Genetic Unit Commitment Model In A Deregulated Power Energy Environment

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Abstract: In the last decade, Australia had applied a large program of privatisation in many sectors of the economy. As a result, the power industry has been deregulated and undergone partial privatisation, creating new specific issues. In present, the bid price has a crucial role in the unit commitment problem. This paper describes a genetic algorithm approach which solves the unit commitment problem for two interconnected regions of the National Electricity Market. This 'biological' algorithm is an alternative to classical optimisation methods and is applied to optimise the scheduling of units, including the economic dispatch, in Queensland and New South Wales. A comparison between the results of this model and a sequential model applied to the same problem is presented.

Keywords: *Unit commitment; Genetic algorithms; Bid price; Electricity*

1. INTRODUCTION

The aim of this paper is to determine if a model based on genetic algorithms can find an optimal or near optimal solution for a large multi-area unit commitment problem (two regions) in a deregulated energy market.

The objective of the *multi–area unit commitment problem* is to find an optimal scheduling of units, including the allocation of the generation quantities of each unit, in order to minimize the total cost of dispatched electricity for all regions, during a time horizon, subject to a set of constraints.

Radcliffe (1992) and Michaelewic (1994) revealed statements concerning the suitability of genetic algorithms to solve a large range of unconstrained or constrained problems.

Smith (1994) shown that "from the multitude of examples of genetic algorithms applied to different optimisation problems, there is a small number of examples published of where they are successfully applied to practical applications".

Genetic algorithms replace totally classical optimisation techniques and it is considered that this intelligent technique can solve suitable difficult problems in the new power electricity environment.

The power of a genetic algorithm arises from the concept of 'implicit parallelism' (Holland 1975, Goldberg 1989). Holland (1975) defined a schema as a similarity template describing a subset of structures with similarities of certain gene positions. During the search, the similarities between structures conduct the algorithm to better and better solutions.

A candidate solution is a chromosome whose length is the product of the number of units and the number of trading periods. In conformity with the biological terminology, a solution is called *chromosome* and contains a sequence of *genes*. All the chromosomes create a population.

The fundamental optimisation process encompasses a combination of chromosomes which produces better and better chromosomes (solutions) with almost each generation during the search algorithm.

In this paper, the unit commitment problem is solved in a deregulated environment and the units, scheduled based on the *bid price*, can dispatch any quantity of electricity starting with the minimum quantity up to their full capacity instead to be simple on (at full capacity) or off.

2. GENETIC ALGORITHMS METHOD

A genetic algorithm is a stochastic search technique based on natural inheritance and the Darwinian 'survival of the fittest' law (Goldberg 1989). Since the nature is in a permanent process of adaptation, genetic algorithms appear to be suitable to solve optimisation applications in real life.

On brief, a genetic algorithm starts with a 'randomly' generated initial population of feasible solutions. Each solution is evaluated and selected according to its fitness. Genetic operators are applied to the population and, in most of the cases, a new generation of better solutions is obtained. The algorithm is performed until an optimal or near optimal solution is obtained.

In order to solve a problem using this method, a series of components must be defined:

- A coding for parameters;
- A way to create an initial population of feasible solutions;
- A fitness function;
- A set with the probabilities of genetic operators and population size.

The values of the parameters used by a genetic algorithm are not universally suitable for any problem. These values are different, being problem dependent and there is a complex task to find them. Thus, for any type of problem, a series of experiments are recommended in order to find the most appropriate parameter values.

3. TWO REGIONS GENETIC UNIT COMMITMENT MODEL (GA_2_51)

3.1. Introduction

The model uses both decimal and binary representation. Each generator is represented by two strings of nine genes. The initial population is generated by randomly creating 2 decimal numbers between 0 and 511 for each generator. Each of these numbers can be represented binary by a string of nine genes.

After the first generation is randomly created, the total cost, quantity and fitness are evaluated. The quantity allocated to each generator is:

$$Q_i = \text{Minimum generation} + \Delta_i\,(X_i + 1),$$

where X_i is the value of the random numbers transformed in a decimal number and Δ_i is the interval width.

The price corresponding to the allocated quantity is calculated taken into consideration each of the band of the scheduled offers.

The objective is to schedule the units in such a way that the total demand is attained and the interconnector limits are met and the total sum paid to the generators is minimal. For each member of the population, the deviation from the load is Φ_i, that is the difference between the total generation of the units and total demand for the two regions.

