduce the size of the search space.

In this case, one way to reduce the search space is to start the solution from a reasonably adapted system, i.e. a system that does not have a considerably larger amount of generation capacity than is needed to meet the peak demand.

3.3 Heuristic constraints: priority ordering

Sets of relatively small generating units with similar technical and cost characteristics are prime candidates for providing flexibility. The optimization algorithm can spend a considerable amount of time comparing solutions involving one or the other of these units for no significant gain because their characteristics are by definition almost identical. Introducing an artificial priority order among these units can cut the search short and hence save a considerable amount of computing time. Units in a set are then committed in order of priority unless one of them is subjected to a minimum down time constraint. The constraints needed to implement this heuristic using integer programming are described below.

1. If unit i is on at hour t-1, it should be committed at hour t before any other unit with a larger index in the set of similar units S:

$$\text{if } u(i,t-1)=1 \quad \text{then } u(i,t) \geq u(i+1,t) \forall i \in S \tag{4}$$

2. If unit i is off at hour t-1 and has been off for at least the minimum down time, then it should be committed at hour t before any other unit with a larger index in the set of similar units S.

$$\text{if } \sum_{t-\min\_down\_time}^{t-1} u(i,t)=0 \quad \text{then } u(i,t) \geq u(i+1,t) \forall i \in S \tag{5}$$

3. If unit i is off at hour t-1, and has not yet been off for the minimum down time it must remain off and no longer has priority over similar units:

$$\sum_{t-\min\_down\_time}^{t-1} u(i,t) \geq 0 \tag{6}$$

4 TEST RESULTS

The proposed optimization model has been implemented using the FICO™ Xpress optimization engine. Tests have been conducted using the IEEE-RTS [13], which consists of 26 units when the hydro generating units are omitted and has a total installed capacity of 3105 MW. This system contains a variety of base, intermediate and peaking generating units.

Table 2 shows the investment costs, elbows points on the cost curve, no-load costs, incremental costs, start-up costs and minimum up and down times associated with each identical group of units. Investment costs are originally from the Energy Information Administration (EIA) [14] and the expected life time of all units is assumed to be 30 years.

Units 1-9 are peaking units, 10-15 are intermediate units and 16-26 are base units. The peaking units are obviously the most flexible. However they are also the most expensive units in terms of operating cost. In the following tests, the model determines which of the units included in the original RTS system are actually needed to provide the optimal amount of flexibility. For all the tests, the duality gap of the mixed integer linear programming optimization has been set at 0.005.

Units	INVEST $/KW	P_{min} MW	e_1 MW	e_2 MW	P_{max} MW	nlc_i $/MW	inc_1 $/MW	inc_2 $/MW	inc_3 $/MW	stc $	M_{up} h	M_{dn} h
1-5	536	2.4	5.6	8.8	12	24.0	25.7	25.9	26.0	68	1	1
6-9	409	4	9.3	14.6	20	117.3	37.7	37.8	37.9	5	1	1
10-12	536	15.2	35.4	55.7	76	76.4	13.7	14.1	14.4	655.6	3	2
13-15	536	25	50	75	100	210.1	18.4	18.7	19.0	566	4	2
16-19	1154	54.24	87.8	121.4	155	120.6	11.3	11.6	11.9	1048.3	5	3
20-23	1154	68.95	111.6	154.3	197	239.1	23.4	23.6	23.9	775	5	4
24	1154	140	210	280	350	132.0	11.3	11.6	11.8	4468	8	5
25-26	2117	100	200	300	400	271.2	8.0	8.4	8.8	0	8	5

Table 2: Key parameters of the 26 units test system

4.1 Effect of the load profile

The shape of the load profile directly affects the flexibility requirement of the system. Theoretically, more flexibility is needed to cope with sharp increases in demand. On the contrary, a load profile with smooth changes doesn't require as many flexible units. For example, in Figure 4, by comparison with profile 1, profile 2 involves a sharper valley that may require more flexible units.

