

Power System Scheduling with Fuzzy Reserve Requirements

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Abstract—The modeling of constraints is an important issue in power system scheduling. Constraints can be generally classified into two categories: 1) physical limits and 2) operating limits. A schedule violating physical limit or constraint would not be acceptable. An operating limit, however, is often imposed to enhance system security but does not represent a physical bound. This kind of “soft limits” can be temporarily violated “a little bit” if necessary, but not “too much.” These constraints are therefore “fuzzy” in nature, and crisp treatment of them may lead to over conservative solutions. In this paper, a fuzzy optimization-based method is developed to solve power system scheduling problem with fuzzy reserve requirements. The problem is first converted to a crisp and separable optimization problem. Lagrange multipliers are then used to relax system-wide constraints and decompose the problem into a number of unit-wise subproblems and a membership subproblem. These subproblems can be efficiently solved, and the multipliers are updated by using a subgradient method. Heuristics are then used to construct a feasible schedule based on subproblem solutions. Numerical testing results show that near optimal schedules are obtained, and the method can provide a good balance between reducing costs and satisfying reserve requirements.

Keywords: Power System Scheduling, Fuzzy Optimization, Unit Commitment.

I. INTRODUCTION

Power system scheduling is to minimize the total generation cost subject to system demand and reserve requirements and individual unit constraints. It has been an active research subject over the years because of its significant economic impact ([1-4]). To solve this difficult mixed-integer programming problem, many optimization-based methods have been developed ([1]). Among them, Lagrangian relaxation and its extensions are among the most successful ones ([1-7]). Many new requirements such as transmission network and environment constraints have also been incorporated in the problem formulation ([5-7]). In our previous work, efficient algorithms are developed to schedule thermal, hydro and pumped-storage units within the

Lagrangian relaxation framework ([14], [15], [16]). However, inadequate system models many times limit the applicability of these methods especially in on-line environments.

The description of constraints is a major step in developing system models. Constraints can be generally classified into two categories: 1) physical limits and 2) operating limits. A physical limit or constraint, e.g., the minimum or maximum generation of a unit or the system demand constraint, should not be violated. A schedule violating these constraints would not be acceptable except in emergencies. An operating limit, such as system reserve requirement, however, is often imposed to enhance system security and does not represent a physical bound. This kind of “soft limits” can be temporarily violated “a little bit” if necessary, but not “too much.” These constraints are therefore “fuzzy” in nature, and crisp treatment of them (requiring them to be satisfied 100% all the time) may lead to over conservative solutions. For example, to satisfy spinning reserve requirements crisply, some expensive thermal units may have to be committed just for the reserve purpose. If the requirements at some hours can be relaxed slightly, significant cost savings can be achieved without much impact on system security. Currently, most models treat all constraints crisply. Although operating limits can be successively relaxed until a satisfactory schedule is obtained, such a trial-and-error method may not be efficient and it is difficult to have a deep insight into the issues. A systematic investigation of the balance between cost savings and the satisfaction of “soft” operating limits would lead to further advancements of the scheduling methodology.

Fuzzy set theory provides a natural platform to model fuzzy relationships such as “a little bit” and “too much” as described above. Fuzzy optimization techniques have been developed to solve optimal power flow with fuzzy constraints ([8-12]), and to schedule manufacturing systems with possible machine breakdowns ([13]). An important issue in fuzzy optimization is whether the problem can be efficiently solved since very often the original crisp problem itself is NP-hard.

In this paper, a fuzzy optimization-based method is developed to solve power system scheduling problem with fuzzy reserve requirements. The problem formulation is presented in Section II. The problem is first converted to a crisp and separable optimization problem as described in Section III. Lagrange multipliers are then used to relax system-wide constraints and decompose the problem into a number of unit-wise subproblems and a membership

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subproblem. These subproblems can be efficiently solved, and the multipliers are updated by using a subgradient method. Heuristics are then used to construct a feasible schedule based on subproblem solutions. Numerical testing results presented in Section IV show that near optimal schedules are obtained, and the method provides a good balance between reducing costs and satisfying reserve requirements.

