Volatility of Unit Commitment in Competitive Electricity Markets[1]

Shmuel S. Oren,
University of California at Berkeley
Berkeley, CA 94720
Oren@IEOR.Berkeley.edu

Alva J. Svoboda,
Consultant to Pacific Gas and Electric Co.
San Francisco, CA 94177
AJSh%AsiEss%CTS@go50.comp.pge.com

Raymond B. Johnson,
Pacific Gas and Electric Co.
San Francisco, CA 94177
RBJ3%AsiEss%CTS@go50.comp.pge.com

Abstract

We examine the effects of competition and decentralized ownership on resource scheduling. We show that centralized scheduling of multi-owned resources under imperfect information may face difficulties that do not arise when resources are centrally owned. We perform a simulation case study using a Lagrangian relaxation-based unit commitment algorithm modified to simulate proposed second-price pool auction procedures. This algorithm is based on the Hydro-Thermal Optimization (HTO) program used in short-term resource scheduling at PG&E. We demonstrate both the volatility of simulation outcomes for resources not base loaded, and the especially negative consequences of volatility for marginal resources (i.e., resources that frequently determine system marginal costs). Specifically, we show that variations in near optimal unit commitments that have negligible effect on total costs could have significant impact on the profitability of individual resources. These results raise serious question regarding the feasibility of proper mechanisms to oversee the efficiency and equity of a mandatory centrally dispatched pool.

1. Introduction

In direct access competitive electricity markets, generators contract freely with customers to supply electricity according to the terms of contracts, which might for example stipulate price and quantity for periods of time. Actual delivery, however, is over a constrained transmission network controlled by a system operator who is responsible for, at least, the physical security of the system.

Many market restructuring proposals and implementation schemes, including the market structure mandated by the recent CPUC ruling [1], advocate an Independent System Operator (ISO) with various degrees of economic authority. In the UK system, for instance, the ISO (there the National Grid Company) operates a mandatory power pool and has the authority to schedule suppliers based on daily bids and set spot prices based on an optimal dispatch. In the CPUC ruling, the power pool (referred to as power exchange) is a separate entity but is managed in close coordination with the ISO which schedules transactions and manages congestion based on economic dispatch considerations. A general discussion advocating the generic POOLCO model which embodies many features of the UK system is given by Ruff [2]. A more recent article by Joskow [3] advocates the POOLCO paradigm in the context of California. Hogan [4] argues in favor of extending complete economic authority to the ISO, which would include administration of the exchange, scheduling, dispatch and price setting.

An important premise underlying the rationale for giving economic authority to the ISO is that the problem of scheduling electric supply resources is well understood but an efficient solution requires a central decision-maker to coordinate resource scheduling and operations. Many POOLCO proponents have even argued that in the absence of an economic motive for inefficient operation, the ISO is no more that "the keeper" of a computer program which will ensure efficient system operation, determine economically efficient price signals and manage congestion optimally. Indeed, the UK system has been structured around an existing scheduling and dispatch algorithm (GOAL). Furthermore, the bidding protocol and compensation scheme in the UK has been designed to emulate the inputs that would be provided to the computer program in a centralized system by replacing the cost and constraints information with bid prices and dispatch restrictions. Shortcomings of the UK approach and the lessons to be learned have been the subject of many presentations and public discourse. Newbery [5] highlights some of the defects in the UK system and analyses their consequences.

The purpose of this paper is to draw attention to important drawbacks of using a central scheduling and dispatch computer algorithm as a basis for organizing a competitive electricity market. In particular, we examine the effects of competition and decentralized ownership on resource scheduling, and show that centralized scheduling of multi-owned resources under imperfect information may face

[1] Concepts and methodologies presented in this paper do not necessarily represent PG&E's position on this subject. Furthermore, errors or omissions contained in this paper are the sole responsibility of the authors.

difficulties that do not arise when resources are centrally owned. As in many complex engineering economic systems, "the devil is in the details". Consequently, many of the impediments to the efficient operation of a system controlled through centralized coordination and economic authority are likely to result from the technical realities glossed over by the proponents of such an approach. State of the art scheduling and optimal dispatch algorithms contain inherent indeterminacies which provide broad latitude to the operator with potentially severe distributional implications.

