18

Generation Control: Economic Dispatch and Unit Commitment

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An area of power system control having a large impact on cost and profit is the optimal scheduling of generating units. A good schedule identifies which units to operate, and the amount to generate at each online unit in order to achieve a set of economic goals. These are the problems commonly referred to as the unit commitment (UC) problem, and the economic dispatch calculation, respectively. The goal is to choose a control strategy that minimizes losses (or maximizes profits), subject to meeting a certain demand and other system constraints. The following sections define EDC, the UC problem, and discuss methods that have been used to solve these problems. Realizing that electric power grids are complex interconnected systems that must be carefully controlled if they are to remain stable and secure, it should be mentioned that the tools described in this chapter are intended for steady-state operation. Short-term (less than a few seconds) changes to the system are handled by dynamic and transient system controls, which maintain secure and stable operation, and are beyond the scope of this discussion.

18.1 Economic Dispatch

18.1.1 Economic Dispatch Defined

An *economic dispatch calculation* (EDC) is performed to *dispatch*, or schedule, a set of online generating units to collectively produce electricity at a level that satisfies a specified demand in an economical manner. Each online generating unit may have many characteristics that make it unique, and which must be considered in the calculation. The amount of electricity demanded can vary quickly and the schedule produced by an EDC should leave units able to respond and adapt without major implications to cost or profit. The electric system may have limits (e.g., voltage, transmission, etc.) that impact the EDC and hence should be considered. Generating units may have prohibited generation levels at which resonant frequencies may cause damage or other problems to the system. The impact of transmission losses, congestion, and limits that may inhibit the ability to serve the load in a particular region from a particular generator (e.g., a low-cost generator) should be considered. The market structure within an operating region and its associated regulations must be considered in determining the specified demand, and in determining what constitutes economical operation. An independent system operator (ISO) tasked with maximizing social welfare would likely have a different definition of "economical" than does a generation company (GENCO) wishing to maximize its profit in a competitive environment. The EDC must consider all of these factors and develop a schedule that sets the generation levels in accordance with an economic objective function.

18.1.2 Factors to Consider in the EDC

18.1.2.1 The Cost of Generation

Cost is one of the primary characteristics of a generating unit that must be considered when dispatching units economically. The EDC is concerned with the short-term operating cost, which is primarily determined by fuel cost and usage. Fuel usage is closely related to generation level. Very often, the relationship between power level and fuel cost is approximated by a quadratic curve: $\mathbf{F} = \mathbf{aP^2} + \mathbf{bP} + \mathbf{c}$. $\mathbf{c}$ is a constant term that represents the cost of operating the plant, $\mathbf{b}$ is a linear term that varies directly with the level of generation, and $\mathbf{a}$ is the term that accounts for efficiency changes over the range of the plant output. A quadratic relationship is often used in the research literature. However, due to varying conditions at certain levels of production (e.g., the opening or closing of large valves may affect the generation cost [Walters and Sheblé, 1992]), the actual relationship between power level and fuel cost may be more complex than a quadratic equation. Many of the long-term generating unit costs (e.g., costs attributed directly to starting and stopping the unit, capital costs associated with financing the construction) can be ignored for the EDC, since the decision to switch on, or *commit*, the units has already been made. Other characteristics of generating units that affect the EDC are the minimum and maximum generation levels at which they may operate. When binding, these constraints will directly impact the EDC schedule.

18.1.2.2 The Price

The price at which an electric supplier will be compensated is another important factor in determining an optimal economic dispatch. In many areas of the world, electric power systems have been, or still are, treated as a natural monopoly. Regulations allow the utilities to charge rates that guarantee them a nominal profit. In competitive markets, which come in a variety of flavors, price is determined through the forces of supply and demand. Economic theory and common sense tell us that if the total supply is high and the demand is low, the price is likely to be low, and vice versa. If the price is consistently below a GENCO's average total costs, the company may soon be bankrupt.

18.1.2.3 The Quantity Supplied

The amount of electric energy to be supplied is another fundamental input for the EDC. Regions of the world having regulations that limit competition often require electric utilities to serve all electric demand within a designated service territory. If a consumer switches on a motor, the electric supplier must provide the electric energy needed to operate the motor. In competitive markets, this *obligation to serve* is limited to those with whom the GENCO has a contract. Beyond its contractual obligations, the GENCO may be willing (if the opportunity arises) to supply additional consumer demand. Since the consumers have a choice of electric supplier, a GENCO determining the schedule of its own online generating units may choose to supply all, none, or only a portion of that additional consumer demand. The decision is dependent on the objective of the entity performing the EDC (e.g., profit maximization, improving reliability, etc.).

18.1.3 EDC and System Limitations

A complex network of transmission and distribution lines and equipment are required to move the electric energy from the generating units to the consumer loads. The secure operation of this network depends on bus voltage magnitudes and angles being within certain tolerances. Excessive transmission line loading can also affect the security of the power system network. Since superconductivity is a relatively new field, lossless transmission lines are expensive and are not commonly used. Therefore, some of the energy being transmitted over the system is converted into heat and is consequently lost. The schedule produced by the EDC directly affects losses and security; hence, constraints ensuring proper system operation must be considered when solving the EDC problem.

18.1.4 The Objective of EDC

In a regulated, vertically integrated, monopolistic environment, the obligated-to-serve electric utility performs the EDC for the entire service area by itself. In such an environment, providing electricity in an "economical manner" means minimizing the cost of generating electricity, subject to meeting all demand and other system operating constraints. In a competitive environment, the way an EDC is done can vary from one market structure to another. For instance, in a decentralized market, the EDC may be performed by a single GENCO wishing to maximize its expected profit given the prices, demands, costs, and other constraints described above. In a power pool, a central coordinating entity may perform an EDC to centrally dispatch generation for many GENCOs. Depending on the market rules, the generation owners may be able to mask the cost information of their generators. In this case, bids would be submitted for various price levels and used in the EDC.