II. PROBLEM FORMULATION

II.1 Crisp Problem Formulation

To lay the foundation for fuzzy modeling, the crisp version is presented first. Consider a power system with I thermal units, J hydro units and K pumped-storage units. The objective is to minimize the total generation cost. This minimization is subject to system-wide demand and reserve requirements, and individual unit constraints. The time unit is one hour and the planning horizon may vary from one day to ten days.

To formulate the problem mathematically, the following notation is introduced:

$C_{ti}(p_{ti}(t))$:	cost of thermal unit i at hour t , in dollars;
I :	total number of thermal units;
J :	total number of hydro units;
K :	total number of pumped-storage units;
$P_d(t)$:	system demand at hour t , in MW;
$p_{hj}(t)$:	power generated by hydro unit j at hour t , in MW;
$p_{pk}(t)$:	power generated (positive) or used for pumping (negative) by pumped-storage unit k at hour t , in MW;
$P_r(t)$:	system reserve at hour t , in MW;
$p_{ti}(t)$:	power generated by thermal unit i at hour t , in MW;
$r_{hj}(p_{hj}(t))$:	reserve contribution of hydro unit j at hour t , in MW;
$r_{pk}(p_{pk}(t))$:	reserve contribution of pumped-storage unit k at hour t , in MW;
$r_{ti}(p_{ti}(t))$:	reserve contribution of thermal unit i at hour t , in MW;
$S_i(t)$:	start up cost of thermal unit i at hour t , in dollars;
T :	scheduling horizon, in hours;

The scheduling problem is formulated as the following mixed-integer programming problem:

Object Function -- total generation cost

$$\min_{\substack{J, \\ p_{ti}(t), \\ p_{hj}(t), \\ p_{pk}(t)}} J, \text{ with } J = \sum_{t=1}^T \left[\sum_{i=1}^I [C_{ti}(p_{ti}(t)) + S_i(t)] \right] \quad (2.1)$$

System-wide Constraints

-- system demand

$$\sum_{i=1}^I p_{ti}(t) + \sum_{j=1}^J p_{hj}(t) + \sum_{k=1}^K p_{pk}(t) = P_d(t) \quad (2.2)$$

-- reserve requirement

$$\sum_{i=1}^I r_{ti}(p_{ti}(t)) + \sum_{j=1}^J r_{hj}(p_{hj}(t)) + \sum_{k=1}^K r_{pk}(p_{pk}(t)) \geq P_r(t) \quad (2.3)$$

$t = 1, 2, \dots, T$

Individual Thermal Unit Constraints

- capacity and minimum generation
- minimum up/down time
- ramp rate
- minimum generation for the first & last hour generation
- must-run and must-not-run

Individual Hydro Constraints

- capacity and minimum generation
- available hydro energy

Individual Pumped-Storage Unit Constraints

- pond level constraints
- generation and pumping level constraints

The detailed descriptions of individual thermal, hydro and pumped-storage constraints are presented in [14], [15], and [16], respectively.

II.2 Fuzzy Problem Formulation

As mentioned, fuzzy set theory is a natural platform to model fuzzy or imprecise constraints and/or objectives ([8-13]). Given a collection of objects, Y , a fuzzy set \tilde{A} is defined as:

$$\tilde{A} = \{(y, \mu_{\tilde{A}}(y)) | y \in Y\}, \quad (2.4)$$

$$0 \leq \mu_{\tilde{A}}(y) \leq 1,$$

where $\mu_{\tilde{A}}(y)$ is the membership of y , representing the degree that y belongs to \tilde{A} (ranging from zero to one for a normalized fuzzy set). If $\mu_{\tilde{A}}(y)$ could only be 0 or 1, \tilde{A} degenerates to a crisp set. A fuzzy or inexact relation, such as "roughly greater than or equal to" or "slightly less than or equal to," is also associated with a membership function representing the degree of certainty of that relation.