Earlier work by Wu, Varaiya, Spiller and Oren [6], [7] has pointed out that any feasible power dispatch, optimal or not, will yield a corresponding market equilibrium with a corresponding set of locational spot prices. Discretionary enforcement of constraints by the operator so as to meet subjective security considerations could lead to different market equilibria and although such equilibria may not differ by much in terms of global criteria (e.g. total cost or social surplus) they may have strong distributional implications. While congestion management increases the operator's discretion the inherent latitude in near- optimal scheduling of power resources is present even in the absence of transmission constraints.

In order to illustrate the above phenomena we perform a simulation case study using a state-of-the-art Lagrangian relaxation-based unit commitment algorithm modified to simulate proposed second-price pool auction procedures. This algorithm is based on the Hydro-Thermal Optimization (HTO) program used in short-term resource scheduling at PG&E. We assume that a mandatory power pool sets both the prices paid to generators and generation schedules, and that the pool's objective is to minimize payments to generators, based on generator bids and a requirement that pricing be uniform (though possibly unbundled), subject to the same sorts of fixed demand and possibly reserve requirements previously seen by integrated utilities.

In the following sections we first describe the role of optimal unit commitment methods in the context of power pool auctions. We then introduce a mathematical formulation of the unit commitment problem in an integrated utility environment and its adaptation to a pool environment with central unit commitment. This is followed by a description of the Lagrangian relaxation approach underlying the HTO algorithm employed in our simulation study. We then present the results of a case study based on simulated unit commitment runs on a benchmark system and load, followed by general observations and conclusions.

2. Central Unit Commitment In The Context Of A Pool Auction

The pool auction procedure is generally assumed to be an economic dispatch or unit commitment based on bids rather than costs. Bids are treated as costs although actual payments to suppliers may be based on system marginal bids, in hopes of persuading resources to bid based on their true costs (and required profit margins) rather than on attempts to second-guess the market price or, worse, use their market power to directly distort the market price. When the auction procedure (as in, for example, the British day-ahead pool) allows resources to include operating characteristics such as startup costs, minimum up time, and minimum down time, these characteristics are in fact components of resource bids. The inclusion of these operating characteristics in the auction algorithm transforms the auction from an economic dispatch algorithm, which can in theory be performed independently in each half hour or hour of the period to be scheduled, into a unit commitment algorithm in which there are strong dependencies between decisions in successive hours.

The pool auction may be "first-price," in which case each bidder gets paid the price bid to supply electricity. Seen from the bidders' perspective, the "first-price" pool is equivalent to a system in which all sales are negotiated as bilateral transactions, assuming that the pool is prohibited from exercising its monopsony buying power for its own benefit. A "second-price" auction, in which all bidders are paid the same price for providing the same product (e.g., firm electricity supply in a given hour), is on the other hand quite different from a bilateral system in that the price bid and the price paid differ for most if not all bidders (in its pure form a second-price auction pays the lowest losing bid to all suppliers with lower winning bids). From the pool's perspective, the need to develop a single set of uniform prices to be paid to all bidders strongly influences the choice of auction algorithm.

An economic dispatch to match average production to expected demand in each period to be priced is an obvious candidate for an auction algorithm yielding uniform prices. Dispatch costs are minimized when all resources operate as if in response to a single price for energy in each hour. A resource whose cost as a function of generation is $C(p)$, where p=generation level, with increasing marginal cost $c(p)=C'(p)$, should operate at its minimum generation level p_{min} if the energy price $\lambda < c(p_{min})$, at maximum generation level p_{max} if $\lambda < c(p_{max})$, and at $p=c^{-1}(\lambda)$ for $c(p_{min}) < \lambda < c(p_{max})$. Thus all resources operating between their minimum and maximum levels should have equal incremental costs.

Clearly, however, the economic dispatch price does not guarantee the profitability of resources dispatched. "No-load" operating costs (operating costs at minimum operating point), startup costs, and sunk capital costs are obviously not considered by the dispatch unless they are somehow rolled in to resource incremental cost functions. In hopes of not distorting marginal cost signals too much, auction algorithms like the British system's ask for a separate capacity bid component, along with operational constraints. These components are then used within the algorithm itself to affect both the commitment and the dispatch. The heuristic modification of economic dispatch prices can ensure that the prices offered cover resource fixed costs, but not that these prices correctly incent the desired commitments.

