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VPP Resource Commitment based on Evolutionary Algorithm

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Abstract

The paper represents an evolutionary algorithm (EA) solution to the unit commitment problem for Virtual Power Plants. EAs are general optimization techniques based on principles inspired from the biological evolution, using metaphors of mechanism such as natural selection, genetic recombination and survival of the fittest. One of EA implementation using the standard crossover and mutation operators could locate near optimal solution. Theoretical results and expectations are proved through simulations of a realistic scenario.

Keywords: *Unit Commitment, Evolutionary Algorithm, Resource Scheduling*

1. Introduction

The Virtual Power Plant (VPP) integrates the operation of supply- and demand-side assets to meet customer demand for energy services in both the short- and long-term. To match short-interval load fluctuations, the VPP makes extensive and sophisticated use of information technology, advanced metering, automated control capabilities, and electricity storage. The VPP concept also treats long-term load reduction achieved through energy efficiency investments, distributed generation, and verified demand response on an equal footing with supply expansion. Thus, this approach extends the boundary of utility capacity investments through the meter, with its expanding communication and control capabilities, all the way to customer-side equipment.

The VPP includes conventional generators and renewable energy sources, controllable loads and storage systems. The VPP suppliers are exposed to competition of sale of electric power and have to aim at an economic operation of power systems to obtain maximum profits. Then, the unit commitment problem is mandatory in planning and operation of power systems. The basic goal of the unit commitment problem is to properly schedule the on/off states of all the units in the system. In addition to fulfilling a large number of constraints, the optimal unit commitment should be met the predicted load demand at every time interval such that the total cost is minimum [1-2].

The unit commitment problem is formulated as a combinatorial optimization problem with 0-1 variables which represents on/off status and continuous variables which represents unit power. However, the number of combinations of 0-1 variables grows exponentially as being a large scale problem. Therefore, this problem is known as one of the problems which is the most difficult to solve in power systems.

This paper presents a genetic algorithm based approach to the scheduling of generators in VPP. All the usual unit commitment constraints are considered. The main advantage of the genetic algorithm is that fairly accurate results can be obtained with a very simple algorithm. The proposed algorithm has been tested on a power system with 10 generators.

The paper is organized as follows: next section describes problem formulation of power generation cost function. Section 3 describes genetic algorithm to find the optimal scheduling of power. Section 4 describes the results of the optimal algorithm in a one-day case study. Finally, the last section summarizes the results and future works.

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2. Unit Commitment Problem Formulations

The objective of the generation scheduling problem is to minimize the system operation cost. This cost includes the fuel cost for generating power and the start up cost over the entire study time span, while satisfying the system operating constraints, *e.g.*, power balance, unit generation limits, minimum up/down times, *etc.*, [3].

The list of symbols used in this paper is as follows:

T	: scheduling period in hours
N	: number of generator units
t	: index of hour $(t = 1,2,\cdots,T)$
i	: index of unit $(i = 1,2,\cdots,N)$
$I_i(t)$	: unit off/on [0, 1] state of unit i at hour t
$P_i(t)$	: power generation of unit i at hour t
$P_{\max\ i}$	: maximum generation limit of unit i
$P_{\min\ i}$	: minimum generation limit of unit i
$D(t)$	: system load demand at hour t
MUT_i	: minimum up time of unit i
MDT_i	: minimum down time of unit i
$T_i^{ON}(t)$	: time duration for which unit i has been on at hour t
$T_i^{OFF}(t)$	: time duration for which unit i has been off at hour t
$F_i(P_i(t))$	: fuel cost of unit i at hour t when generating power is $P_i(t)$
$SC_i(t)$	: start up cost of unit i at hour t
$OM_i(t)$	: operating and maintenance cost of unit i at hour t
CF	: total cost function

The objective of the problem is to minimize,

$$\min\ CF = \sum_{t=1}^{T}\sum_{i=1}^{N}\left[I_i(t)F_i(P_i(t)) + I_i(t)(1 - I_i(t-1))\,SC_i(t) + I_i(t)OM_i(t)\right]. \tag{1}$$

Generally, the fuel cost, $F_i(P_i(t))$ per unit in any given time interval is a function of the generator power output. Most frequently used cost function is in the form of

$$F_i(P_i(t)) = a_i + b_i P_i(t) + c_i P_i^2(t) \tag{2}$$

where a_i, b_i, and c_i represents the unit cost coefficients.