18.1.5 The Traditional EDC Mathematical Formulation

Assuming operation under a vertically integrated, monopolistic environment, we must meet all demand, D. We must also consider minimum and maximum limits for each generating unit, $P_i^{\min}$ and $P_i^{\max}$. We will assume that the fuel costs of the ith operating plant may be modeled by a quadratic equation as shown in Eq. (18.1), and shown graphically in Fig. 18.1. Note that the average fuel costs are also shown in Fig. 18.1.

$$F_i = a_i P_i^2 + b_i P_i + c_i \quad \text{(fuel costs of ith generator)} \tag{18.1}$$

Thus, for N online generating units, we can write a Lagrangian equation, L, which describes the total cost and associated demand constraint, D.

$$\mathrm{L} = \mathrm{F_T} + \lambda\left(D - \sum_{i=1}^{N} P_i\right) = \sum_{i=1}^{N}\left(a_i P_i^2 + b_i P_i + c_i\right) + \lambda \cdot \left(D - \sum_{i=1}^{N} P_i\right)$$

$$F_T = \sum_{i=1}^{N} F_i \qquad \text{(Total fuel cost is a summation of costs for all online plants)}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \quad \text{(Generation must be set between the min and max amounts)} \tag{18.2}$$

Additionally, note that c_i is a constant term that represents the cost of operating the ith plant, b_i is a linear term that varies directly with the level of generation, P_i, and a_i are terms that account for efficiency changes over the range of the plant output.

In this example, the objective will be to minimize the cost of supplying demand with the generating units that are online. From calculus, a minimum or a maximum can be found by taking the N + 1 derivatives of the Lagrangian with respect to its variables, and setting them equal to zero. The shape of the curves is often assumed well behaved—monotonically increasing and convex—so that determining the second derivative is unnecessary.

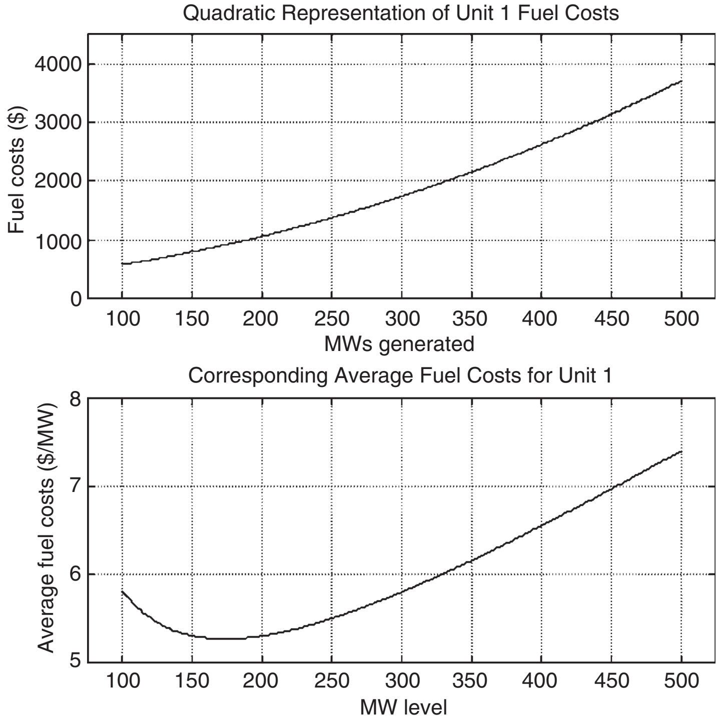

FIGURE 18.1 Relationship between fuel input and power output.

$$\frac{\partial L}{\partial P_i} = 2a_iP_i + b_i - \lambda = 0 \Rightarrow \lambda = 2a_iP_i + b_i \tag{18.3}$$

$$\frac{\partial L}{\partial \lambda} = \left(D - \sum_{1}^{N} P_i\right) = 0 \tag{18.4}$$

λ_i is the commonly used symbol for the "marginal cost" of the *i*-th unit. At the margin of operation, the marginal cost tells us how many additional dollars the GENCO will have to spend to increase the generation by an additional MW. The marginal cost curve is an positively sloped line if a quadratic equation is being used to represent the fuel curve of the unit. The higher the quantity being produced, the greater the cost of adding an additional unit of the goods being produced. Economic theory says that if a GENCO has a set of plants and it wants to increase production by one unit, it should increase production at the plant that provides the most benefit for the least cost. The GENCO should do this until that plant is no longer providing the greatest benefit for a given cost. At that point it finds the plant now giving the highest benefit-to-cost ratio and increases its production. This is done until all plants are operating at the same marginal cost. When all unconstrained online plants have the same marginal cost, λ (i.e., $\lambda_1 = \lambda_2 = \ldots = \lambda_i = \ldots = \lambda_{SYSTEM}$), then the cost is at a minimum for that amount of generation. If there were binding constraints, it would prevent the GENCO from achieving that scenario.

If a constraint is binding on a particular unit (e.g., P_i becomes $P_i^{\max}$ when attempting to increase production), the marginal cost of that unit is considered to be infinite. No matter how much money is available to increase plant production by one unit, it cannot do so. (Of course, in the long term, things may be done that can reduce the effect of the constraint, but that is beyond the scope of this discussion.)

18.1.6 EDC Solution Techniques

There are many ways to obtain the optimum power levels that will achieve the objective for the EDC problem being considered. For very simple situations, one may solve the solution directly; but when the number of constraints that introduce nonlinearities to the problem grows, iterative search techniques become necessary. Wood and Wollenberg (1996) describe many such methods of calculating economic dispatch, including the graphical technique, the lambda-iteration method, and the first and second-order gradient methods. Another method that works well, even when fuel costs are not modeled by a simple quadratic equation, is the genetic algorithm.

In highly competitive scenarios, each inaccuracy in the model can result in losses to the GENCO. A very detailed model might include many nonlinearities, (e.g., valve-point loading, prohibited regions of operation, etc.). Such nonlinearities may mean that it is not possible to calculate a derivative. If the relationship is not well-behaved, there may be no proof that the solution can ever be optimal. With greater detail in the model comes an increase in the amount of time to perform the EDC. Since the EDC is performed quite frequently (on the order of every few minutes), and because it is a real-time calculation, the solution technique should be quick. Since an inaccurate solution may produce a negative impact on the company profits, the solution should also be accurate.

18.1.7 An Example of Cost Minimizing EDC

To illustrate how the EDC is solved via the graphical method, an example is presented here. Assume that a GENCO needs to supply 1000 MW of consumer demand, and that Table 18.1 describes the system on-line units that it is dispatching in a traditional, i.e., vertically integrated, monopolistic environment. Figure 18.2 shows the marginal costs of each of the units over their entire range. It also shows an aggregated marginal cost curve that could be called the system marginal cost curve. This aggregated system curve was created by a horizontal summation of the four individual graphs. Once the system curve is created, one simply finds the desired power level (i.e., 1000 MW) along the x-axis. Follow it up to the curve, and then look to the left. On the y-axis, the system marginal cost can be read. Since no limits were reached, each of the individual λ_is is the same as the system λ. The GENCO can find the λ_i on each of the unit curves and draw a line straight down from the point where the marginal cost, λ, crosses the curve to find its power level. The generation levels of each online unit are easily found and the solution is shown in the right-hand columns of Table 18.1. The procedure just described is the graphical method of EDC. If the system marginal cost had been above the diagonal portion of an individual unit curve, then we simply set that unit at its P^{max}.