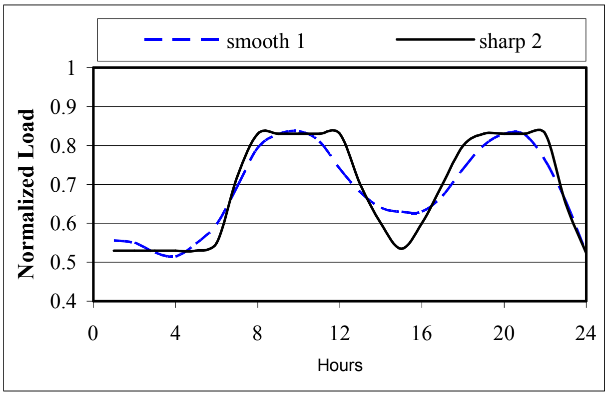


Figure 4: Test load profiles with smooth valley (dotted line) and sharp valley

Table 3 shows that the model produces results that are consistent with these expectations. The profile with a sharper valley requires the availability of all 26 units while only 23 units are needed to handle optimally the smoother valley.

Load profile	Investment Decisions	Total cost ($)
Smooth (1)	Units 3, 7, and 8 are not needed	299,102,687
Sharp (2)	All units are needed	305,871,876

Table 3: Test results for different load profiles

4.2 Effect of the penetration of wind generation

Theoretically, wind penetration in power system has three main effects:

1. Wind generation reduces the net demand to be supplied by conventional units

$$\sum_{i=1}^{I} p_{i,t} = P_{Dt} - P_{wt} \quad (7)$$

where:

- $p_{i,t}$ is the amount of power produced by unit i at period t
- P_{Dt} is the total demand of system at period t
- P_{wt} is the predicated wind power at period t

2. The reserve requirement must be increased to be able to cope not only with the sudden loss of the largest generating unit but also a simultaneous error in the wind power:

$$r_{d,t}^{s} \geq \max(P_{i,t}^{\max}) + 3.5\sigma_{d,t} \quad (8)$$

where:

- $r_{d,t}^{s}$ is the reserve requirement at period t
- $P_{i,t}^{\max}$ is the largest capacity of online unit at period t
- $\sigma_{d,t}$ is the standard deviation of wind forecast error at period t. This wind forecast error is assumed to follow a normal distribution [15].

3. More flexibility is required to compensate the fluctuations in wind power.

Four cases, described in Table 4, illustrate how the model handles reduction in the net demand, fluctuations in the wind generation and errors in the wind generation forecast. In order to demonstrate clearly, here we take one day's load profile as an example to show the effect of wind penetration. Case 1 is the base case of load profile with no wind penetration. The peak load is 2600 MW. In case 2, wind power provides 10% of the peak demand, i.e. the net demand is 10% lower than in case 1. The wind is assumed constant over the time horizon considered. Wind power also covers 10% of the peak demand in case 3, but this wind generation fluctuates over the time horizon. In case 4, wind power again covers 10% of the peak demand without fluctuations. However, the uncertainty on the wind generation is larger than in case 2. This effect is modeled using the standard deviation of the wind forecast error, which is $\sigma = 0.1$ in case 2 and is $\sigma = 0.3$ in case 4. Table 5 shows the results of the flexibility optimization and illustrates the three effects of wind penetration.

The first observation is that the original system provides more generation capacity and flexibility than is optimal under the base case conditions. Not investing in the construction of some generating units reduces the total cost. Case 2 shows that, as one would expect, wind generation displaces some of the base generating units and further reduces the total cost. However, in case 3 a decision is made to build peaking units 4 and 5, which shows that fluctuations in wind power increase the optimal amount of flexibility. A comparison of cases 2 and 4 shows that, when the reserve requirement is increased to cope with a larger uncertainty on the wind forecast, more flexible generating units are needed to achieve the minimum total cost. Figure 5 summarizes the proportions of peaking and base units for the different cases.

In conclusion, constant wind integration can be treated as a negative demand, which reduces the need for base units as in case 2. Peaking units are not affected here.

Fluctuations in the wind power require more peaking units to provide the additional flexibility requirement. That's why the proportion of flexible peaking units increases sharply in case 3.

The larger uncertainty caused by wind forecast errors requires more units to provide spinning reserve. Therefore, in case 4, the proportion of peaking units and base units both increase compared with case 2.