3. Lagrangian Relaxation And Price-Based Resource Scheduling

In contrast to heuristic economic dispatch-based algorithms, unit commitment algorithms based on Lagrangian relaxation seek a single set of price signals that incent an optimal commitment of all resources. These algorithms have become popular because of their modularity and extendibility in the representation of diverse resource operating constraints. Lagrangian relaxation-based algorithms solve a dual problem which is separable in the individual resources, so that relatively small and simple scheduling subproblems can be solved for each resource in each evaluation of the dual. The association of Lagrange multipliers with each constraint applying to multiple resources (e.g., system reserve and capacity requirements, area requirements, and fuel limits as well as the basic load balance requirements) also provides an unbundled set of price signals for satisfaction of each such constraint.

In a centrally operated system with perfect information, the commitment problem whose objective is to minimize energy production costs over a specified time horizon (typically a week) may be formulated as follows:

$$\underset{\{x_{it},p_{it}\}}{Minimize} \sum_{t=1}^{T}\sum_{i=1}^{I}[S_{it}(x_{(i,t-1)},x_{it}) + C_{it}(p_{it})]$$

$$subject\ \ to\ \ \sum_{i=1}^{I} p_{it} = D_t,\ \ t=1,...,T \qquad (1)$$

(demand constraints)

$$\sum_{i=1}^{I} p_i^{\max} u_i(x_{it}) \geq R_t,\ \ t=1,...,T \qquad (2)$$

(spinning reserve requirement)

$$\overline{x}_i \in \overline{X}_i,\ \ i=1,...,I \qquad (3)$$

$$p_{it}^{\min} u_i(x_{it}) \leq p_{it} \leq p_{it}^{\max} u_i(x_{it}), i=1,...,I, t=1,...,T$$

In this formulation, the i'th resource's commitment state in period t is denoted by x_{it}, and its generation level is denoted by p_{it}. The costs to be minimized in the objective function are the change of state costs, denoted by $S_{it}(x_{(i,t-1)},x_{it})$, and the costs of generation, denoted by $C_{it}(p_{it})$ for generation level p_{it}.. Constraint set (1) represents the supply-demand balance requirements applying in each of the T periods of the scheduling horizon.

Constraint set (2) represents spinning reserve requirements. Typically the spinning reserve is specified as a fixed percentage (usually 7%) above total demand in each time period. Constraints set (3) represents additional constraints on individual resource schedules over the scheduling horizon. $u_i(x_{it})$ is a function which gives the fraction of the i'th resource's capacity considered to be available given the resource's commitment state. Thus, $0 \leq u_i(x_{it}) \leq 1$, and in cases where the commitment state is either "off" or "on," $u_i(x_{it}) \in \{0,1\}$. Constraints on $\overline{x}_i = (x_{i1}, x_{i2}, ..., x_{iT})$, the trajectory of commitment states, may be arbitrarily complicated, depending on the i'th resource's operating characteristics. $\overline{X}_i$ may for example represent all allowed paths in a dynamic program's state-transition network. The resource generation levels are assumed to be constrained between time-dependent minimums and maximums when resources are committed, and constrained to be zero when resources are not committed.

In the context of a power pool with centralized economically based unit commitment, the above formulation still represents the ISO resource scheduling problem (ignoring transmission constraints) but the cost components in the objective function are replaced by day ahead bids and the individual resource constraints are specified by the supplier as part of the bid as dispatch restrictions. The demand and spinning reserve constraints are determined by the ISO.

The use of Lagrangian relaxation to solve the resource scheduling problems was described nearly two decades ago by Muckstadt and Koenig [8]. It was further demonstrated by Bertsekas et al. [9] that the quality of the solution yielded by Lagrangian relaxation actually improves with increases in the size of the scheduling problem, where size is measured in terms of the number of non-identical resources and the number of periods in the scheduling horizon.