For the total cost function (TCF), it is necessary to impose penalties for not meeting the demand and for exceeding each interconnector limit. The penalty for exceeding the limit of the interconnector from region 1 to 2 is denoted by Int_{12}_Penalty and for the reverse direction Int_{21}_Penalty.

The penalty for exceeding the limit of interconnector from region k to region j Int_{kj}_Penalty, k = 1 and j = 2 or k = 2 and j = 1, applies only when the generation of region k exceeds the sum of the demand for region k and interconnector limit from region k to region j. In this case the penalty is applied to the exceeding amount. Therefore, the total cost function (TCF) is calculated as follows:

$$\text{TCF} = \text{Total gen. cost} + \text{D Penalty} * |\Phi_i| + Int_{12}\text{\_Penalty} * \text{Max}\,(0, \text{Total gen. region 1} - \text{D region 1} - \text{Interconnector limit}_{12}) + Int_{21}\text{\_Penalty} * \text{Max}\,(0, \text{Total gen. region 2} - \text{D region 2} - \text{Interconnector limit}_{21})$$

The fitness function was defined as:

$$\text{Fitness} = 1/\text{TCF}*1{,}000{,}000.$$

After the fitness is evaluated for each member of the initial population, the population is sorted descending function of the individual fitness.

Roulette wheel was employed as a mean of selection. Each member has assigned an equal sector between 0 and 1, such that the sum of all the sectors is 1.

Each string is assigned a random number between 0 and 1 and function of its sector and this number, the string is selected for participating in the crossover. The crossover and mutation rates are set at the beginning of the modelling.

The new population is translated back into decimal notation and the process of calculating all the statistics starts again.

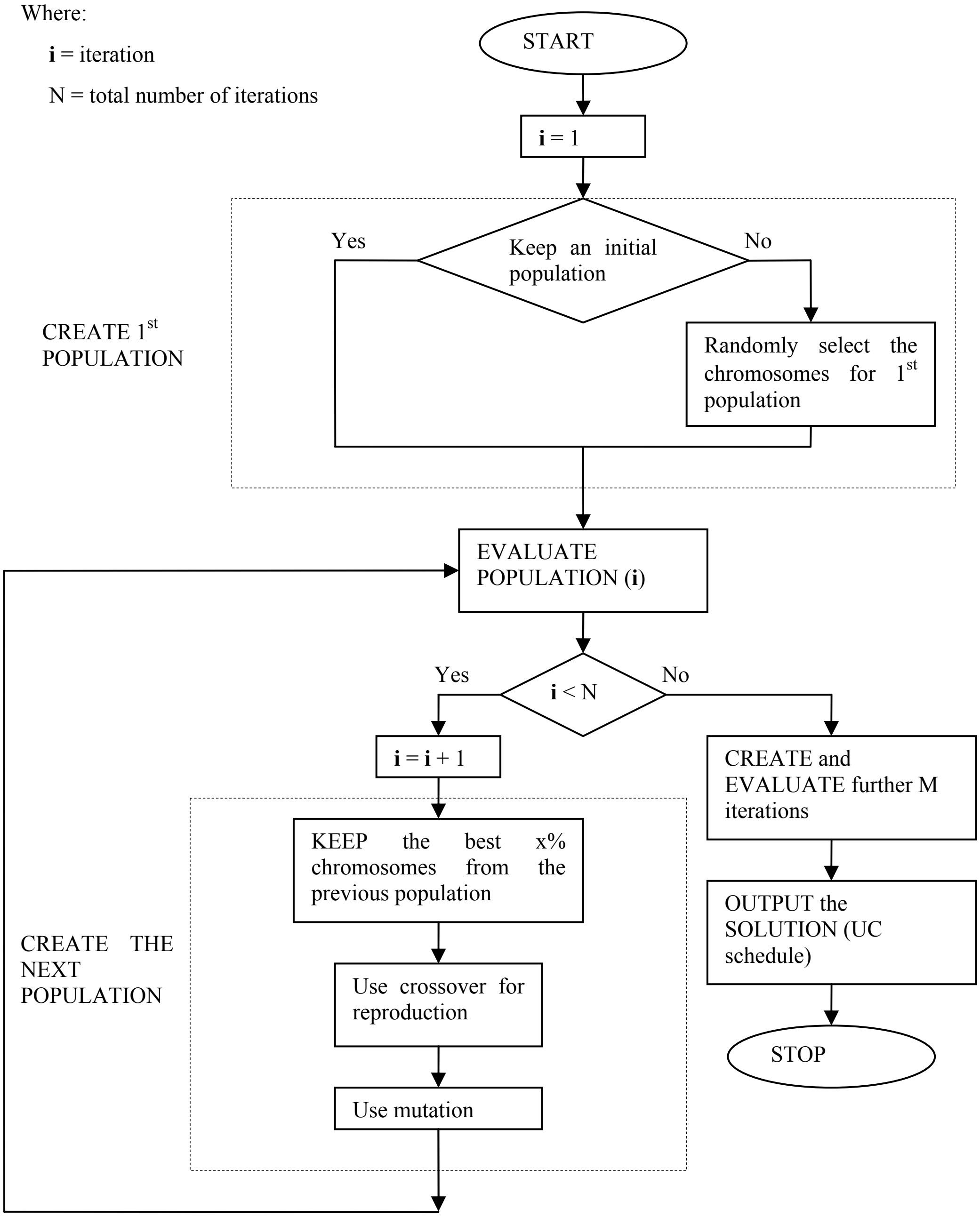
The model was developed in exclusivity on the genetic algorithm method. It was applied on a deregulated two–region interconnected power system in the Australian national market. Queensland (region 1) contains 27 units and NSW (region 2) has 24 units.