18.1.8 EDC and Auctions

Competitive electricity markets vary in their operating rules, social objectives, and in the mechanism they use to allocate prices and quantities to the participants. Commonly, an auction is used to match buyers with sellers and to achieve a price that is considered fair. Auctions can be sealed bid, open out-cry,

TABLE 18.1 Generator Data and Solution for EDC Example

	Unit Parameters					Solution		
Unit Number	P_{min}	P_{max}	A	B	C	P_i (MW)	\$/MW (λ_i)	Cost \$/hour
1	100	500	.01	1.8	300	233.2456	6.4649	1263.90
2	50	300	.012	2.24	210	176.0380	6.4649	976.20
3	100	400	.006	2.35	290	342.9094	6.4649	1801.40
4	100	500	.008	2.5	340	247.8070	6.4649	1450.80

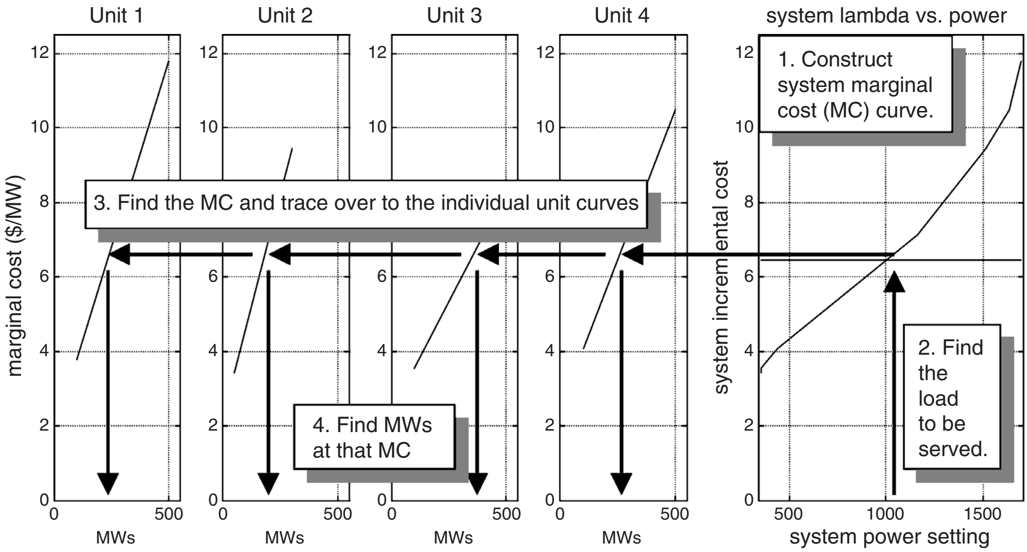

FIGURE 18.2 Unit and aggregated marginal cost curves for solving EDC with the graphical method.

ascending ask English auctions, descending ask Dutch auctions, etc. Regardless of the solution technique used to find the optimal allocation, the economic dispatch is essentially performing the same allocation that an auction would. Suppose an auctioneer were to call out a price, and ask the participating/online generators how much power they would generate at that level. The reply amounts could be summed to determine the production level at that price. If all of the constraints, including demand, are met, then the most economical dispatch has been achieved. If not, the auctioneer adjusts the price and asks for the amounts at the new price. This procedure is repeated until the constraints are satisfied. Prices may ascend as in the English auction, or they may descend as in the Dutch auction. See Fig. 18.3 for a graphical depiction of this process. For further discussion on this topic, the interested reader is referred to Sheblé (1999).

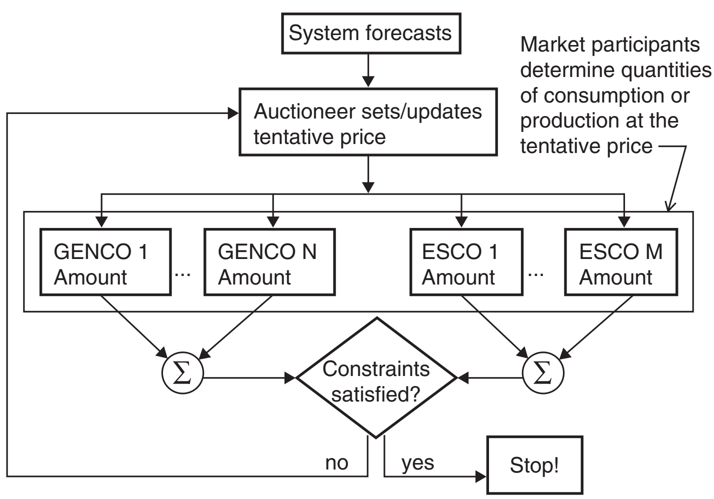

FIGURE 18.3 Economic dispatch and/or unit commitment as an auction.

18.2 The Unit Commitment Problem

18.2.1 Unit Commitment Defined

The *unit commitment* (UC) problem is defined as the scheduling of a set of generating units to be on, off, or in stand-by/banking mode for a given period of time to meet a certain objective. For a power system operated by a vertically integrated monopoly, committing units is performed centrally by the utility, and the objective is to minimize costs subject to supplying all demand (and reserve margins). In a competitive environment, each GENCO must decide which units to commit, such that profit is maximized, based on the number of contracted MW; the additional MWhr it forecasts that it can profitably wrest from its competitors in the spot market; and the prices at which it will be compensated.

UC Schedule

Hour	1 2 3 4 5 6 ... T
Gen#1:	1 1 1 1 1 1 ... 0
Gen#2:	0 0 0 1 1 1 ... 1
Gen#3:	1 1 1 0 0 0 ... 1
...	
Gen#N:	1 1 1 1 1 1 ... 0

0 = unit off-line   1 = unit on-line

FIGURE 18.4 A typical unit commitment schedule.