The degree of detail in the system representation allowed by Lagrangian relaxation implies potentially very large input and output data sets in practical applications, but advances in computer memory and database technology have made such applications more feasible over the years since the technique was first proposed for the resource scheduling problem. Electricite de France developed several applications of the method which are described by Merlin and Sandrin [10]. Similar approaches and improvement are described by Zhuang [11] and Guan et al. [12]. Applications intended for general use by power system planners have been developed by Decision Focus, Inc. [13]. Pacific Gas and Electric has developed one of the first practical implementations of Lagrangian relaxation based unit commitment algorithms in its Hydro Thermal Optimization (HTO) package which includes detailed modeling of its interconnected hydro resources and its large pumped-storage plant (see Ferreira et al [14]). Further extensions of that application acommodating ramping constraints are described by Svoboda et al. [15]. The authors have previously described an application of HTO to investigate the scheduling of endogeneously priced resources such as dispatchable demand-side management (Svoboda And Oren [16]).

In Lagrangian relaxation algorithms, solution of the resource scheduling problem is based on maximizing a Lagrangian dual of the problem. For the formulation given above, the dual takes the form:

$$\underset{\bar{\lambda},\bar{\mu}}{Maximize}\ \ q(\bar{\lambda},\bar{\mu})$$

$$subject\ \ to\ \ \lambda_t \geq 0,\ \ \mu_t \geq 0,\ \ t=1,...,T.$$

$$q(\bar{\lambda},\bar{\mu}) = \underset{\{x_{it},p_{it}\}}{Min} \sum_{t=1}^{T}\sum_{i=1}^{I}[S_{it}(x_{(i,t-1)},x_{it}) + C_{it}(p_{it})]$$

$$+\sum_{t=1}^{T}\lambda_t[D_t - \sum_{i=1}^{I}p_{it}] + \sum_{t=1}^{T}\mu_t[R_t - \sum_{i=1}^{I}p_i^{\max}u_i(x_{it})]$$

$$subject\ to\ \bar{x}_i \in \bar{X}_i,\ \ i=1,...,I$$

$$p_{it}^{\min}u_i(x_{it}) \leq p_{it} \leq p_{it}^{\max}u_i(x_{it}),$$

$$i=1,...,I,\ \ t=1,...,T.$$

The dual function $q(\bar{\lambda},\bar{\mu})$ is separable in the contributions to the dual objective of the individual resources, and thus can be written as:

$$\underset{\bar{\lambda}\geq 0,\bar{\mu}\geq 0}{Maximize}\ \ q(\bar{\lambda},\bar{\mu}) = \sum_{i=1}^{I}q_i(\bar{\lambda},\bar{\mu}) + \sum_{t=1}^{T}\lambda_t D_t + \sum_{t=1}^{T}\mu_t R_t$$

where

$$q_i(\bar{\lambda},\bar{\mu}) = \underset{\{x_{it},p_{it}\}}{Min} \sum_{t=1}^{T}[S_{it}(x_{(i,t-1)},x_{it}) + C_{it}(p_{it})]$$

$$-\sum_{t=1}^{T}[\lambda_t p_{it}] - \sum_{t=1}^{T}[\mu_t p_i^{\max}u_i(x_{it})]$$

$$subject\ \ to\ \ \bar{x}_i \in \bar{X}_i,$$

$$p_{it}^{\min}u_i(x_{it}) \leq p_{it} \leq p_{it}^{\max}u_i(x_{it}),\ \ t=1,...,T.$$

Each $q_i(\bar{\lambda},\bar{\mu})$ is evaluated by solving a subproblem involving only the i'th resource. This subproblem may be interpreted as the i'th resource's profit maximization when it sees the price vectors $\bar{\lambda}$ and $\bar{\mu}$ for its hourly generation and spinning capacity. The vector of optimal dual multipliers $\bar{\lambda}^*$ and $\bar{\mu}^*$ has been interpreted as the marginal values to the system of the marginal energy production and spinning capacity, in each hour. Since there are I resources, I resource subproblems must be solved to evaluate $q(\bar{\lambda},\bar{\mu})$ for particular vectors $\bar{\lambda}$ and $\bar{\mu}$.

Lagrangian relaxation algorithms maximize the dual iteratively. On each iteration, the multipliers are updated and $q(\bar{\lambda},\bar{\mu})$ reevaluated by solving the resource subproblems given the new multiplier values.