Reserve requirements can be described as a fuzzy relation, i.e., the total reserve contribution at hour t should roughly be greater than or equal to the reserve requirement at that hour:

$$r(t) \tilde{\geq} P_r(t) \quad (2.5)$$

where

$$r(t) \equiv \sum_{i=1}^I r_{ti}(p_{ti}(t)) + \sum_{j=1}^J r_{hj}(p_{hj}(t)) + \sum_{k=1}^K r_{pk}(p_{pk}(t)) \quad (2.6)$$

is the total reserve contribution, and " \gtrsim " is the fuzzy relation "roughly greater than or equal to." The membership function of this relation is assumed to be

$$\mu_{r(t)} = \begin{cases} 1, & r(t) \geq P_r(t), \\ (r(t) + \delta_{r(t)} - P_r(t)) / \delta_{r(t)}, & P_r(t) > r(t) \geq P_r(t) - \delta_{r(t)}, \\ 0, & r(t) < P_r(t) - \delta_{r(t)}, \end{cases} \quad (2.7)$$

where $P_r(t)$ is the "normal" reserve requirement at hour t , and $P_r(t) - \delta_{r(t)}$ the minimum reserve acceptable. The above membership is linearly decreasing between the two values. Equation (2.5) states that the solution should satisfy the reserve requirements as much as possible, and not to be short of $P_r(t)$ "too much."

Following above thinking, the total generation cost should be essentially smaller than or equal to some "aspiration level" J_0 :

$$\min J \lesssim J_0, \quad (2.8)$$

The membership for the fuzzy inequality in (2.8) is assumed to be:

$$\mu_J(J(p_{ii}(t))) = \begin{cases} 1, & J \leq J_0, \\ (J_0 + \delta_J - J) / \delta_J, & J_0 < J \leq J_0 + \delta_J, \\ 0, & J > J_0 + \delta_J. \end{cases} \quad (2.9)$$

The aspiration level J_0 represents the desired generation cost. A schedule becomes less acceptable as the cost increases above J_0 as indicated by the reduced membership function. The highest acceptable generation cost is $J_0 + \delta_J$. Selecting the aspiration level may be subjective and dependent on specific operational practice. One good candidate for the desired cost J_0 is the cost of the crisp scheduling problem with all lowest acceptable reserve requirement $P_r(t) - \delta_{r(t)}$ satisfied. The highest acceptable generation cost $J_0 + \delta_J$ can be selected as the cost of the crisp problem with all normal reserve requirements. It can also be determined by choosing δ_J as a certain percentage of J_0 based on experience. The overall scheduling problem with fuzzy objective and reserve constraints can thus be formulated as the satisfaction of (2.8) subject to (2.2), (2.5), and individual unit constraints.

III. SOLUTION METHODOLOGY

III.1 Solving the Fuzzy Optimization Problem

The key step of fuzzy optimization is to convert the fuzzy problem to a crisp one. Since both the fuzzy objective and

reserve constraints are desired to be satisfied simultaneously, the problem is to maximize the minimum degree of satisfaction among all fuzzy constraints ([8-13]). Defining z as the minimum degree of satisfaction among these fuzzy constraints subject to all the crisp constraints, i.e.,

$$z \equiv \min\{\mu_J, \mu_{r(t)}\}, t = 1, 2, \dots, T, \quad (3.1)$$

the fuzzy scheduling problem becomes maximizing z by scheduling thermal, hydro and pumped-storage units:

$$\max_{z \in [0,1]} z = \max_{z \in [0,1]} \min\{\mu_J, \mu_{r(t)}\}, t = 1, 2, \dots, T, \quad (3.2)$$

