A Profit-Based Unit Commitment GA for the Competitive Environment

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Abstract: As the electrical industry restructures, many of the traditional algorithms for controlling generating units need modification or replacement. Previously utilized to schedule generation units in a manner that minimizes costs while meeting all demand, the unit commitment (UC) algorithm must be updated. A UC algorithm that maximizes profit will play an essential role in developing successful bidding strategies for the competitive generator. Simply bidding to win contracts is insufficient; bidding strategies must result in contracts that, on average, cover the total generation costs. No longer guaranteed to be the only electricity supplier, a generation company's share of the demand will be more difficult to predict than in the past. Removing the obligation to serve softens the demand constraint. In this paper the authors provide a price/profit-based UC formulation which considers the softer demand constraint and allocates fixed and transitional costs to the scheduled hours. The authors describe a genetic algorithm solution to this new UC problem and present results for an illustrative example.

Keywords: Unit commitment, competitive auction markets, optimization, genetic algorithms, bidding strategies, deregulation, power systems.

I. INTRODUCTION

The US electric marketplace is in the midst of major changes designed to promote competition. No longer vertically integrated with guaranteed customers and suppliers, electric generators and distributors will have to compete to sell and buy electricity. The stable electric utilities of the past will find themselves in a highly competitive environment. Although some states (e.g., California) are already operating in a restructured environment, a standardized final market structure for the rest of the US has not yet been fully defined. The authors believe that regional commodity exchanges, in which electricity contracts are traded, will play a key role.

In previous papers [5,6,12,17,18] the authors have described a framework in which distribution companies (DISTCOs), generation companies (GENCOs), energy services companies (ESCOs) and transmission companies (TRANSCOs) interact via contracts. The contract prices are determined through an auction. Electricity traders make bids and offers that are matched subject to the approval of an independent contract administrator (ICA) who ensures that the system is operating safely within limits.

Operating within the framework described in [5,6,12,17,18], traders will create and implement bidding strategies to make their bids and offers. These bidding strategies might be designed to limit the traders' risk, to maximize profit, or some combination of both. The authors have reported research that uses genetic algorithms and genetic programming to evolve bidding strategies that maximize profit for the spot market [11,12,14]. In [13], the authors investigated managing an energy trader's risk and profitability by combining spot market contracts with options and futures. For simplification, the previous work avoided the unit commitment (UC) problem by ignoring start-up and shut-down costs, minimum up-times and down-times, ramp rates etc. In this paper we consider a profit-based UC and discuss its implication for bidding strategies.

In [7] Maifeld and Sheblé developed and implemented a genetic based UC algorithm. Their algorithm was able to consistently find multiple good unit commitment schedules in a reasonable amount of time. Another reason that it was advantageous over other UC solution techniques is that it was able to use true costing. These attributes will remain desirable qualities. We have updated this algorithm for the price/profit based competitive environment and provide results of its use on some illustrative examples. Recent research describes a genetic algorithm unit commitment program for the less regulated environment [4]. Although there is some overlap between his work and the work described in this chapter, the market framework assumptions described in chapter 2 lead to different conclusions primarily regarding the way EDC is done and the obligation to serve.

This paper is organized as follows. Part II briefly describes the UC problem and formulation and highlights modifications needed for the competitive environment. Part III describes the genetic algorithm we are using to solve the UC problem. Part IV presents the results of some illustrative examples. Part V discusses implications of the updated UC on bidding strategies. Finally, Part VI provides some conclusions and identifies areas of future work.

II. UPDATING UNIT COMMITMENT

For the vertically integrated monopolistic environment, UC is loosely defined as scheduling generating units to be on, off, or in stand-by/banking mode such that costs are minimized and constraints like demand and reserves are met. Considering other inputs including varying fuel costs, start-up and shut-down parameters/constraints of each power plant, and crew constraints adds to the complexity of the problem. In order to determine the cost associated with a given schedule, an economic dispatch calculation, (EDC) where each of the non limit-constrained operating units is set so that their marginal costs are equal, must be performed for each hour under consideration. 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 the amount of time it would take is too long. Solving the problem generally involves using methods like

Lagrangian relaxation, dynamic programming, genetic algorithms or other using heuristic search techniques. Many references for the traditional UC can be found in Sheblé and Fahd [20] and in Wood and Wollenberg [26].

