GENETIC ALGORITHM BASED MULTI-STAGE REACTIVE POWER PLANNING STUDY

by

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Abstract

This paper presents a Genetic Algorithm approach to optimal location and sizing of capacitor banks in multi-stage (dynamic) transmission network expansion planning. The main objective of this optimization is to minimize the capital investments for capacitor banks, power and energy losses while maintaining node voltages within the accepted limits. This algorithm has been tested with modified Garver's 6-bus network and Sri Lanka transmission network. Problem formulation and results corresponding to both networks are presented for 3-stage (Garver's 6-bus) and 2-stage (Sri Lanka transmission network) planning studies respectively.

Keywords

Reactive power planning, Multi-stage planning, Genetic Algorithms

1. Introduction

Dynamic reactive power (VAR) planning problem is a sub-problem of multi-stage network expansion exercise. More generally, network expansion planning model determines the *timing* and the *type* of the new transmission facility that should be added to the existing network in order to ensure adequate transmission network capacity with future generation options and load requirements. In other words, *"Electric power system planning is the process of determining an expansion strategy, that is WHEN WHAT facilities should be provided WHERE in order to insure "adequate" electric service so as to "maximize the welfare" of the community being serviced* [1]." Within this context, network planner has to decide exact sizing and locations for reactive power compensation. This basic information implies that reactive power planning problem can be formulated into a combinatorial optimization problem. The key objective is to minimize the long-term capital investment costs (for capacitor banks) and operating costs (cost associated with power and energy losses) while maintaining adequate level of reliability and service quality (accepted node voltages).

In this Paper the combinatorial optimization formed by the problem formulation is solved with Genetic Algorithm (GA). GA approach is specifically selected because it shows inherent advantages over multi-criteria decision-making problems, as well as, it gives a large set of possibly good (sub-optimal) solutions with the optimal.

2. Review of Genetic Algorithms

Genetic Algorithms (GA) are search and optimization algorithms based on natural evolution and genetics [2]. GA optimizes a function (objective) or a process with respect to encoded problem variables (individuals). Initially, algorithm generates randomly a *population* of encoded finite-length strings of bits called *"Chromosomes"*. Each Chromosome represents a possible solution to the problem. Thereafter each Chromosome is evaluated by the objective function (Called *"fitness function"*). The genetic algorithm object determines which individual should survive, which should reproduce, and which should die. When GA is run, the Evaluation, Population, and Reproduction modules work together to effect the evolution of a population of chromosomes [3]. New populations are generated by the evolution mechanism comprising selection, crossover, fitness proportionate reproduction and mutation.

2.1 Genetic Operators

2.1.1 Selection

The *Selector* operator selects parents to generate a new population (next generation), which is more biased towards the best-fit individuals of the old population.

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The Chromosomes with higher fitness value have higher probability of producing copies and those with lower fitness have lower probability of producing copies.

The Selection operator may be implemented in a number of ways e.g. Rank Selector, Roulette Wheel Selector, Tournament Selector or Uniform Selector.

Tournament Selector:

In this selection process we choose two individuals randomly for reproduction and best wins with higher probability.

Roulette Wheel Selector:

In this selection, each chromosome of the old population has a survival probability proportional to the ratio of its fitness to total population fitness. More generally, individuals will reproduce its copies depending on its fitness values.

Tournament Selector and Roulette Wheel Selector are quite extensively used in applications. Rank Selector and Uniform Selector are not quite popular in applications. As its name implies in rank selection, individuals are ranked before selection and each individual has possibility being selected for mating based on its rank. In uniform selection each individual has uniform chance for being selected for mating.

2.1.2 Crossover

Crossover is the main genetic process, which happens between individual strings in the mating pool. The simplest crossover operator can be performed by exchanging the rightmost segments of the parents above the crossover point. This is known as single point crossover. For example consider **A** and **B** chromosomes (parents) of length 12-bits in the Fig. 1. The resultant chromosomes **A′** and **B′** (children) are as shown.