The above equation can be rewritten as

$$\max z, \quad (3.3)$$

subject to

$$z \leq \mu_J(J(p_{ii}(t))), \quad (3.4)$$

$$z \leq \mu_{r(t)}(r(t)), t = 1, 2, \dots, T, \quad (3.5)$$

$$0 \leq z \leq 1. \quad (3.6)$$

and all original crisp constraints. Substituting the membership functions (2.9) and (2.7) into (3.4) and (3.5), respectively, the fuzzy scheduling problem can be converted to the following crisp optimization problem:

$$\min -z, \quad (3.7)$$

subject to

$$J + \delta_J z \leq J_0 + \delta_J \quad (3.8)$$

$$r(t) - \delta_{r(t)} z \geq P_r(t) - \delta_{r(t)}, t = 1, 2, \dots, T, \quad (3.9)$$

(2.2), (3.6), and all crisp individual constraints. Note that (3.8) can be viewed as a "cost constraint."

To make the problem approximately equivalent to the crisp case when all fuzzy constraints can be satisfied with membership equal to 1, the objective function is modified as:

$$\min -z + sJ, \quad (3.10)$$

where s is a small positive number such that $sJ \ll 1$. If $z = 1$ can be obtained, the solution to (3.10) is equivalent to that of the crisp scheduling problem (2.1). On the other hand if $z = 1$ cannot be achieved, the term $-z$ will dominate the objective function.

III.2 The Lagrangian Relaxation Approach

The basic idea of Lagrangian relaxation is to relax system-wide constraints by using Lagrange multipliers. The

problem is then decomposed into subproblems that are much easier to solve. A necessary condition for the effective use of this approach is that the objective function and system-wide constraints should be additive in terms of subproblem decision variables, or the problem is "separable." Clearly the objective function of (3.10) and the constraints in (3.8), (3.9) and (2.2) are additive. The linear objective functions of some subproblems, however, may cause subproblem solutions to oscillate from their minimum to maximum or vice versa with a slight change of multipliers as discussed in [16]. The objective function in (3.10) is therefore equivalently formulated as

$$\min b(z-2)^2 + J, \quad (3.11)$$

where b is any large positive number such that $b \gg J$. Note that (3.10) and (3.11) are equivalent when z is between 0 and 1.

Lagrangian relaxation is then applied to relax the system-wise constraints of the converted crisp problem (3.11), (2.2), (3.8) and (3.9). The Lagrangian is written as

$$L = b(z-2)^2 + J + \lambda_J [J + \delta_J z - J_0 - \delta_J] + \sum_{t=1}^T \{ \lambda(t) [P_d(t) - p(t)] + \gamma(t) [P_r(t) - r(t) - (1-z)\delta_r(t)] \}, \quad (3.12)$$

where

$$p(t) \equiv \sum_{i=1}^I p_{ti}(t) + \sum_{j=1}^J p_{hj}(t) + \sum_{k=1}^K p_{pk}(t) \quad (3.13)$$

is the sum of generations of all units.

Given a set of multipliers, the following subproblems are obtained by re-grouping relevant terms in (3.12).

Thermal unit subproblems:

$$\min_{p_{ti}(t)} L_{ti}, \text{ with } L_{ti} \equiv \sum_{t=1}^T \{ (1 + \lambda_J) [C_{ti}(p_{ti}(t) + S_i(t)) - \lambda(t)p_{ti}(t) - \gamma(t)r_{ti}(p_{ti}(t))] \} \quad (3.14)$$

subject to individual thermal unit constraints;

Membership subproblem:

$$\min_z L_z, \text{ with } L_z \equiv b(z-2)^2 + \lambda_J \delta_J z + \left[\sum_{t=1}^T \delta_r(t) \gamma(t) \right] z, \quad (3.15)$$

subject to (3.6). In the membership subproblem, the optimal membership variable z tends to decrease as the cost and reserve constraint violations become larger and the associated multipliers increase. If z is less than one, the cost would be higher than J_0 and/or the normal reserver requirement may not be satisfied.