In the past, demand forecasts advised power system operators of the amount of power that needed to be generated. In the future, bilateral spot and forward contracts will make part of the total demand known apriori. The remaining part of the demand will be predicted as in the past. However, the GENCO's share of the remaining demand may be difficult to predict since it will depend on how its price compares to that of other suppliers. The GENCO's price will depend on its prediction of its share of this remaining demand as that will determine how many units they have switched on or in banking mode. The UC schedule directly affects the average cost and indirectly the price, making it an essential input to any successful bidding strategy.

In the past, utilities had an obligation to serve their customers. This was translated into a demand constraint that ensured all demand would be met. For the UC problem, this might have meant switching on an additional unit just to meet a remaining MW or two. With the obligation to serve gone, the GENCO can now consider a schedule that produces less than the predicted demand. They can allow others to provide that 1 or 2 MW that might have increased their average costs (they might not have secured that contract for which they would have had to compete).

Demand forecasts and expected market prices are an important input to the profit-based UC algorithm; they are used to determine the expected revenue, which affects the expected profit. If a GENCO comes up with two potential UC schedules each having different expected costs and different expected profits, it should take the one that provides for the largest profit, which will not necessarily be the one that costs least. Since prices and demand are so important in determining the optimal UC schedule, price prediction and demand forecasts become crucial. Takriti, Krasenbrink, and Wu [23] present a good description and a stochastic solution of the UC problem that considers spot markets. Their research differs in that they choose to minimize costs rather than maximize profits.

Mathematically the traditional cost-based UC problem has been formulated as follows[19]:

$$\text{Minimize } F = \sum_{n}^{N} \sum_{t}^{T} \left(C_{nt} + MAINT_{nt}\right)\cdot U_{nt} + SUP_{nt}\cdot U_{nt}\left(1 - U_{nt}\right) + SDOWN_{nt}\cdot\left(1 - U_{nt}\right)\cdot U_{nt-1} \qquad (1.0)$$

subject to the following constraints:

$$\sum_{n}^{N} \left(U_{nt}\cdot P_{nt}\right) = D_t \qquad \text{(demand constraint)} \qquad (1.1)$$

$$\sum_{n}^{N} \left(U_{nt}\cdot P\max_n\right) \geq D_t + R_t \qquad \text{(capacity constraint)} \qquad (1.2)$$

$$\sum_{n}^{N} \left(U_{nt}\cdot Rs\max_n\right) \geq R_t \qquad \text{(system reserve constraint)} \qquad (1.3)$$

Redefining the UC problem for the competitive environment involves changing the demand constraint from an equality, to less than or equal, and changing the objective function from cost minimization, to profit maximization. Note that we assume that the buyers purchase reserves per contract, but the algorithm could easily be modified to handle different market rules.

$$\text{Max } \Pi = \sum_{n}^{N} \sum_{t}^{T} \left(P_{nt}\cdot fp_t\right)\cdot U_{nt} - F \qquad \text{(revenue - costs)} \qquad (1.4)$$

subject to:

$$\sum_{n}^{N} \left(U_{nt}\cdot P_{nt}\right) \leq D'_t \qquad \text{(new demand constraint)} \qquad (1.5)$$

where individual terms are defined as follows:

$Pmin_n <= P_{nt} <= Pmax_n$ (Capacity limits)
$| P_{nt} - P_{n,t-1}| <= Ramp_n$ (Ramp rate limits)
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 w/ reserves for period t
fp_t := forecasted price 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

There may be a tendency to think that maximizing the profit is essentially the same as minimizing the cost. This is not necessarily the case. We have to remember that since we no longer have the obligation to serve, the GENCO may choose to generate less than the demand. This allows a little more flexibility in the UC schedules. In addition, we are assuming that prices fluctuate according to supply and demand. Often engineers used to assume that if they could level the load curve, they would be minimizing 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.

EDC is an important part of UC. Formerly used to minimize costs, for the price-based UC that we present in this paper, it was necessary to redefine EDC. Where the old EDC ignored transition and fixed costs to adjust the power level of the units until they each had the same incremental cost (i.e, $\lambda_1=\lambda_2=...=\lambda_i=...=\lambda_T$), our new EDC attempts to set λ equal to a pseudo price (i.e., produce until the marginal cost equal the price). This pseudo price is the hourly forecasted price modified to account for transition and fixed costs as is shown in the following formula:

$$\lambda_t = fp_t - \frac{\sum_{t}^{T}\sum_{n}^{N}\left(transition.costs\right) + \sum_{t}^{T}\sum_{n}^{N}\left(fixed.costs\right)}{\sum_{t}^{T}\sum_{n}^{N} P_{nt}} \qquad (2.0)$$

which results in a \$/MWh pseudo price. Transition costs include start-up, shut-down and banking costs, and fixed costs (present for each hour that the unit is on), would be represented by the constant term in the typical quadratic cost curve approximation. For each period, we account for the fixed and transition costs by adding an average value to the incremental cost. Note that this is one method of allocating the transition and fixed costs, but there are many other ways that this could be done. For instance, if our generators are able to produce energy far less expensively than the competition during the night, but don't have that advantage during the daytime, we could shift some of our daytime costs to be allocated through bids from the nighttime periods. For the results presented in this paper, we approximate the summation of the power generated by the forecasted demand.