The demand for period 1 of 1 July 1999 was 2980 MW for Queensland and 6770 MW for NSW. Each unit has 10 price bid offers and 10 quantity bids (for each half-hourly period). The interconnector limits are as follows:

- From Region 1 to 2 is 800 MW;
- From Region 2 to 1 is 600 MW.

The code is written in Visual Basic for Applications with an Excel interface. The algorithm stops when the number of iterations set has been reached. The genetic flow chart is shown in **Table 1**.

Table 1 Flow chart of the genetic algorithm model GA_2_51



GA_2_51 uses as an initial feasible solution the chromosome which has all the values equal to zero, in order to have selected only the minimum generation given by the baseload units. GA_2_51 was run 5 times and parameters for each trial were:

- Mutation percent = 10%
- Crossover percent = 95%
- Number of iterations = 150
- Penalty for not meeting demand = \$100/MWh
- Penalty for exceeding the interconnector limit = \$100/MWh
- Elitism – keep the best chromosome.

A sequential model (SQM_2_51) is applied to the same unit commitment problem and the results between the two models are compared. The sequential model is exclusively developed using the sequential method. Based on *bid price*, this model employs a bidding procedure to sequentially identify the next most economic unit to be committed.

Both models were run for one period and all the units are not operational.

3.2. Results and analysis

The SQM_2_51 find the solution in 0.12 seconds:

- Total cost of electricity dispatched is $25,382.35;
- Pool price for Queensland is $3.80/MWh and $7.67/MWh in NSW;
- Queensland generated 3135 MW and exported 155 MW to NSW;
- NSW generated the remaining 6615 MW.

The computational time for GA model was 2.5 hours per trial. The average total cost solution of the 5 trials was $27,962 and the minimum attained in Trial 1 was $26,794 compared with SQM_2_51 solution of $25,382 (at minimum a variation of 6.27%).

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Trial 1 has the pool price for Queensland of $3.80/MWh (same as SQM_2_51) and $9.82/MWh for NSW. The interconnector transfer between 44 MW to 442 MW. The statistic results are presented in **Table 2**, total cost of dispatch in **Figure 1**, dispatch schedules are shown in **Table 3** and best fitness in **Figure 2**.