Compared to the subproblems obtained in the crisp case ([14-16]), there is one more membership subproblem, and thermal subproblems have a slightly modified objective function (generation and start up costs are multiplied by $1 + \lambda_J$). When the cost constraint (3.8) is not satisfied, the cost multiplier λ_J becomes positive. The thermal units would be more expensive, therefore tend to generate less. The hydro and pumped-storage subproblems are identical to those obtained in [15] and [16].

III.3 Solving Subproblems and Updating Multipliers at the High Level

Individual thermal, hydro and pumped-storage subproblems are efficiently solved by using dynamic programming following the methods presented in [14-16]. For the membership subproblem, the optimal membership can be obtained analytically by minimizing a quadratic function (3.15) subject to the bounds on z (3.6), since a quadratic function of z is selected in (3.11).

The high level dual problem is to update the Lagrange multipliers, and a subgradient method with adaptive step sizing is used ([1-3], [6], [14], [17], [18]).

III.4 Constructing a Feasible Schedule

Subproblem solutions are generally associated with an infeasible schedule since the Lagrange multipliers are used to relax constraints (2.2), (3.8), and (3.9). Heuristics have to be developed to obtain a feasible schedule. Comparing with the crisp case, one more constraint - the cost constraint of (3.8) - has to be satisfied. Our approach is to first fix the membership variable z obtained in the dual solution. The heuristics developed in [14] and [15] are used to construct a solution satisfying (2.2) and (3.9). The cost J is then calculated. If (3.8) is satisfied, this solution is feasible. Otherwise, membership variable is adjusted as

$$z = (J_0 - J + \delta_J) / \delta_J, \quad (3.16)$$

to satisfy the cost constraint.

IV. NUMERICAL TESTING RESULTS

The algorithm is implemented in FORTRAN on HP 700. Numerical testing is performed based on Northeast Utilities power system data. There are about 65 thermal units, 7 hydro units, 1 large pumped-storage unit and 2-10 schedulable contracts which are modeled as one block thermal units. Two data sets, March Week 3, 1991 and April W3, 1991 are used for testing. The system characteristics and parameters for these two data sets are summarized in Table 1.

As a first step in implementation, only thermal units are considered in the testing. The schedules of hydro and pumped-storage units are fixed based on Northeast Utilities heuristics, and the generation contributions of these units are deducted from system demand. It is assumed that thermal units should meet 30% of the total reserve

requirements since the hydro and pumped-storage units generally contribute significantly to the total reserve requirements.

Testing results for the two data sets are respectively summarized in Table 2 and Table 3 with different values of J_0 , and δ_J taken as 5% of J_0 . The costs of Cases 1.1 and 2.1 are less than J_0 with membership variable $z = 1$, implying that all normal reserve requirements are 100% satisfied. The costs obtained are thus similar to those obtained by the crisp algorithm, and near optimal schedules are obtained. Cases 1.2, 1.3, 1.4, 2.2, 2.3 and 2.4 indicate that when the desired cost J_0 is less than the cost of the crisp schedule, the final cost obtained would be lower. However, the membership variable z is no longer 1, implying that some normal reserve requirements are "violated." The lower the desired cost J_0 , the lower the cost obtained but the smaller the z and the larger the "violation" of the normal reserve requirements. This clearly indicates the trade-off between minimizing generation cost and satisfying constraints. The total system reserves and the reserve requirements of Case 1.1 and Case 1.3 are shown in Fig. 1. It can be seen that the total system reserve $r(t)$ (marked by "o") does go below the normal requirement $P_r(t)$ "a little bit" in Case 1.3, while as in the crisp equivalent Case 1.1, the normal reserve requirement is always satisfied ($r(t)$ is marked by "x"). In Case 1.5 and Case 2.5, the minimum allowable reserve requirements, $P_r(t) - \delta_{r(t)}$, are smaller than those of Cases 1.2 and 2.3, respectively. Therefore, satisfying the reserve requirement becomes "less important." Consequently, the costs in Case 1.5 and Case 2.5 are lower than those in Cases 1.2 and 2.3, respectively.