III. GENETIC BASED UC ALGORITHM

A. The Basics of Genetic Algorithms

Derived from the biological model of evolution, genetic algorithms (GAs) operate on the Darwinian principle of natural selection [8]. A population of data structures appropriate for the optimization problem is “randomly” initialized. Each of these candidate solutions is termed an individual or a creature. Each creature is assigned a fitness, which is simply a heuristic measure of its quality. Then during the evolutionary process, those creatures that have a higher fitness are favored and allowed to procreate.

During each generation of the evolutionary process, creatures are randomly selected for reproduction with some bias toward higher fitness. After parents are selected for reproduction, they produce children via the processes of *crossover* and *mutation*. The creatures formed during reproduction explore different areas of the solution space than did the parents. These new creatures replace lesser fit creatures of the existing population. The basic algorithm can be written as follows:

1. Randomly initialize a population and set the generation counter to zero.
2. Until done or out of time, do the following:
   - Calculate the fitness of each member of the population.
   - Select parents using some fitness bias.
   - Crossover the parents to create candidate offspring.
   - Mutate these new offspring.
   - Replace the lesser fit members with the offspring.
   - Increment the generation counter and go to step 2.

The parents are required to be in pairs for reproduction, and the result is two children. Children are created by copying the contents of parent 1 into child 1, and the contents of parent 2 into child 2 until a randomly selected crossover location is reached. At this point, bits are copied from parent 1 into child 2, and from parent 2 into child 1.

Following the crossover process, the children are mutated. Mutation introduces new genetic material into the gene at some low rate. If the gene to be mutated in the child is represented by a binary string, mutation involves flipping the bit (0 goes to 1, 1 goes to 0) at each location in the string with some probability. If the gene is represented by an integer, mutation might involve adding an integer that will result in a different valid integer occupying that gene location (loci).

B. GA for price-based UC

The algorithm presented in this paper for solving the new UC problem is a modification of the genetic-based UC algorithm described by Maifeld and Sheblé [7]. Most of the modifications are to the fitness function, which no longer minimizes cost, but maximizes profit. In addition, more user friendly I/O routines were added to make it easier to load input data and to export the results. The intelligent mutation operators are preserved in their original form. The form of the schedules is the same. The updated algorithm is as shown in block diagram format in Fig. 1.

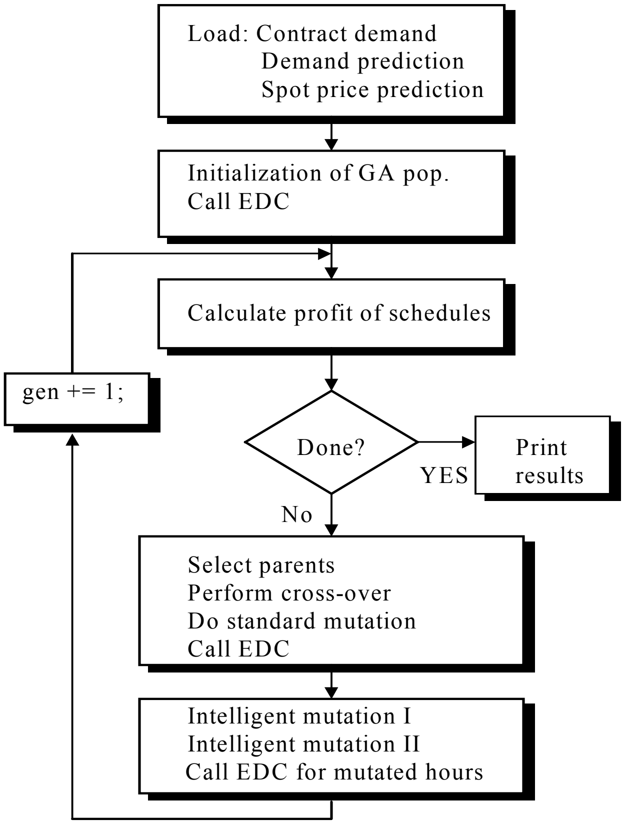
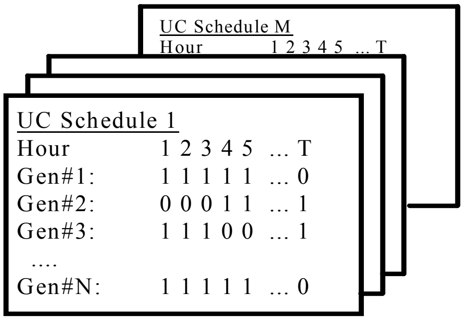