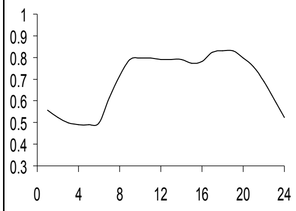
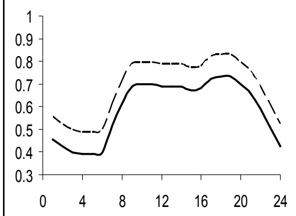
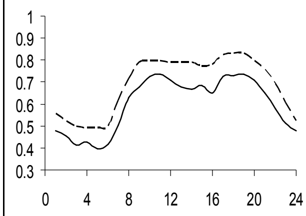
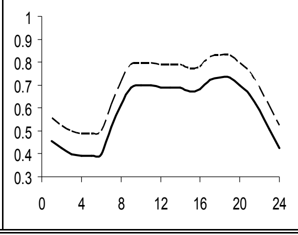
	Load profile	Wind forecast	Standard deviation of wind forecast error
1		No wind	No forecast error
2		10% wind without fluctua-tions	$\sigma = 0.1$
3		10% wind with fluctua-tions	$\sigma = 0.1$
4		10% wind without fluctua-tions	$\sigma = 0.3$

Table 4: Definition of the four cases used to study the effect of wind generation on the need for flexibility. (dotted lines: base case with no wind.)

Case	Investment Decisions	Total cost ($)
1	Units 4,5,19 are not needed	280,016,775
2	Units 4, 5, 17, 18, 19 are not needed	246,083,666
3	Units 18, 19 are not needed	248,827,119
4	Units 5, 19 are not needed	254,921,958

Table 5: Test results for 4 cases with different wind penetrations

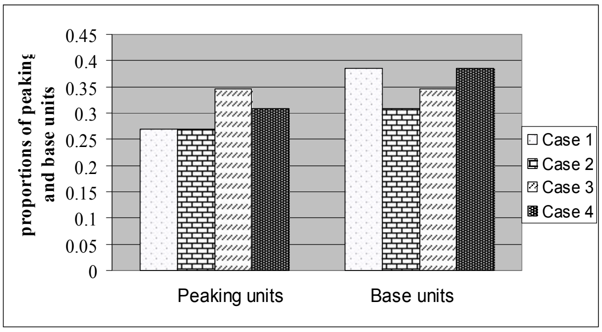


Figure 5: Proportions of peaking units and base units for the different test cases

These test results show that the enhanced UC program is able to optimize the flexibility of the generation mix for different wind penetrations.

4.3 Computing efficiency

As mentioned above, the optimization method proposed requires a large amount of computing time or resources unless some heuristic techniques are used to reduce the search space. It is therefore useful to examine the effect that these techniques have on the computational speed and on the optimality of the solution.

Case	Annual peak demand 2600MW, 10%wind with fluctuations		Annual peak demand 2550MW, 10% wind with fluctuations	
	Without priority ordering	With priority ordering	Without priority ordering	With priority ordering
Computing time (hours)	1.5	1.1	40.7	12.6
Difference in total cost	0.068%		0.12%	
Investment decisions (units not built)	10, 13	12, 13	4, 8, 9, 10, 11, 13	4, 5, 9, 11, 12, 13
Total cost (k$)	248,656	248,827	243,218	243,516

Table 6: Effect of the heuristic constraints used to reduce the computing time

Table 6 shows that priority ordering of similar generating units significantly reduces the computing time required, while producing solutions whose costs are within the duality gap of the optimal solution obtained without priority ordering. These results also show that starting from a system that is reasonable well adapted (i.e. that does not have far too much capacity compared to the peak demand) also significantly reduces the amount of computing time.

5 CONCLUSION

This paper proposes a technique to optimize the flexibility of the generation mix. The starting point for the development of this technique is a mixed-integer linear programming-based unit commitment program. Several enhancements to this program have been introduced to give it the ability to make investment as well as commitment decisions and to carry out the optimization over a period representative of a whole year.

Several heuristic constraints aimed at improving computational efficiency have been developed and tested.

This paper provides a basic structure of the flexibility planning model, and on top of that, it allows the study of various technical and environmental restrictions for a new investment. Nowadays, most European electrical power systems are confronted with challenges of reorganization on conventional thermal generating units to cope with huge renewable energy integration. This type of optimization is likely to become increasingly important as the amount of renewable energy (and hence the amount of uncertainty in the system) increase.

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