A UC schedule is developed for N units and T periods. A typical UC schedule might look like the one shown in Fig. 18.4. Since uncertainty in the inputs becomes large beyond one week into the future, the UC schedule is typically developed for the following week. It is common to consider schedules that allow unit-status change from hour to hour, so that a weekly schedule is made up of 168 periods. In finding an optimal schedule, one must consider fuel costs, which can vary with time, start-up and shut-down costs, maximum ramp rates, the minimum up-times and minimum down-times, crew constraints, transmission limits, voltage constraints, etc. Because the problem is discrete, the GENCO may have many generating units, a large number of periods may be considered, and because there are many constraints, finding an optimal UC is a complex problem.

18.2.2 Factors to Consider in Solving the UC Problem

18.2.2.1 The Objective of Unit Commitment

The objective of the unit commitment algorithm is to schedule units in the most economical manner. For the GENCO deciding which units to commit in the competitive environment, economical manner means one that maximizes its profits. For the monopolist operating in a vertically integrated electric system, economical means minimizing the costs.

18.2.2.2 The Quantity to Supply

In systems with vertically integrated monopolies, it is common for electric utilities to have an obligation to serve all demand within their territory. Forecasters provide power system operators an estimated amount of power demanded. The UC objective is to minimize the total operational costs subject to meeting all of this demand (and other constraints they may be considering).

In competitive electric markets, the GENCO commits units to maximize its profit. It relies on spot and forward bilateral contracts to make part of the total demand known *a priori*. The remaining share of the demand that it may pick up in the spot market must be predicted. This market share may be difficult to predict since it depends on how its price compares to that of other suppliers.

The GENCO may decide to supply less demand than it is physically capable of. In the competitive environment, the obligation to serve is limited to those with whom the GENCO has a contract. The GENCO may consider a schedule that produces less than the forecasted demand. Rather than switching on an additional unit to produce one or two unsatisfied MW, it can allow its competitors to provide that 1 or 2 MW that might have substantially increased its average costs.

18.2.2.3 Compensating the Electricity Supplier

Maximizing profits in a competitive environment requires that the GENCO know what revenue is being generated by the sale of electricity. While a traditional utility might have been guaranteed a fixed rate of return based on cost, competitive electricity markets have varying pricing schemes that may price electricity at the level of the last accepted bid, the average of the buy, ask, and sell offer, etc. When submitting offers to an auctioneer, the GENCO's offer price should reflect its prediction market share, since that determines how many units they have switched on, or in banking mode. GENCOs recovering costs via prices set during the bidding process will note that the UC schedule directly affects the average cost, which indirectly affects the offering price, making it an essential input to any successful bidding strategy.

Demand forecasts and expected market prices are important inputs to the profit-based UC algorithm; they are used to determine the expected revenue, which in turn affects the expected profit. If a GENCO produces two UC schedules each having different expected costs and different expected profits, it should implement the one that provides for the largest profit, which will not necessarily be the one that costs the least. Since prices and demand are so important in determining the optimal UC schedule, price prediction and demand forecasts become crucial. An easy-to-read description of the cost-minimizing UC problem and a stochastic solution that considers spot markets has been presented in Takriti, Krasenbrink, and Wu (1997).

18.2.2.4 The Source of Electric Energy

A GENCO may be in the business of electricity generation, but it should also consider purchasing electricity from the market, if it is less expensive than its own generating unit(s). The existence of liquid markets gives energy trading companies an additional source from which to supply power that may not be as prevalent in monopolistic systems. See Fig. 18.5. To the GENCO, the market supply curve can be thought of as a pseudo-unit to be dispatched. The supply curve for this pseudo-unit represents an aggregate supply of all of the units participating in the market at the time in question. The price forecast essentially sets the parameters of the unit. This pseudo-unit has no minimum uptime, minimum downtime, or ramp constraints; there are no direct start-up and shutdown costs associated with dispatching the unit.

The liquid markets that allow the GENCO to schedule an additional pseudo unit, also act as a load to be supplied. The total energy supplied should consist of previously arranged bilateral or multilateral contracts arranged through the markets (and their associated reserves and losses). While the GENCO is determining the optimal unit commitment schedule, the energy demanded by the market (i.e., market demand) can be represented as another DISTCO or ESCO buying electricity. Each entity buying electricity should have its own demand curve. The market demand curve should reflect the aggregate of the demand of all the buying agents participating in the market.

18.2.3 Mathematical Formulation for UC

The mathematical formulation for UC depends upon the objective and the constraints that are considered important. Traditionally, the monopolist cost-minimization UC problem has been formulated (Sheblé, 1985):

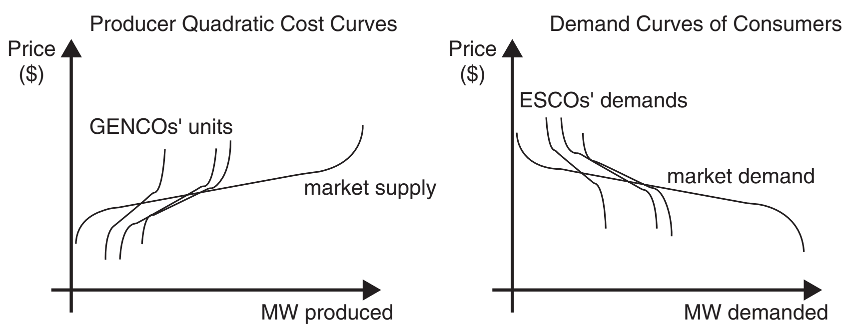

FIGURE 18.5 Treating the market as an additional generator and/or load.

$$\text{Minimize F} = \sum_{n}^{N} \sum_{t}^{T} [(C_{nt} + MAINT_{nt}) \cdot U_{nt} + SUP_{nt} \cdot U_{nt}(1 - U_{nt}) + SDOWN_{nt} \cdot (1 - U_{nt}) \cdot U_{nt-1}] \tag{18.5}$$

subject to the following constraints:

$$\sum_{n}^{N} (U_{nt} \cdot P_{nt}) = D_t \qquad \text{(demand constraint)}$$

$$\sum_{n}^{N} (U_{nt} \cdot \text{Pmax}_n) \geq D_t + R_i \qquad \text{(capacity constraint)}$$

$$\sum_{n}^{N} (U_{nt} \cdot \text{Rsmax}_n) \geq R_t \qquad \text{(system reserve constraint)}$$

When formulating the profit-maximizing UC problem for a competitive environment, the obligation-to-serve is gone. The demand constraint changes from an equality to an inequality ($\leq$). In the formulation presented here, we lump the reserves in with the demand. Essentially we are assuming that buyers are required to purchase a certain amount of reserves per contract. In addition to the above changes, formulating the UC problem for the competitive GENCO changes the objective function from cost minimization to profit maximization as shown in Eq. (18.6) below. The UC solution process is shown in block diagram form in Fig. 18.6.