The start up cost of generator depends on times that the unit has been off prior to start up.

$$SC_i(t) = \alpha_i + \beta_i\left[1 - e^{-T_i^{OFF}(t)/\tau_i}\right] \tag{3}$$

where α_i, β_i, and τ_i represents the start up cost coefficients.

The constraints for the problem are:

(1) System power balance

$$\sum_{i=1}^{N} I_i(t) P_i(t) = D(t) \tag{4}$$

(2) Unit generation limits

$$P_{\min\ i} \le P_i(t) \le P_{\max\ i} \tag{5}$$

(3) Unit minimum up/down time

$$[T_i^{ON} - MUT_i][I_i(t-1) - I_i(t)] \ge 0 \tag{6}$$

$$[T_i^{OFF} - MDT_i][I_i(t) - I_i(t-1)] \ge 0 \tag{7}$$

3. Evolutionary Algorithm

Evolutionary algorithms have been applied to many different problem domains with successful results. All variants of evolutionary algorithms are based on the same natural principles; however they mainly differ in the solution representations and operators used and sometimes in the order in which these operators are applied.

Genetic algorithms (GA) are among the earlier variants of evolutionary algorithms developed by John Holland, who presented them as an abstraction of biological evolution and gave a theoretical mathematical framework for adaptation. GA are a method of moving from one population of “chromosomes” (bit strings representing candidate solutions to a problem), to a new population of solutions using selection, together with a set of genetic operators of crossover, mutation and inversion. Each chromosome consists of “genes” (*e.g.*, bits) with each gene representing an instance of a particular “allele” (*e.g.*, a 0 or 1). Genetic algorithms have become increasingly popular in recent years in science and engineering disciplines [4-6].

The distinguishing feature of a GA with respect to other function optimization techniques is that the search towards an optimum solution proceeds not by incremental changes to a single structure (candidate solution) but by maintaining a population of solutions from which new structures are created using the genetic operators. GA use random choice as a tool to guide a highly adaptive and explorative search through a coding of the parameter space.

The basic GA is given in Figure 1.

```
randomly select initial population;
repeat
    select one mating pair;
    generate one offspring through reproduction;
    evaluate offspring;
    if offspring better than current worst individual
    then  offspring  replaces worst   individual;
    endif
until max_fitness_evaluations reached;
```

Figure 1. Genetic Algorithm

The cost is to be minimized for each unit in each time interval over the whole scheduling period. The fitness function for the minimization problem is given in equation (1).

For mating pair selection, binary tournament selection is used. The two selected individuals go through reproduction, which consists of crossover and mutation. A two-point crossover method is used, in which the offspring gets a segment of its solution, defined by two cutoff points, from one parent while the rest is taken from the other. Crossover occurs with a predefined crossover probability (P_c). If crossover does not occur between the parents, the new offspring becomes an exact copy of one of the parents which is randomly determined. Point mutation is used on the offspring generated as a result of crossover. In this type of mutation, the value of a parameter on the solution string is inverted with a predefined mutation probability (P_m). After the fitness value of the offspring is calculated, it is compared to the fitness of the worst individual in the current population. If the offspring has a better fitness, it replaces the worst individual, otherwise it is discarded. The loop continues until a fixed amount of fitness evaluations have been performed

4. Experiments

The test system consists of 10 generating units. The generator parameters, fuel costs and the load demand profiles used for the GA analysis are shown in Table 1 and 2. The time step interval is one hour. The program is written in Matlab using Global Optimization Toolbox [7].

A number of tests on the performance of the genetic algorithm have been carried out. The following control parameters have been used:

- Population size: 100
- Generation: 200
- Crossover probability: 0.8
- Mutation probability: 0.01
- Elite copies: 10

Table 1. Generating Unit Characteristics

Unit	Generator limits		Fuel cost coefficients			Up/down time		Start up cost coefficients			Initial States
	P_{min}	P_{max}	a	b	c	MUT	MDT	α	β	τ	
1	250	520	105	1.395	0.0013	10	4	60	207	11	10
2	120	320	49	1.264	0.0029	7	5	50	137	7	7
3	75	200	82	1.214	0.0015	6	6	70	157	9	6
4	75	280	72	1.350	0.0026	6	3	30	146	6	-3
5	50	150	29	1.540	0.0021	1	3	30	130	5	-3
6	50	150	100	1.329	0.0014	3	2	80	202	11	3
7	25	120	32	1.500	0.0038	3	3	12	100	5	3
8	30	100	40	1.350	0.0039	4	4	25	110	5	4
9	20	80	25	1.500	0.0040	3	4	15	123	5	3
10	15	60	15	1.400	0.0051	3	2	15	123	5	3