The unit commitment algorithm employed in this paper is based on the Lagrangian relaxation approach outlined above where the multipliers are updated using a subgradient method. Specifically, the algorithm makes use of the fact that a subgradient of the dual objective function $q(\bar{\lambda},\bar{\mu})$ can be formed as a vector of the differences between the right-hand and left-hand sides of the coupling constraints. Thus, in the subgradient vector of the dual objective function $q(\bar{\lambda},\bar{\mu})$, the elements g_t and f_t corresponding to the respective demand constraint and spinning reserve constraint in period t, are computed as:

$$g_t = D_t - \sum_{i=1}^{I}p_{it}\ \ \text{and}\ \ f_t = \max[0,\ \ R_t - \sum_{i=1}^{I}p_i^{\max}u_i(x_{it})]$$

The multipliers are then updated using the recursion

$$\bar{\lambda}^k = \bar{\lambda}^{k-1} + \beta^k\bar{g}^k\ \ \text{and}\ \ \bar{\mu}^k = \bar{\mu}^{k-1} + \beta^k\bar{f}^k.$$

This update is performed for a maximum number of iterations K, or until some other stopping criterion is met. A near-optimal solution to the Lagrangian dual problem represents a consistent set of uniform prices and resource schedules incented by these prices. Indeed, any set of uniform prices may be thought of as a solution to the Lagrangian dual problem, and the multipliers associated with the dual optimum as a set of prices that come closest (by the measure of total production costs) to yielding the optimal solution to the original scheduling problem.

The dual optimum and the optimal solution to the original scheduling problem are not identical: because of the discrete nature of the commitment decisions and constraints (which makes the problem NP-hard), the "duality gap" between dual and primal optima may be significant. A Lagrangian relaxation unit commitment algorithm must include a procedure for obtaining a feasible primal solution given the dual solution. The resulting schedules will in general be suboptimal even if based on the dual optimum (and in general, they are in fact based on a suboptimal dual solution). The structure of the unit commitment problem (a near-degeneracy resulting from near-redundancy of the capacity and energy constraints) is such that there may be many near-optimal solutions to the problem. Thus, solutions which are equally good in total cost terms may yield very different schedules of individual resources which in turn vary significantly in terms of costs, profits, and commitments.

The problems inherent in Lagrangian relaxation are, by the above argument, inherent also in the use of uniform pricing combined with centralized commitment and dispatch in the scheduling of resources. Two equally efficient sets of price incentives may yield very different resource schedules and hence levels of profit for individual resources. And since the Lagrangian relaxation approaches, like other currently used unit commitment algorithms which recognize dynamic operating constraints, fix unit commitment before dispatching economically to the load forecast, the prices offered simulate a "bait-and-switch" in which the central operator offers a given set of prices for energy, but then doesn't allow winning bidders into the pool to commit and dispatch so as to maximize their own profits. One might justify fixing schedules on grounds of system reliability, but not to the point of making a given resource's operations unprofitable.

4. Case Study Results

Our simulation study employs the Hydro Thermal Optimization (HTO) unit commitment algorithm developed at PG&E to schedule a benchmark system over a period of 168 hours. We make use of the CALECO system data developed by Marnay and Strauss [17] for the evaluation of chronological production costing simulation models. We have eliminated never-used resources from the resource set for simplicity of presentation. In the case study, peak load for the 168 hour period is 9749 MW, and minimum load is 4990 MW. Total load is 1178.861 GWH, giving a load factor of 74%. Figure 1 summarizes some significant unit characteristics for the resource set. Pond Hydro is scheduled by peak shaving, and thus is not included in the optimization. The QF is scheduled manually as a base load unit at fixed cost (which may exceeds the marginal system cost) hence it does not affect the optimization but is included for accounting purposes and for illustrating the opportunity cost of the fixed price QF contract. In running HTO we assume perfect knowledge of the cost characteristics and constraints of individual resources which are assumed to be independently owned. Such a scenario would represent an ideal bidding system providing perfect information to the ISO who needs to schedule the units in a pool based environment. In addition to the total system cost we keep track for each resource of the profits as measured by the differences between revenues and operating costs. In the case of the QF resource we calculate the opportunity cost of the contract, i.e., the net efficiency losses due to nondispatchability. Since the total operating cost of the QF is fixed, the variation in the unit's opportunity cost are identical to the variation in the QF's profits had it been dispatched economically. The revenues are based on the uniform market clearing prices which equal the dual prices produced by the HTO algorithm, while the cost includes both energy costs and state transition costs (e.g. start-up and shutdown costs).