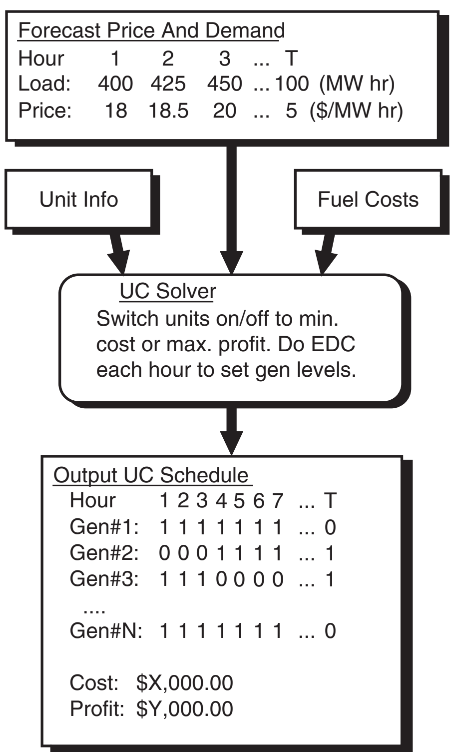

FIGURE 18.6 Block diagram of the UC solution process.

$$\text{Max}\Pi = \sum_{n}^{N} \sum_{t}^{T} (\mathrm{P_{nt}} \cdot fp_t) \cdot U_{nt} - F \tag{18.6}$$

subject to:

$$D_t^{contracted} \leq \sum_{n}^{N} (U_{nt} \cdot P_{nt}) \leq D'_t \quad \text{(demand constraint w/out obligation-to-serve)}$$

$$P\text{min}_n \leq P_{nt} \leq P\text{max}_n \quad \text{(capacity limits)}$$

$$|P_{nt} - P_{n,t-1}| \leq \text{Ramp}_n \quad \text{(ramp rate limits)}$$

where individual terms are defined as follows:

U_{nt} = up/down time status of unit n at time period t ($U_{nt} = 1$ unit on, $U_{nt} = 0$ unit off)
P_{nt} = power generation of unit n during time period t
D_t = load level in time period t
D'_t = forecasted demand at period t (includes reserves)
$D_t^{contract}$ = contracted demand at period t (includes reserves)
fp_t = forecasted price/MWhr for period t
R_t = system reserve requirements in time period t
C_{nt} = production cost of unit n in time period t
SUP_{nt} = start-up cost for unit n, time period t
$SDOWN_{nt}$ = shut-down cost for unit n, time period t
$MAINT_{nt}$ = maintenance cost for unit n, time period t
N = number of units
T = number of time periods
$Pmin_n$ = generation low limit of unit n
$Pmax_n$ = generation high limit of unit n
$Rsmax_n$ = maximum contribution to reserve for unit n

Although it may happen in certain cases, the schedule that minimizes cost is not necessarily the schedule that maximizes profit. Providing further distinction between the cost-minimizing UC for the monopolist and the profit maximizing competitive GENCO is the obligation-to-serve; the competitive GENCO may choose to generate less than the total consumer demand. This allows a little more flexibility in the UC schedules. In addition, our formulation assumes that prices fluctuate according to supply and demand. In cost-minimizing paradigms, it is assumed that leveling the load curve helps to minimize the cost. When maximizing profit, the GENCO may find that under certain conditions, it may profit more under a non-level load curve. The profit depends not only on cost, but also on revenue. If revenue increases more than the cost does, the profit will increase.

18.2.4 The Importance of EDC to the UC Solution

The economic dispatch calculation (EDC) is an important part of UC. It is used to assure that sufficient electricity will be available to meet the objective each hour of the UC schedule. For the monopolist in a vertically integrated environment, EDC will set generation so that costs are minimized subject to meeting the demand. For the price-based UC, the price-based EDC adjusts the power level of each online unit each has the same incremental cost (i.e., $\lambda_1 = \lambda_2 = \ldots = \lambda_i = \ldots = \lambda_T$). If a GENCO is operating in a competitive framework that requires its bids to cover fixed, start-up, shutdown, and other costs associated with transitioning from one state to another, then the incremental cost used by EDC must embed these costs. We shall refer to this modified marginal cost as a pseudo λ. The competitive generator will generate if the pseudo λ is less than or equal to the competitive price. A simple way to allocate the fixed and transitional costs that result in a \$/MWhr figure is shown in Eq. (18.7):

$$\lambda_t = fp_t - \frac{\sum_t \sum_n (transition\ costs) + \sum_t \sum_n (fixed\ costs)}{\sum_t^T \sum_n^N P_{nt}} \tag{18.7}$$

Other allocation schemes that adjust the marginal cost/price according to the time of day or price of power would be just as easy to implement and should be considered in building bidding strategies. Transition costs include start-up, shutdown, and banking costs, and fixed costs (present for each hour that the unit is on), which would be represented by the constant term in the typical quadratic cost curve approximation. For the results presented later in this chapter, we approximate the summation of the power generated by the forecasted demand.

The competitive price is assumed to be equal to the forecasted price. If the GENCO's supply curve is indicative of the system supply curve, then the competitive price will correspond to the point where the demand and supply curves cross. EDC sets the generation level corresponding to the point where the GENCO's supply curve crosses the demand curve, or to the point where the forecasted price is equal to the supply curve, whichever is lower.

18.2.5 Solution Methods

Solving the UC problem to find an optimal solution can be difficult. The problem has a large solution space that is discrete and nonlinear. As mentioned above, solving the UC problem requires that many economic dispatch calculations be performed. One possible way to determine the optimal schedule is to do an exhaustive search. Exhaustively considering all possible ways that units can be switched on or off for a small system can be done, but for a reasonably sized system this would take too long. Solving the UC problem for a realistic system generally involves using methods like Lagrangian relaxation, dynamic programming, genetic algorithms, or other heuristic search techniques. The interested reader may find many useful references regarding cost-minimizing UC for the monopolist in Sheblé and Fahd (1994) and Wood and Wollenberg (1996). Another heuristic technique that has shown much promise and that offers many advantages (e.g., time-to-solution for large systems and ability to simultaneously generate multiple solutions) is the genetic algorithm.