The CPU time of the method is about 1-2 minutes on an HP 700 workstation, which is about three times the speed of a Sun Sparc2. In comparison with the CPU times reported in [14], the current algorithm is similar to the crisp algorithms. The method is therefore efficient for daily scheduling.

TABLE 1
SUMMARY OF NU POWER SYSTEM

System Characteristics	Number of units	Total capacity or requirements(MW)
Steam units	14 - 22	1230 - 1565
Turbine units	24 - 34	274 - 473
Nuclear units	8	1062 - 2024
Hydro units	7	247 - 254
Pumped-storage unit (generation/pump)	1	565/554 - 640/616
Schedulable contracts	2 - 10	0-800
All units	56 - 82	3534 - 5223
Peak load		3376 - 4434
Minimum load		1357 - 1887
Maximum reserve		152 - 189

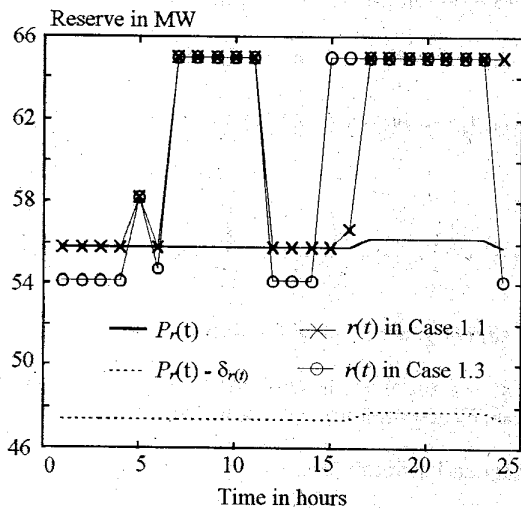
TABLE 2
TESTING RESULTS OF MARCH WEEK 3, 1991 DATA SET

Case	1.1	1.2	1.3	1.4	1.5
J_0 (\$)	6,200,000	6,060,000	6,040,000	6,020,000	6,060,000
δ_J (\$)	310,000	303,000	302,000	301,000	303,000
$\delta_{r(t)}$ (MW)	15% $r(t)$	15% $r(t)$	15% $r(t)$	15% $r(t)$	25% $r(t)$
J (\$)	6,079,183	6,069,118	6,065,656	6,062,527	6,067,900
z	1.00000	0.93632	0.88491	0.81266	0.93632
CPU	73	82	71	72	81

CPU: CPU time in second on HP 700

TABLE 3
TESTING RESULTS OF APRIL WEEK 3, 1991 DATA SET

Case	2.1	2.2	2.3	2.4	2.5
J_0 (\$)	5,700,000	5,540,000	5,520,000	5,500,000	5,520,000
δ_J (\$)	285,000	277,000	276,000	275,000	276,000
$\delta_{r(t)}$ (MW)	15% $r(t)$	15% $r(t)$	15% $r(t)$	15% $r(t)$	25% $r(t)$
J (\$)	5,556,539	5,554,849	5,553,200	5,550,577	5,548,217
z	1.00000	0.96935	0.87592	0.81317	0.96935
CPU	71	112	72	82	77



Note: for a better view of $r(t)$, only one day is shown and $r(t)$ is truncated when above 65 MW.

Fig 1. Total system reserves and reserve requirements

V. CONCLUSIONS

A fuzzy optimization-based method is developed to solve power system scheduling problem with fuzzy reserve requirements. The problem is first converted to a crisp and separable optimization problem, and then efficiently solved by using the Lagrangian relaxation method. Numerical testing results clearly show the trade-off between minimizing cost and satisfying constraints. For a given desired cost, the fuzzy optimization-based method can generate a near optimal schedule and provide an effective trade-off between minimizing cost and satisfying constraints.

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