Table 2 Statistics results for GA_2_51 and SQM_2_51

Trial Number	Total Cost ($)	NSW Pool Price ($/MWh)	Qld Pool Price ($/MWh)	NSW Generation (MW)	Qld Generation (MW)	Interconnector transfer (MW)
1	$26,974	$9.82	$3.80	6726	3024	44
2	$29,180	$13.57	$13.79	6509	3241	261
3	$28,291	$5.73	$13.79	6328	3422	442
4	$27,103	$9.82	$11.02	6560	3190	210
5	$28,261	$10.83	$3.80	6717	3033	53
SQM_2	**$25,382**	**$7.67**	**$3.80**	**6615**	**3135**	**155**

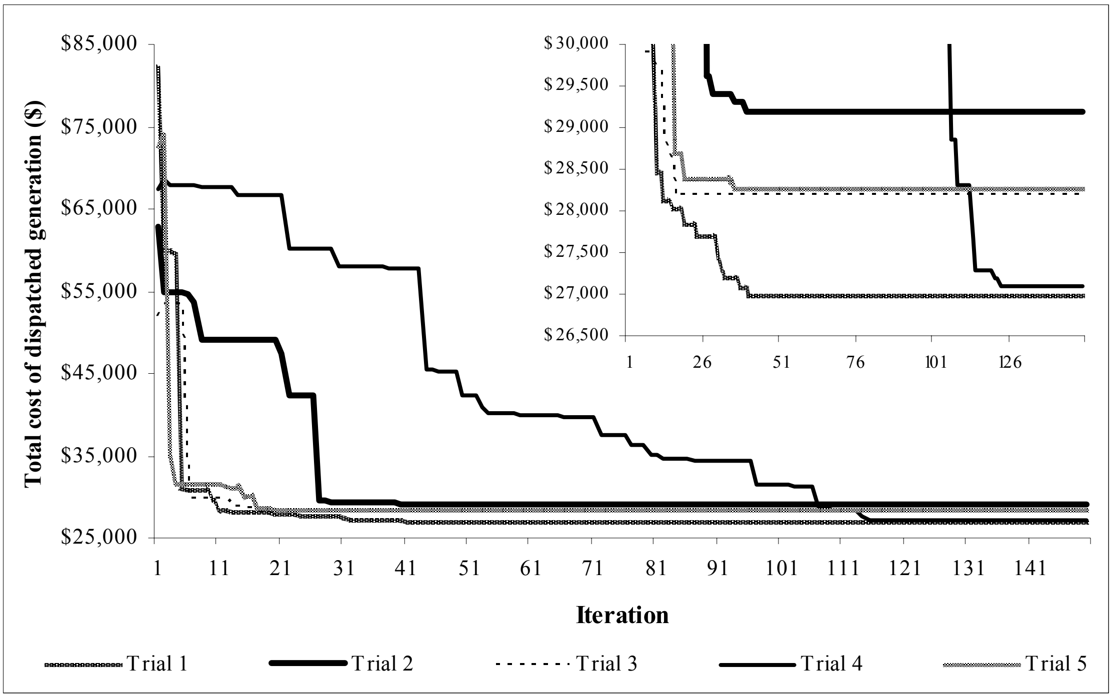

Figure 1 Total cost of dispatched generation ($/MWh)

Table 3 Dispatch results for GA_2_51 and SQM_2_51

Unit name (Qld)	SQM_2	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Unit name (NSW)	SQM_2	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
CALL_A_1	15	15	15	15	15	15	BW01	400	400	444	447	418	400
CALL_A_2	15	15	15	15	15	15	BW02	550	551	550	550	550	550
CALL_A_3	15	15	15	15	15	15	BW03	400	400	511	450	412	438
CALL_A_4	15	15	15	15	15	15	BW04	400	400	406	415	431	405
CALL_B_1	165	167	165	169	174	170	ER01	400	221	227	318	489	221
CALL_B_2	165	165	167	266	228	193	ER02	230	381	374	236	351	436
GSTONE1	195	196	195	195	195	195	ER03	260	304	492	292	330	305
GSTONE2	195	195	195	195	195	195	ER04	230	342	260	241	238	452
GSTONE3	195	195	195	195	195	195	LD01	0	0	0	0	0	0
GSTONE4	180	180	180	180	180	180	LD02	400	413	403	414	403	417
GSTONE5	110	110	110	110	112	110	LD03	400	419	402	406	401	401
GSTONE6	195	195	195	201	195	195	LD04	400	417	412	402	412	409
STAN-1	190	146	145	159	174	145	MM3	120	179	135	152	144	190
STAN-2	190	160	159	175	149	145	MM4	120	187	198	135	155	133
STAN-3	145	145	145	145	145	145	MP1	630	433	292	412	286	440
STAN-4	190	145	206	169	145	145	MP2	630	580	319	365	429	341
SWAN_B_1	50	50	50	50	50	50	NGTS	0	0	0	0	0	0
SWAN_B_2	50	50	50	50	50	50	SHGEN	0	0	0	0	0	0
SWAN_B_3	50	55	50	50	50	50	SHPUMP	0	0	0	0	0	0
SWAN_B_4	50	50	50	50	50	50	SITHE01	80	80	80	80	80	80
TARONG#1	190	190	207	210	217	190	VP5	300	300	300	300	300	300
TARONG#2	190	190	215	261	200	190	VP6	300	300	300	300	300	300
TARONG#3	190	190	198	224	190	190	WW7	200	213	203	210	230	249
TARONG#4	210	190	304	308	236	190	WW8	200	206	201	203	201	250
W/HOE#1	0	0	0	0	0	0							
W/HOE#2	0	0	0	0	0	0							
YABULU	0	0	0	0	0	0							