Table 1 shows the total costs, payments (under uniform marginal cost pricing) and profits resulting from serving the benchmark load for 168 hours under optimal unit commitment. The profit is broken down by individual resource and subtotaled for the non-base loaded units. The results are listed for a dozen simulation runs which only differ in the parameters of the stepsize selection procedure employed in the dual optimization phase. The stepsize selection rule is controlled by a user specified parameter whose selection would be under the purview of an ISO running the unit commitment algorithm. As the results show, variation in the stepsize rule have resulted in slightly different solutions which subsequently produce different near-optimal feasible schedules of roughly equal quality (in terms of total system costs). The bottom half of Table 1 contains summary statistics for the different simulation runs. The shaded portion of the table highlights a subset of runs which spans the outcome variability range. These runs are used in the subsequent graphical illustration of the results.

FIGURE 1:
Description of the CALECO System Used in Pool Simulations

Unit Name	Max Load	Min Load	Startup $	Min Up	Min Down	Fuel
Col-Stm	1000	250	100000	120	48	Coal
Stm1	750	50	15000	24	48	Gas
Stm5	330	50	15000	6	3	Gas
Stm6	330	50	15000	6	3	Gas
Stm7	340	85	15000	6	3	Gas
QF	1000	1000	N/A	N/A	N/A	QF
Pond Hydro	1500	1	0	1	1	Pond Hydro (Limited)
ROR Hydro	900	0	0	1	1	ROR Hydro
Nuke	2000	0	200000	1	1	Nuke
CTs	1000	0	0	1	1	Distillate
Econ01	500	0	0	1	1	Transaction at $17.5/MWH
Econ02	500	0	0	1	1	Transaction at $30/MWH

Load assumptions:

Maximum load = 9749 MW
Minimum load = 4990 MW
Total load = 1178861 MWH
Load factor = 74%
168 hours