18.2.6 A Genetic-Based UC Algorithm

18.2.6.1 The Basics of Genetic Algorithms

A genetic algorithm (GA) is a search algorithm often used in nonlinear discrete optimization problems. The development of GAs was inspired by the biological notion of evolution. Initially described by John Holland, they were popularized by David Goldberg who described the basic genetic algorithm very well (Goldberg, 1989). In a GA, data, initialized randomly in a data structure appropriate for the solution to the problem, evolves over time and becomes a suitable answer to the problem. An entire population of candidate solutions (data structures with a form suitable for solving for the problem being studied) is "randomly" initialized and evolves according to GA rules. The data structures often consist of strings of binary numbers that are mapped onto the solution space for evaluation. Each solution (often termed a creature) is assigned a fitness—a heuristic measure of its quality. During the evolutionary process, those creatures having higher fitness are favored in the parent selection process and are allowed to procreate. The parent selection is essentially a random selection with a fitness bias. The type of fitness bias is determined by the parent selection method. Following the parent selection process, the processes of crossover and mutation are utilized and new creatures are developed that ideally

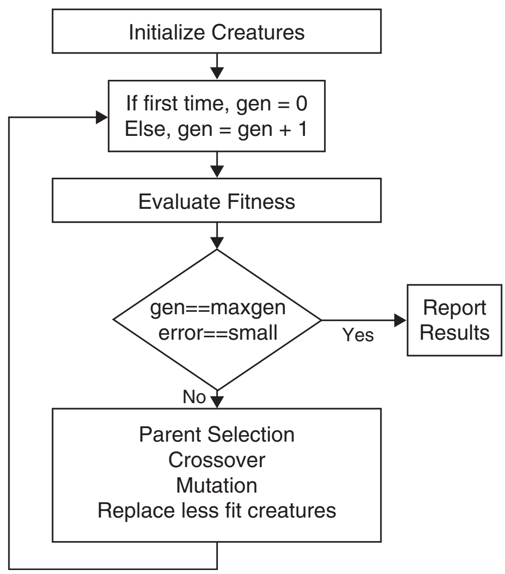

FIGURE 18.7 A simple genetic algorithm.

explore a different area of the solution space. These new creatures replace less fit creatures from the existing population. Figure 18.7 shows a block diagram of the general GA.

18.2.6.2 GA for Price-Based UC

The algorithm presented here solves the UC problem for the profit maximizing GENCO operating in the competitive environment (Richter et al., 1999). Research reveals that various GAs have been used by many researchers in solving the UC problem (Kondragunta, 1997; Kazarlis et al., 1995). However, the algorithm presented here is a modification of a genetic-based UC algorithm for the cost-minimizing monopolist described in Maifeld and Sheblé (1996). Most of the modifications are to the fitness function, which no longer rewards schedules that minimize cost, but rather those that maximize profit. The intelligent mutation operators are preserved in their original form. The schedule format is the same. The algorithm is shown in block diagram format in Fig. 18.8.

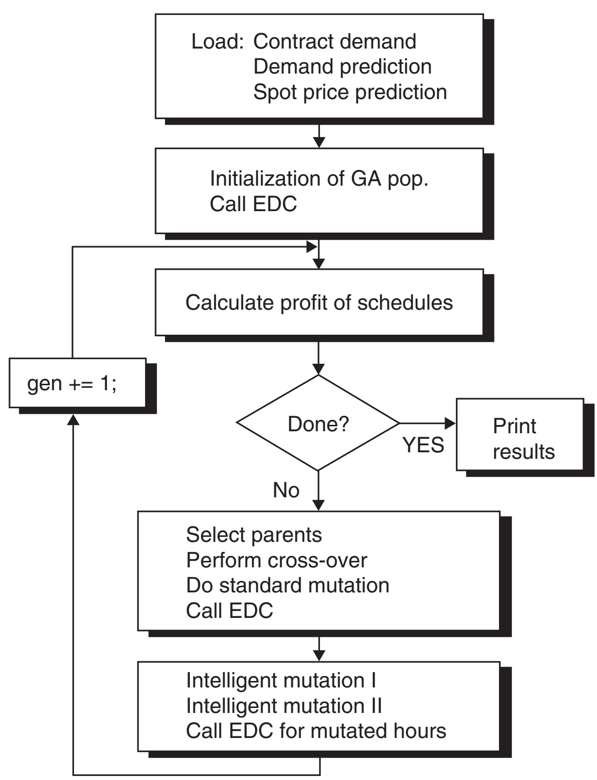

FIGURE 18.8 GA-UC block diagram.

The algorithm first reads in the contract demand and prices, the forecast of remaining demand, and forecasted spot prices (which are calculated for each hour by another routine not described here). During the initialization step, a population of UC schedules is randomly initialized. See Fig. 18.9. For each member of the population, EDC is called to set the level of generation of each unit. The cost of each schedule is calculated from the generator and data read in at the beginning of the program. Next, the fitness (i.e., the profit) of each schedule in the population is calculated. "Done?" checks to see whether the algorithm as either cycled through for the maximum number of generations allowed, or whether other stopping criteria have been met. If done, then the results are written to a file; if not done, the algorithm goes to the reproduction process.

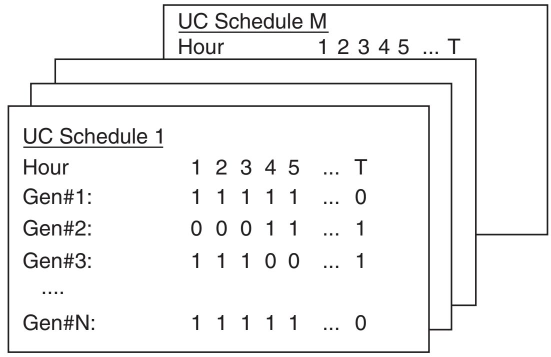

FIGURE 18.9 A population of UC schedules.

During reproduction, new schedules are created. The first step of reproduction is to select parents from the population. After selecting parents, candidate children are created using two-point crossover as shown in Fig. 18.10. Following crossover, standard mutation is applied. Standard mutation involves turning a randomly selected unit on or off within a given schedule.

An important feature of the previously developed UC-GA (Maifeld and Sheblé, 1996) is that it spends as little time as possible doing EDC. After standard mutation, EDC is called to update the profit only for the mutated hour(s). An hourly profit number is maintained and stored during the reproduction process, which dramatically reduces the amount of time required to calculate the profit over what it would be if EDC had to work from scratch at each fitness evaluation. In addition to the standard mutation, the algorithm uses two "intelligent" mutation operators that work by recognizing that, because of transition costs and minimum uptime and downtime constraints, 101 or 010 combinations are undesirable. The first of these operators would purge this undesirable combination by randomly changing 1s to 0s or vice versa. The second of these intelligent mutation operators purges the undesirable combination by changing 1 to 0 or 0 to 1 based on which of these is more helpful to the profit objective.