Table 2. Load Demand

Hour	Load	Hour	Load	Hour	Load
1	1517	9	1317	17	1113
2	1426	10	1293	18	1079
3	1368	11	1238	19	1034
4	1328	12	1226	20	1022
5	1317	13	1203	21	1010
6	1351	14	1180	22	1058
7	1398	15	1170	23	1124
8	1351	16	1136	24	1517

Table 3 is the optimal commitment schedule. The schedule satisfies MUT and MDT constraints and has a minimum value of total operating cost. Figure 2 shows the convergence characteristics of GA processing. The results give the same power generations for all load demands as shown in Figure 3. Figure 4 shows electricity generation of each unit. The total production cost is shown in Figure 5 for the 10-unit system.

Table 3. Unit Commitment Schedule

Unit	Hour																							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1
6	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	1	1	0	0	0	0	0
7	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
8	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1
9	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0
10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1

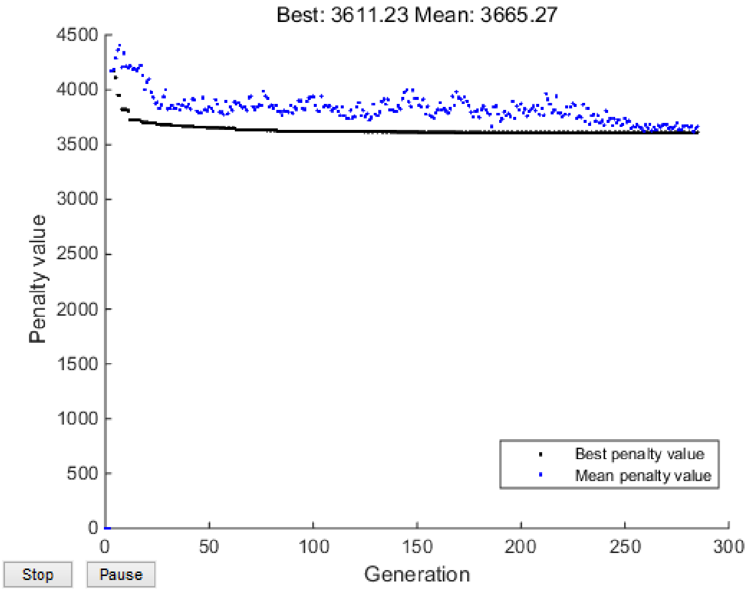

Figure 2. GA Convergence Characteristics

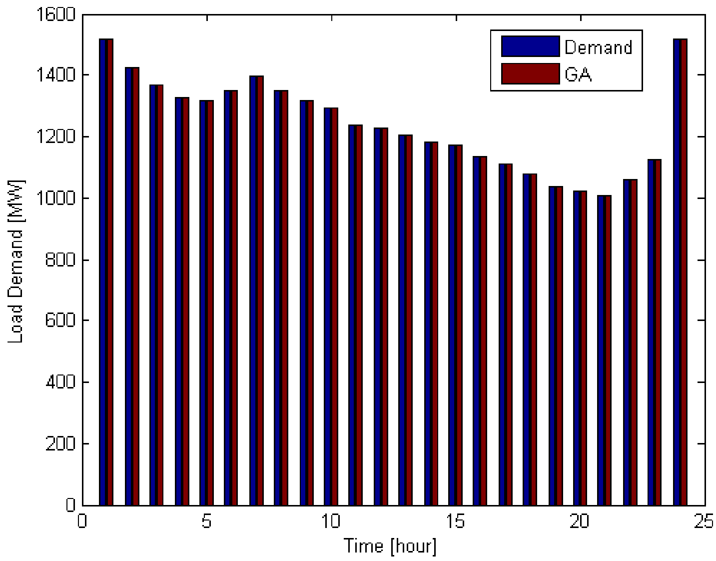

Figure 3. Load Demand and Power Generation at each Hour

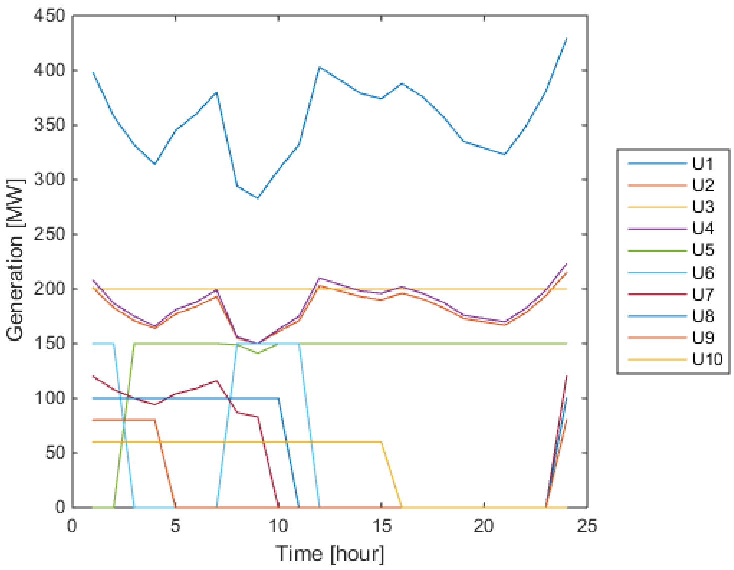

Figure 2. Electricity Generation of each Unit

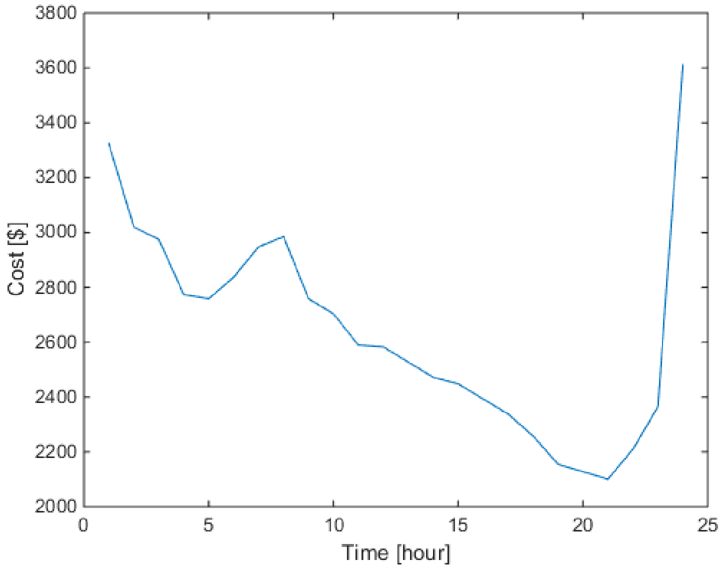

Figure 2. Load Demand and Power Generation at each Hour

5. Conclusions