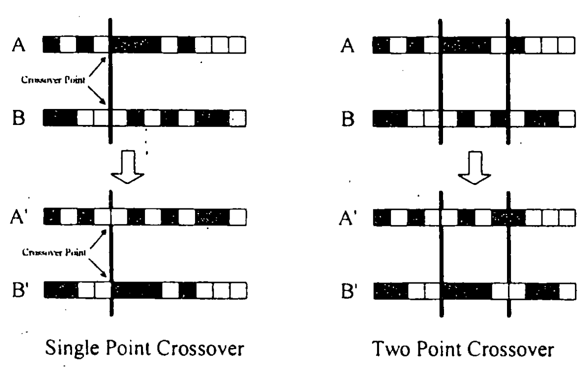

Figure 1: Representation of Crossover

2.1.3 Mutation

This genetic operation is done by simply flipping a random bit in an individual with low probability (*Mutation Probability,* P_c). This ensures the possibility of finding a global optimum without entrapping into a local optimum in a particular problem space.

2.2 How does a GA work?

In this application author uses a simple genetic algorithm, which comprises initialization, fitness evaluation, fitness dependent selection, crossover, mutation and updating of population. Following, explains the GA process briefly.

In the *initialization* process, a population of binary coded chromosomes is generated randomly to represent the solutions of the particular problem being concerned. Each of these chromosomes will be evaluated using the fitness evaluation scheme to calculate the corresponding fitness values.

Next, selection, crossover and mutation operators are applied to the current population to generate the next population. This procedure is repeated for predefined number of generations to reach best possible population (set of answers).

The operational hierarchy of a simple Genetic Algorithm (GA) can be depicted with the following pseudo code.

```
main ()
{
    int gen;
    generate(oldpop);
    for (gen=0; gen < MAXGEN ; gen++)
    {
        evaluate(oldpop);
        newpop=select(oldpop);
        Crossover(newpop);
        Mutation(oldpop);
        oldpop=newpop;
    }
}
```

3. Problem Formulation

The dynamic reactive (VAR) power planning problem can be formulated as a minimization problem of investment and operational costs that occurred during the planning horizon. Investment costs represent the capital costs incurred for reactive power compensation. Operational costs consists two parts namely, cost of power and energy losses and fictitious cost for operational requirement violations. The cash flow during the planning horizon is shown in Fig.2.

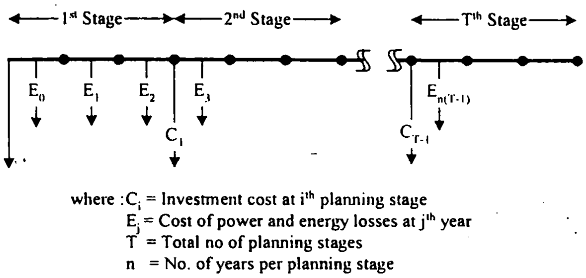

Figure 2: Representation of planning horizon

3.1 Components of the objective function

3.1.1 Total investment costs (associated with Capacitor Bank installations, C_c)

This includes the total discounted capital investments in adding capacitor banks over the planning horizon.

$$C_c = \sum_{t=0}^{T-1} \sum_{k=1}^{N_{c,t}} \frac{C_{cap}}{(1+d)^{t*n}} X_{k,t} \qquad \text{..........................} \qquad (1)$$

where:

C_{cap} : Unit cost of a Capacitor Bank Unit (of fixed size)

$X_{k,t}$: Number of capacitor banks added at candidate bus *k*, in the planning stage *t*

$N_{c,t}$: Number of candidate bus nodes for reactive power compensation at the planning stage *t*

3.1.2 Total cost of power and energy losses (C_L)

The cost of power (C_{PL}) and energy (C_{EL}) loss is calculated using the LRMC values of capacity and energy at transmission level. This is summated throughout the planning horizon

$$C_L = C_{EL} + C_{PL}$$

$$= \sum_{t=0}^{T-1} \sum_{i=1}^{n} P_{loss,n*t+i} \cdot \{\, k_p + 8760\, LLF \cdot k_E \,\} \cdot \frac{1}{(1+d)^{n*t+i-0.5}} \qquad \ldots(2)$$

where:

$P_{loss,nt+i}$: Peak power loss in *kW* in the stage *t*, i^{th} *year*

LLF : Loss Load Factor

k_E : LRMC value of energy at transmission level in *\$/kWh*

k_p : LRMC value of capacity at transmission level in *\$/kW-year*

3.1.3 Penalty due to bus voltage magnitude violations

$$P_v = \begin{cases} \sum_{t=0}^{T-1} \sum_{k=1}^{N_{b,t}} k_v . \left(V_{\max} - |v_k|\right) & \text{if} \quad |v_k| > V_{\max} \\ \sum_{t=0}^{T-1} \sum_{k=1}^{N_{b,t}} k_v . \left(V_{\min} - |v_k|\right) & \text{if} \quad |v_k| < V_{\min} \end{cases} \qquad \text{............}(3)$$

where:

$N_{b,t}$: No. of bus nodes at the stage t

K_v : Penalty Coefficient

v_k : Bus voltage magnitude in p.u.

V_{max} : 1.0 pu for all load bus nodes

V_{min} : 0.95 pu for all load bus nodes

3.2 Overall problem formulation

The above three components of the objective (fitness) function are formulated as a minimization problem.

$$Min_{\forall X_i} Z = C_c(X_i) + C_L(X_i) + P_V(X_i) \qquad \text{.............} (4)$$

where:

X_i: represents the number of capacitor banks to be added at each planning stage for pre-identified reactive power compensation busses

3.3 Coding of the Problem

A direct coding method was adopted to code the above variables into a binary chromosome. Figure 3 shows the chromosome coding of the dynamic reactive power planning problem.

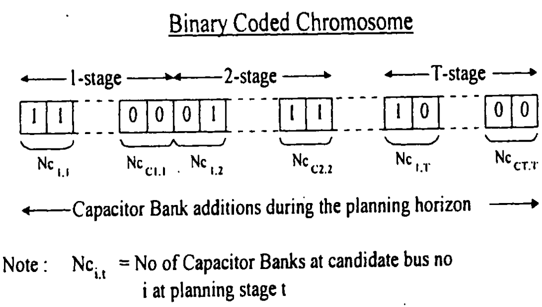

Figure 3: Chromosome Coding

3.4 Fitness Function Evaluation

Fitness (objective) function must reflect both the desired and undesired properties of a solution, rewarding the former strongly and penalizing the latter. Fitness function evaluation scheme for the problem is shown in the Fig. 4.

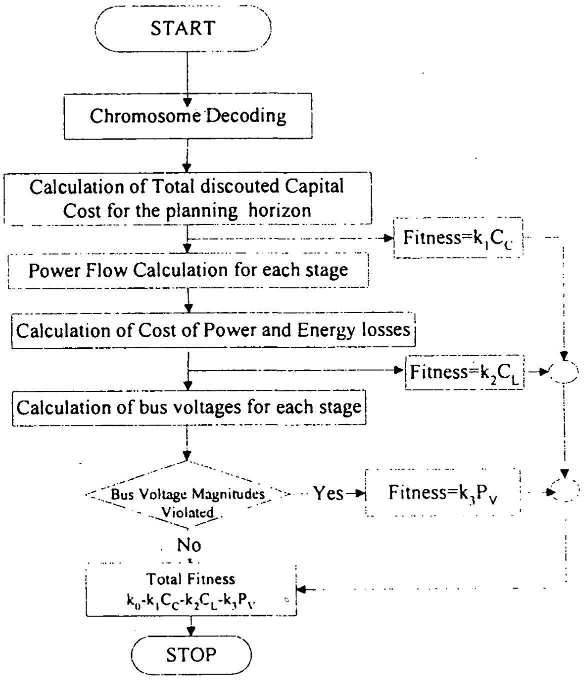

Figure 4: Fitness Evaluation Scheme

4 Test Results

The test results shown in this section illustrate the performances of the proposed algorithm. Three-stage (03) reactive power compensation study has been carried out for the Modified Garver's 6-bus system, in order to validate the developed model and to determine the various parameters used in this algorithm. A real-world application of the proposed algorithm is presented next with Sri Lanka transmission network.