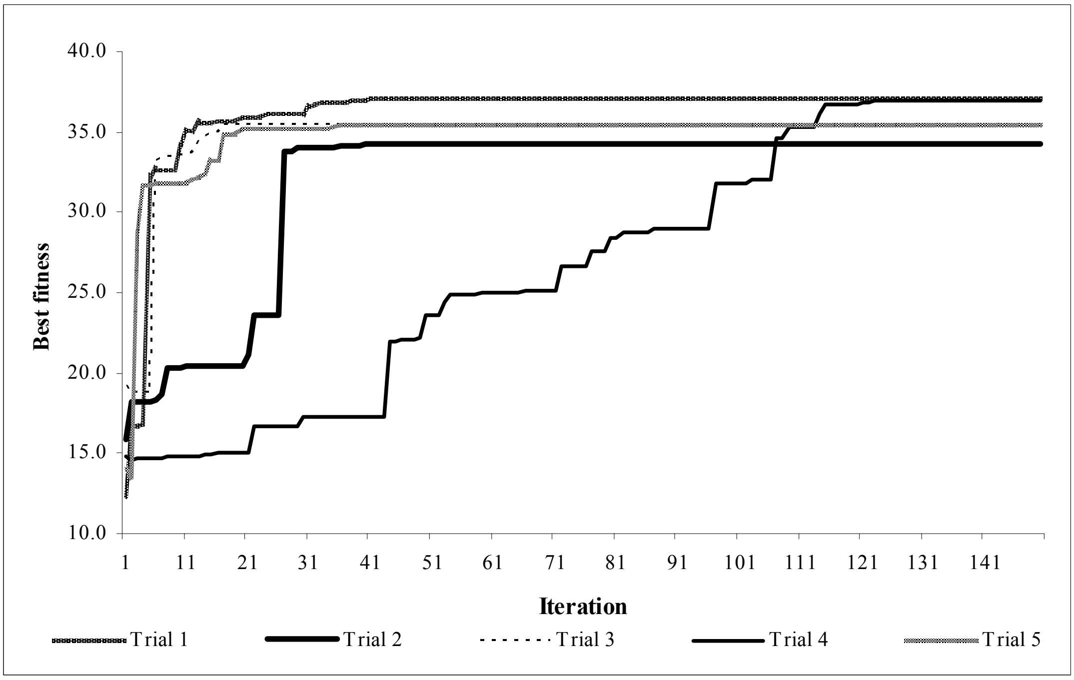

Figure 2 Best fitness

4. CONCLUSION

Recently, noticeable progress has been made towards the application of genetic algorithms in solving some problems of the power energy industry.

This 'biological' algorithm approach, as an alternative to classical optimisation methods, solves the unit commitment problem for two interconnected regions of the national market, based on *bid price*.

Thus, the model is applied on a large scale power system with 51 generation units which are competing in a deregulated environment and provides good schedules of units including the economic dispatch. The units can dispatch any quantity of electricity starting with the minimum quantity up to their full capacity.

The genetic algorithm model found in all cases near optimal solutions and the application of this technique to power energy industry is promising very good results in the future.

Based on the theoretical foundations of genetic algorithms and taken into consideration the computer equipment used in this modelling, the computational time, as expected, is very high. This limiting factor can be addressed using powerful workstations with large memory and many microprocessors, currently available at reasonable price.

In comparison with the genetic approach, sequential model proved to be very efficient, given the 'optimal' solution in real time (0.12 seconds).

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