Fig. 1. GA UC block diagram.

Another difference is that a new EDC routine was written which sets generation so that the marginal cost equal to a pseudo hourly price as described earlier in this paper. Any power generated in excess of the demand will not generate any revenue, but will add to the cost. This will be reflected in the fitness of the schedule, which is equal to the profit and these schedules should die out quickly.

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). Accurately forecasting demand and prices is a difficult problem, which is not to be taken lightly, but we for now assume that it can be done. The authors have recently published another paper extending this algorithm to handle uncertain forecasts [15]. During the initialization step, a population of UC schedules is randomly initialized. See Fig. 2. 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 data read in at the beginning of the program. Next, the fitness/profit is calculated. “Done?” checks to see whether we have reached the maximum generations allowed, or whether we have met other stopping criteria (at this time we are simply using the number of generations). If done, then the results are written to a file, which will be used as an input for our bidding strategy builder described in other papers. If not done, the algorithm goes to the reproduction process.



UC Schedule M

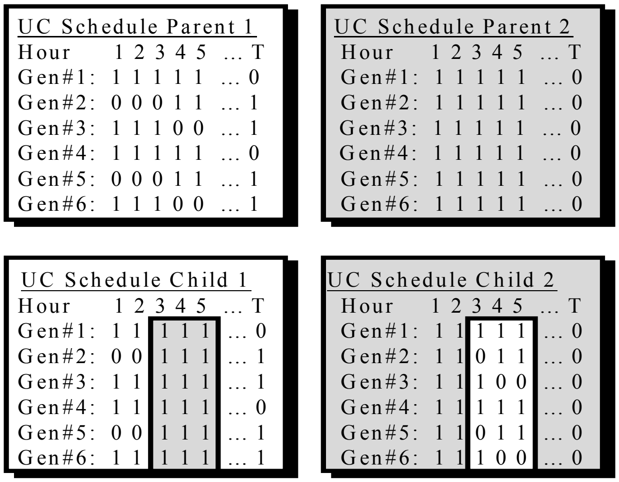
Hour 1 2 3 4 5 … T

UC Schedule 1

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

Fig. 2. 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. 3. Following crossover, standard mutation is applied. Standard mutation involves turning a randomly selected unit off within a given schedule.



UC Schedule Parent 1

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

UC Schedule Parent 2

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

UC Schedule Child 1

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

UC Schedule Child 2

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

Fig. 3. Two point crossover on UC schedules.

An important feature of the UC-GA developed by Maifeld and Sheblé [7] is that it spends as little time as possible doing EDC. After standard mutation, EDC is called to update the profit 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 up and down times, 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 it by changing 1 to 0 or 0 to 1 based on which of these is more helpful to the profit objective.

IV. RESULTS

The UC-GA was run on a small system so that its solution could 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 this paper. For the results presented in this section, the forecasted load and prices are taken to be those shown in Table 1. 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., $A + B(P) + C(P)^2$). The data for the 2 unit case is shown in Table 2.

TABLE 1
FORECASTED DEMAND AND PRICES (2 GEN CASE)

HR	load forecast (MWh)	price forecast ($/MWh)	HR	load forecast (MWh)	price forecast ($/MWh)
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

In addition to the 2 unit cases, a 10 unit, 48 hour case is included in this paper 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 4 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 apriori. The dashed line in the load forecast shows the maximum output of the 10 units.

TABLE 2
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 ($)	192	223
start cost($)	443	441
stop cost($)	750	750
min up (hr)	4	4
min down (hr)	4	4

Before running the UC-GA, the user needs to specify the control parameters shown in Table 3, 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 local sub-optimal 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.