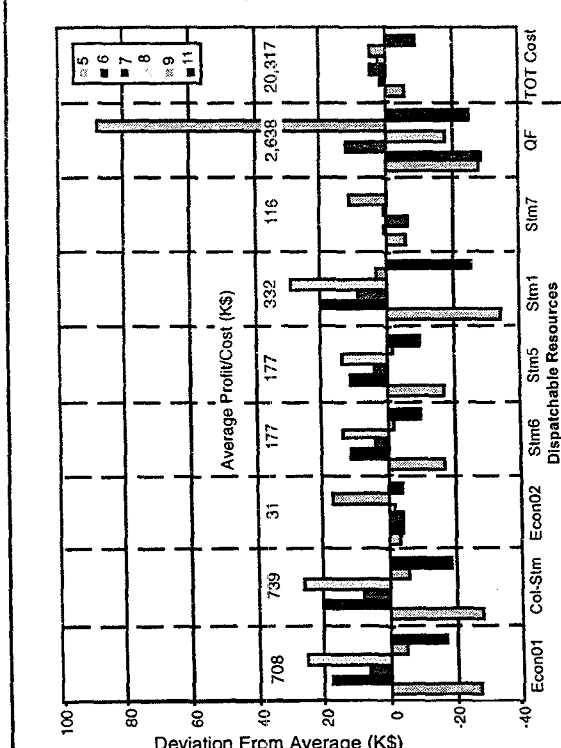
TABLE 1: SIMULATION RESULTS SUMMARY

	TOTALS(K$)			UNIT PROFITS (K$)												Comp. Units
Run	Cost	Payment	Profits	Pond	ROR	Nuke	CT	Econ01	Col-Stm	Econ02	Stm6	Stm5	Stm1	Stm7	QF (Losses)	SUBTOTAL
1	20,306.94	30,176.44	9,869.51	1,878.26	2,923.25	2,408.05	6.15	682.52	712.49	27.80	161.49	161.48	303.15	116.28	2,631.95	4,797.16
2	20,310.31	30,275.33	9,965.01	1,892.07	2,935.28	2,421.42	5.99	689.68	719.66	27.92	166.22	166.21	304.57	113.50	2,618.58	4,806.34
3	20,305.80	30,303.42	9,997.62	1,892.80	2,944.11	2,431.23	6.06	687.30	717.33	27.47	164.66	164.65	305.49	116.71	2,608.77	4,792.39
4	20,307.91	30,237.94	9,930.04	1,889.83	2,924.64	2,409.60	7.29	691.20	721.21	28.30	167.22	167.21	306.53	116.61	2,630.40	4,828.68
5	20,311.07	30,255.59	9,944.51	1,887.43	2,943.01	2,430.01	7.04	680.56	710.53	27.76	160.22	160.22	296.85	110.33	2,609.99	4,756.47
6	20,318.74	30,509.02	10,190.28	1,869.84	2,944.20	2,431.33	7.16	726.09	758.35	27.04	188.35	188.34	351.69	116.87	2,608.67	4,965.40
7	20,321.90	30,238.11	9,916.21	1,828.61	2,906.60	2,389.55	7.30	714.51	746.74	27.01	180.73	180.73	340.61	109.96	2,650.45	4,950.75
8	20,319.36	30,438.41	10,119.05	1,806.64	2,933.46	2,419.40	8.77	732.76	764.88	29.17	190.76	190.74	361.36	117.42	2,620.60	5,007.69
9	20,321.70	29,929.26	9,607.56	1,813.98	2,837.95	2,313.28	25.97	702.90	732.97	48.00	175.00	175.00	335.39	127.58	2,726.72	5,023.56
10	20,305.80	30,283.39	9,977.59	1,890.20	2,939.48	2,426.09	7.11	687.50	717.47	27.98	164.77	164.76	305.74	116.84	2,613.91	4,798.97
11	20,307.90	30,293.28	9,985.38	1,880.87	2,940.50	2,427.22	6.94	690.76	720.70	27.29	166.92	166.91	305.82	116.29	2,612.78	4,807.47
12	20,310.30	30,307.03	9,996.73	1,878.00	2,945.42	2,432.69	6.56	690.05	719.96	26.99	166.44	166.44	305.09	113.74	2,607.31	4,796.01
average	20,312.31	30,270.60	9,958.29	1,867.21	2,926.49	2,411.66	8.53	697.99	728.53	29.40	171.06	171.06	318.52	116.01	2,628.34	4,860.91
std	6.28	140.08	140.61	32.06	30.14	33.49	5.54	17.30	18.24	5.89	10.28	10.28	22.21	4.46	33.49	96.10
max	20,321.90	30,509.02	10,190.28	1,892.80	2,945.42	2,432.69	25.97	732.76	764.88	48.00	190.76	190.74	361.36	127.58	2,726.72	5,023.56
min	20,305.80	29,929.26	9,607.56	1,806.64	2,837.95	2,313.28	5.99	680.56	710.53	26.99	160.22	160.22	296.85	109.96	2,607.31	4,756.47
range	16.10	579.77	582.72	86.17	107.47	119.41	19.99	52.20	54.35	21.01	30.54	30.52	64.50	17.62	119.41	267.09
range/avg	0.08%	1.92%	5.85%	4.61%	3.67%	4.95%	234.38%	7.48%	7.46%	71.49%	17.85%	17.84%	20.25%	15.19%	4.54%	5.49%
std/mean	0.03%	0.46%	1.41%	1.72%	1.03%	1.39%	65.02%	2.48%	2.50%	20.05%	6.01%	6.01%	6.97%	3.84%	1.27%	1.98%

Figures 2 and 3 illustrate absolute and percentage variability in the profits of individual units. Variability is measured in terms of the deviation from the corresponding profits averaged over the relevant runs. Base loaded units are excluded, however, the QF unit is kept to illustrate the potential variability in that resource's profits, had it been dispatchable. Figure 2 also illustrates the absolute variability in total operating cost. The percentage variability in total cost is not displayed in Figure 3 since it is under 0.05%. The aggregation by simulation run in Figure 3 shows that the near-optimal schedule may vary in different ways. In some runs the dispatchable resources are under utilized, thus shifting load to the base load units while in other runs, load is shifted away from the base load units to the dispatchable resources. Yet in other runs load is shifted among the dispatchable units.