The performance of the genetic algorithm on the test system demonstrates that it can provide good unit schedules for a power system. The power of the GA presented above relies on the selection and grading of the fitness function to differentiate between good and bad solutions. The method guarantees the production of solutions that do not violate system or unit constraints, so long as there are enough generators available in the selection pool to meet the required load demand.

The GA approach has demonstrated an ability to provide accurate and feasible solutions within reasonable computational times, making this a very attractive method for the solution of the generator scheduling problem.

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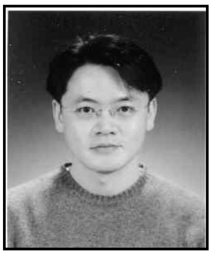
References

[1] D. Aloini, E. Crisostomi, M. Raugi, and R. Rizzo, Optimal power scheduling in a Virtual Power Plant. 2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies, **(2011)** December 5-7; Manchester, United Kingdom
[2] J. Kumagai, IEEE Spectrum, 49, 3 **(2012)**
[3] C. Wan, and S. M. Shahidehpour, IEEE Transactions on Power Systems, 8, 3 **(1993)**
[4] D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley Professional **(1989)**
[5] Deep Malya Mukhopadhyay, Maricel O. Balitanas, Alisherov Farkhod A., Seung-Hwan Jeon, and Debnath Bhattacharyya, International Journal of Grid and Distributed Computing, 2, 3 **(2009)**
[6] T. Venkat Narayana Rao and Srikanth Madiraju, International Journal of Hybrid Information Technology, 3, 4 **(2010)**
[7] Global Optimization Toolbox, http://www.mathworks.com/help/gads/index.html

Authors



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