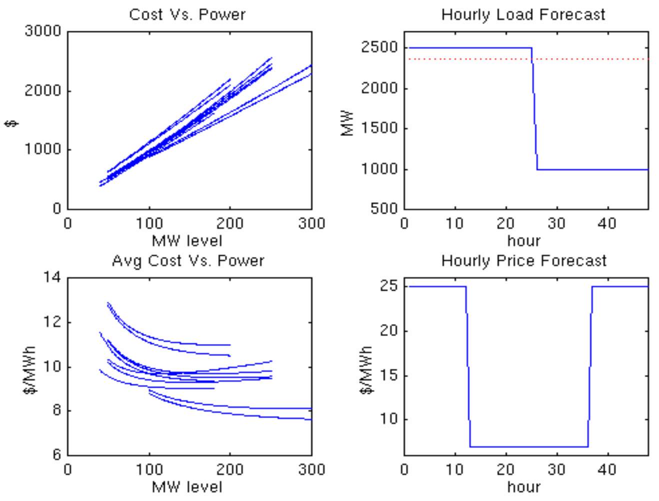


Fig. 4. Data for 10 unit, 48 hour case.

TABLE 3
GA CONTROL PARAMETERS

# 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	.20

In the 2 generator test cases, the UC-GA was run for the units listed in Table 2, and for the forecasted loads and prices listed in Table 1. The parameters listed in Table 3 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 4 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. Cases with known optimal solutions were used to verify that the UC-GA was, in fact, working for the large cases.

TABLE 4
COMPARING UC-GA WITH EXHAUSTIVE SEARCH

No. of generators in schedule	No. of hours in schedule	GA finds optimal solution?	Solution time for GA (sec.)	Solution time exhaustive search (sec.)
2	10	yes	0.5	674
2	12	yes	2	6482
2	14	yes	10	62340 (estimated)
10	48	yes	730	2E138 (estimated)

Table 5 shows the optimal UC schedules found by the UC-GA for selected cases. Figure 5 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 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 generations, which is typical for GA optimization.

TABLE 5
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

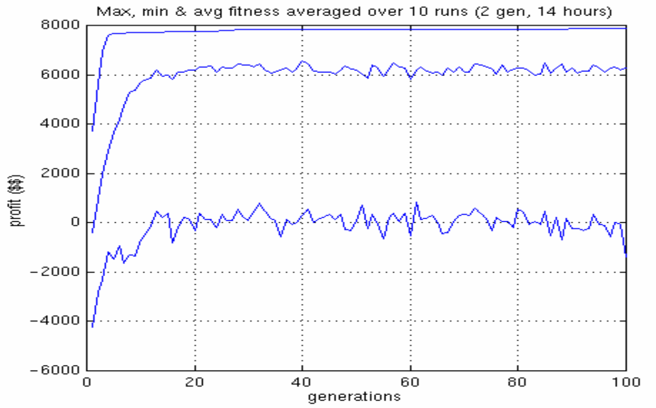


Fig. 5. Max, min, & avg. fitness vs. GA generations for the 2 generator, 14 hour case.

In the schedules shown in table 5, it may appear as though minimum up and down times 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 we only show the best solution of the population for each of the cases. To show more would take too much space. The additional valid solutions, which may have nearly as much profit, are one of the main advantages of using the GA. This gives the system operator the flexibility to choose among a group of schedules to accommodate things like forced maintenance.

V. UC AND BIDDING STRATEGIES

UC will remain an important tool in the new environment. Although customers are no longer guaranteed, bilateral contracts will ensure that the GENCO knows the majority of its load ahead of time. An accurate forecast of the remaining demand and hourly prices will be important inputs for solving the UC problem. Once the UC schedules are generated, they will be of little use to the GENCO unless it can actually win customers from competitors at the price that it assumed in determining the UC schedule. For this reason, the UC schedule becomes an important input to the bidding strategy builder.

VI. CONCLUSIONS & FUTURE RESEARCH

The UC-GA has been rewritten for price-based operation. Some might argue that UC schedulers are no longer needed—a GENCO can just go to the spot market to buy the electricity it needs. This can and should be considered a valuable option, but the GENCO's business is still one of generating electricity and they ultimately need to come up with a schedule by which they operate their generating units. The GA is a useful tool in searching large discrete solution spaces, and the space of solutions is quite large, making GA appropriate for the UC problem.

Ideally, the GENCO would run the UC GA for the expected prices and demands that they consider most likely. These prices and demands may be uncertain. Running several cases would allow the user to know how sensitive the schedules are to variations in the inputs. Our UC GA is presently being enhanced to provide the user with additional information that identifies which schedules allow the user more market flexibility for a given level of profit. We are essentially building in an on-line sensitivity analyzer.

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