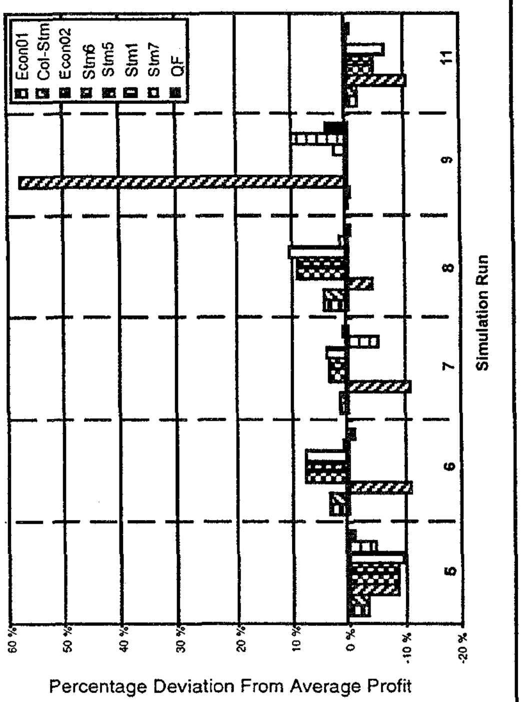
The results demonstrate inherent instability and indeterminacies in the optimal schedule produced by a central unit commitment algorithm. As shown in Figures 2 and 3, alternative near-optimal schedules which are equally good from the perspective of social cost have significantly diverse implications on the profitability of individual resources. The results are particularly volatile for resources at the margin such as Econo2 whose profitability can swing as much as 60%. Any of the schedules produced in our simulation could have been a plausible choice of an efficiency motivated ISO running the unit commitment

FIGURE 2: DEVIATION FROM AVERAGE PROFIT ON DIFFERENT RUNS OF UNIT COMMITMENT



program. Yet, any specific choice could benefit one resource to the detriment of another. It should also be noted that there is very little variability in the aggregate profits of the dispatchable resources. Thus in an integrated utility environment for which the central unit commitment program was designed schedule indeterminacies would not have any adverse effects. It is the use of these programs in a decentralized ownership environment that creates equity problems. On the other hand, a unit commitment program like HTO would continue to serve as a useful decision tool to a multiple resource owner for internal scheduling of resources bid into the pool.

FIGURE 3:
PERCENTAGE PROFIT DEVIATION FROM MEAN
ON DIFFERENT UNITS COMMITMENT RUNS



5. Conclusions

We have demonstrated both the volatility of "near optimal" scheduling outcomes for resources not base loaded, and the especially negative consequences of volatility for marginal resources (i.e., resources that frequently determine system marginal costs). Specifically, we have shown that variations in near optimal unit commitments that have negligible effect on total costs could have significant impact on the profitability of individual resources. Consequently an ISO charged with making efficient central unit commitment decisions is in a delicate position of having to allocate profits equitably among resource owners with no economic rationale to back the decision. These effects are inherent when attempting to optimize unit commitment from the perspective of a central operator, because of the near-degeneracy of the unit commitment problem and the presence of many near-optimal solutions.

The results, raise serious question regarding the feasibility of proper mechanisms to oversee the efficiency and equity of a mandatory centrally commited and dispatched pool. We suggest that centralized scheduling by a mandatory power pool, using models appropriate for solving the integrated and regulated utility's scheduling problem, may be perceived by suppliers as unnecessarily volatile and even inequitable, and hence in the long run yield schedules that do not minimize costs. In particular, our results highlight potential pitfalls in central management of dispatch constraints specified by bidders.

The results of this paper support a more decentralized approach to unit commitment such as physical scheduling of self-nominated transactions or a simple auction with single prices and self-commitment. Proponents of the centralized dispatch may argue that self-commitment is a de facto option in an auction based system which can be realized by bidding a zero price while specifying quantity nomination. Unfortunately, as can be seen from our simulation results, resources that would experience the highest profit volatility are those operating in the price setting range. A process that would induce such units to bid a price of zero will undermine the efficiency of the unit commitment by withholding crucial cost information necessary for achieving an economically efficient schedule.

The simulation results also illustrate potential negative side-effects of resource disaggregation resulting from utility divestment of resources. While such disaggregation reduces the danger of horizontal market power due to concentration of resources, the inherent volatility in the net revenue of individual resources suggests that over-disaggregation is undesirable.

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