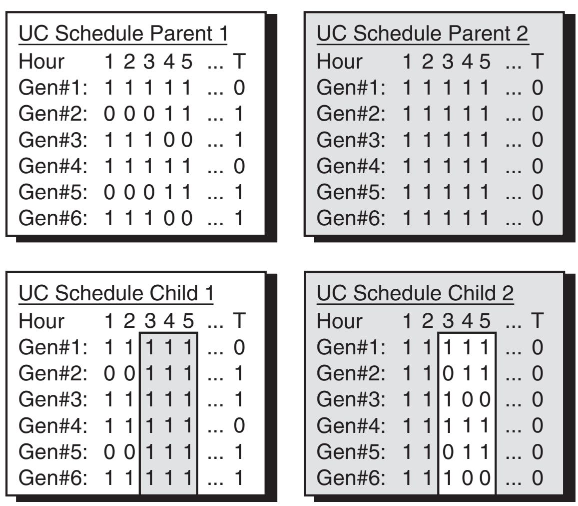

FIGURE 18.10 Two-point crossover on UC schedules.

TABLE 18.2 Forecasted Demand and Prices for 2-Generator Case

Hour	Load Forecast (MWhr)	Price Forecast ($/MWhr)	Hour	Load Forecast (MWhr)	Price Forecast ($/MWhr)
1	285	25.87	8	328	8.88
2	293	23.06	9	326	9.12
3	267	19.47	10	298	8.88
4	247	18.66	11	267	25.23
5	295	21.38	12	293	26.45
6	292	12.46	13	350	25.00
7	299	9.12	14	350	24.00

18.2.6.3 Price-Based UC-GA results

The UC-GA is run on a small system so that its solution can be easily compared to a solution by exhaustive search. Before running the UC-GA, the GENCO needs to first get an accurate hourly demand and price forecast for the period in question. Developing the forecasted data is an important topic, but beyond the scope of our analysis. For the results presented in this section, the forecasted load and prices are taken to be those shown in Table 18.2. In addition to loading the forecasted hourly price and demand, the UC-GA program needs to load the parameters of each generator to be considered. We are modeling the generators with a quadratic cost curve (e.g., $A + B(P) + C(P)^2$), where P is the power level of the unit. The data for the 2-generator case is shown in Table 18.3.

In addition to the 2-unit cases, a 10-unit, 48-hour case is included in this chapter to show that the GA works well on larger problems. While dynamic programming quickly becomes too computationally expensive to solve, the GA scales up linearly with number of hours and units. Figure 18.11 shows the costs and average costs (without transition costs) of the 10 generators, as well as the hourly price and load forecasts for the 48 hours. The data was chosen so that the optimal solution was known *a priori*. The dashed line in the load forecast represents the maximum output of the 10 units.

Before running the UC-GA, the user specifies the control parameters shown in Table 18.4, including the number of generating units and number of hours to be considered in the study. The "popsize" is the size of the GA population. The execution time varies approximately linearly with the popsize. The number of generations indicates how many times the GA will go through the reproduction phase. System reserve is the percentage of reserves that the buyer must maintain for each contract. Children per generation tells us how much of the population will be replaced each generation. Changing this can affect the convergence rate. If there are multiple optima, faster convergence can trap the GA in a local suboptimal solution. "UC schedules to keep" indicates the number of schedules to write to file when finished. There is also a random number seed that is set between 0 and 1.

TABLE 18.3 Unit Data for 2-Generator Case

	Generator 0	Generator 1
Pmin (MW)	40	40
Pmax (MW)	180	180
A (constant)	58.25	138.51
B (linear)	8.287	7.955
C (quadratic)	7.62e-06	3.05e-05
Bank cost ($)	192	223
Start-up cost($)	443	441
Shut-down cost($)	750	750
Min-uptime (hr)	4	4
Min-downtime (hr)	4	4

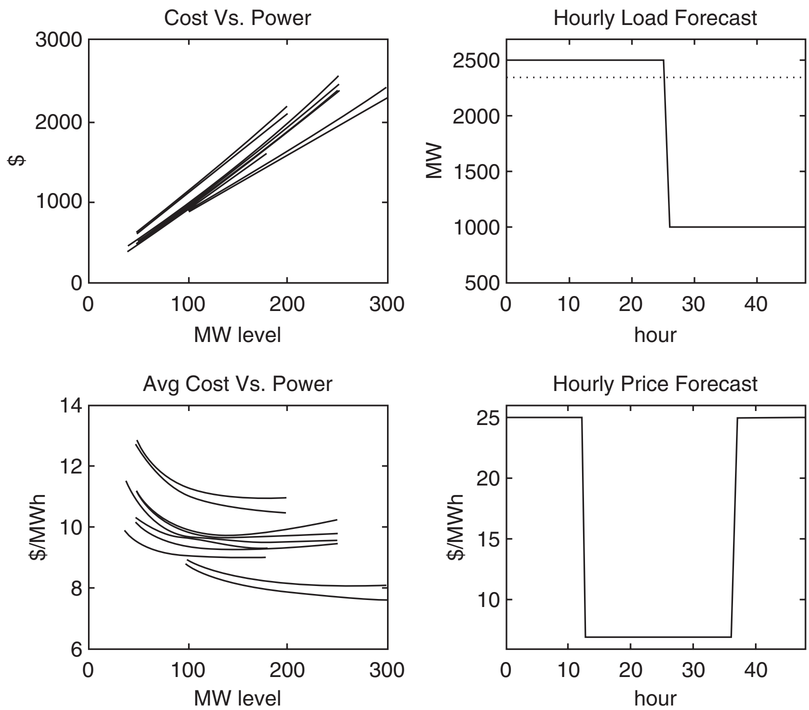

FIGURE 18.11 Data for 10-unit, 48 hour case.

TABLE 18.4 GA Control Parameters

Parameter	Setpoint	Parameter	Setpoint
# of Units	2	System reserve (%)	10
# of Hours	10	Children per generation	10
Popsize	20	UC schedules to keep	1
Generations	50	Random number seed	0.20

In the 2-generator test cases, the UC-GA was run for the units listed in Table 18.3, and for the forecasted loads and prices listed in Table 18.2. The parameters listed in Table 18.4 were adjusted accordingly. To ensure that the UC-GA is finding optimal solutions, an exhaustive search was performed on some of the smaller cases. Table 18.5 shows the time to solution in seconds for the UC-GA and the exhaustive search methods. For small cases, the exhaustive search was performed and solution time compared to that of the UC-GA. Since the exhaustive search solution times were estimated to be prohibitively lengthy, the latter cases were not compared against exhaustive search solutions.

TABLE 18.5 Comparing UC-GA with Exhaustive Search

No. of Generators in Schedule	No. of Hours in Schedule	GA Finds Optimal Solution?	Solution Time for GA (s)	Solution Time Exhaustive Search (s)
2	10	Yes	0.5	674
2	12	Yes	2	6482
2	14	Yes	10	(estimated) 62340
10	48	Yes	730	(estimated) 2E138

TABLE 18.6 The Best UC-GA Schedules of the Population

	Best Schedule for 2-Unit, 10-Hour Case
Unit 1	1111100000
Unit 2	0000000000
Cost	$17,068.20
Profit	$2,451.01
	Best Schedule for 2-Unit, 12-Hour Case
Unit 1	111111000011
Unit 2	000000000000
Cost	$24,408.50
Profit	$4,911.50
	Best Schedule Found by UC-GA for 10-Unit, 48-Hour Case
Unit 1	111111111111000000000000000000000000111111111111
Unit 2	111111111111000000000000000000000000000000000000
Unit 3	111111111111000000000000000000000000000000000000
Unit 4	111111111111000000000000000000000000000000000000
Unit 5	111111111111000000000000000000000000000000000000
Unit 6	111111111111000000000000000000000000000000000000
Unit 7	111111111111000000000000000000000000111111111111
Unit 8	111111111111000000000000000000000000000000000000
Unit 9	111111111111000000000000000000000000111111111111
Unit 10	111111111111000000000000000000000000111111111111
Cost	$325,733.00
Profit	$676,267.00

Cases with known optimal solutions were used to verify that the UC-GA was, in fact, working for the large cases.

Table 18.6 shows the optimal UC schedules found by the UC-GA for selected cases. Figure 18.12 shows the maximum, minimum and average fitnesses (profit) during each generation of the UC-GA on the 2-generator, 14-hour/period case. The best individual of the population climbs quite rapidly to near

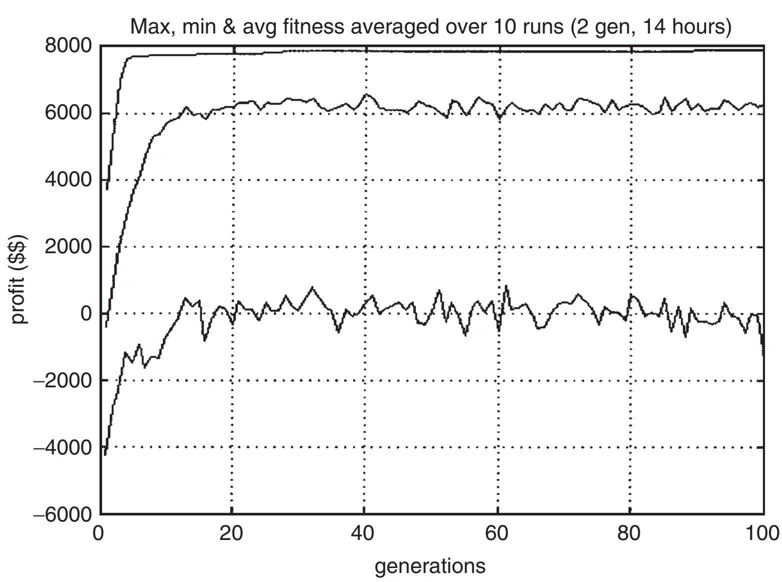

FIGURE 18.12 Max., min., and avg. fitness vs. GA generations for the 2-generator, 14-hour case.

the optimal solution. Half of the population is replaced each generation; often the child solutions are poor solutions, hence the minimum fitness tends to remain low over the generations, which is typical for GA optimization.

In the schedules shown in Table 18.6, it may appear as though minimum up- and downtime constraints are being violated. When calculating the cost of such a schedule, the algorithm ensures that the profit is based on a valid schedule by considering a zero surrounded by ones to be a banked unit, and so forth. In addition, note that only the best solution of the population for each of the cases is shown. The existence of additional valid solutions, which may have been only slightly suboptimal in terms of profit, is one of the main advantages of using the GA. It gives the system operator the flexibility to choose the best schedule from a group of schedules to accommodate things like forced maintenance.

18.2.7 Unit Commitment and Auctions

Regardless of the market framework, the solution method, and who is performing the UC, an auction can model and achieve the optimal solution. As mentioned previously in the section on EDC, auctions (which come in many forms, e.g., Dutch, English, sealed, double-sided, single-sided, etc.) are used to match buyers with sellers and to achieve a price that is considered fair. An auction can be used to find the optimal allocation, and the unit commitment algorithm essentially performs the same allocation that an auction would. Suppose an auctioneer was to call out a price, or a set of prices that is predicted for the schedule period. The auctioneer would then ask all generators how much power they would generate at that level. The generator must consider which units to switch on, and at what level to produce and sell. The reply amounts could be summed to determine the production level at that price. If all of the constraints, including demand, are met, then the most economical combination of units operating at the most economical settings has been found. If not, the auctioneer adjusts the price and asks for the amounts at the new price. This procedure is repeated until the constraints are satisfied. Prices may ascend as in the English auction, or they may descend as in the Dutch auction. See Fig. 18.3 for a graphical depiction of this process. For further discussion on this topic, the interested reader is referred to Sheblé (1999).

18.3 Summary of Economical Generation Operation

Since the introduction of electricity supply to the public in the late 1800s, people in many parts of the world have grown to expect an inexpensive reliable source of electricity. Providing that electric energy economically and efficiently requires the generation company to carefully control their generating units, and to consider many factors that may affect the performance, cost, and profitability of their operation. The unit commitment and economic dispatch algorithms play an important part in deciding how to operate the electric generating units around the world. The introduction of competition has changed many of the factors considered in solving these problems. Furthermore, advancements in solution techniques offer a continuum of candidate algorithms, each having its own advantages and disadvantages. Research continues to push these algorithms further. This chapter has provided the reader with an introduction to the problems of determining optimal unit commitment schedules and economic dispatches. It is by no means exhaustive, and the interested reader is strongly encouraged to see the references at the end of the chapter for more details.

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