4.1 Modified Garver's 6-bus network

The network topology is as shown in the Figure 5, where solid lines represent the existing network, and dotted lines represent possible future expansions. Basic network data are given in Appendix 1 and 2. Other important details can be listed in Table 1.

Number of stages	3 stages
Discount rate	10 %
Candidate bus nos. for reactive power compensation	2,3,4, (stage I) 2,3,4,5 (stage II,III)
Cost of 25 Mvar Capacitor Bank unit	350,000 US$
Available unit sizes	0,25,50,75 Mvar
LRMC Energy value	0.045 US$/kWh
LRMC Capacity value	90.0 US$/kW/year

Table 1

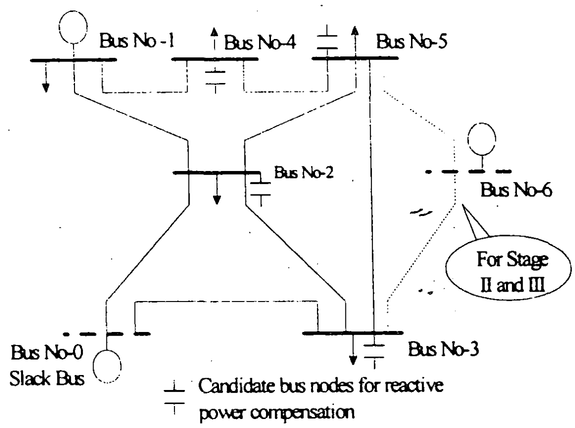

Figure 5: Modified Garver's 6 Bus System

This 6-bus test system was analyzed with the loading and generation levels given in the Appendix I, for three planning stages (excluding reactive power compensation). The resultant bus voltages are as given in Table 2 (pu values).

	Stage I	Stage II	Stage III
Bus No- 2	0.975	0.983	0.970
Bus No- 3	0.980	0.988	0.980
Bus No- 4	0.940	0.953	0.936
Bus No- 5	0.952	0.967	0.945

Table 2

This shows that bus No-4 at the first planning stage and bus No-4, 5 at the third planning stage show voltage criteria violations (± 5 %). Therefore, if a heuristic approach were used to solve these voltage criteria violations, it would suggest 50 Mvar (2 x 25 Mvar) at bus No-4 in the first planning stage and another 50 Mvar at bus No-4 in the third planning stage. The total discounted investment cost associated with this decision is 1.0951 million US$ and the cost of power and energy losses during the 9 year planning horizon become 25.9522 million US$. This implies that any solution that gives more investment cost than the above and reduce the cost of power and energy losses with a magnitude more than that incremental investment cost will be an improvement of the heuristic solution.

However, the proposed GA based algorithm gives a family of possibly good solutions at the end of the evolution process. The "best-so-far" solution presented in Table 3, was obtained with population size 30 and 100 generations. Probability of crossover and mutation were used as 0.9 and 0.02 respectively.

	Stage I	Stage II	Stage III
Bus No- 2	25 Mvar	0	0
Bus No- 3	25 Mvar	0	0
Bus No- 4	75 Mvar	0	0
Bus No- 5	-	75 Mvar	0

Table 3

The total discounted investment cost associated with this solution is 2.5389 million US$, which is 1.4438 million US$ higher than the heuristic solution. However, the cost of power and energy losses becomes 22.853 million US$. This is 3.0992 million US$ reduction from the corresponding heuristic method value. These results clearly stand for the benefits of the proposed GA approach. The following Table 4 shows some of the possibly good solutions obtained with the evolution process. Arranged in the descending order of their fitness value. The values in the table correspond to integer multiples of 25 Mvar. (For example, 1=25 Mvar)

Bus No

2	3	4	2	3	4	5	2	3	4	5
1	1	3	0	0	0	2	0	0	0	0
0	1	3	0	0	0	2	0	0	0	0
1	1	3	0	1	0	1	0	0	0	1

Table 4

Fig. 6 shows the convergence of the algorithm for 6-bus case.

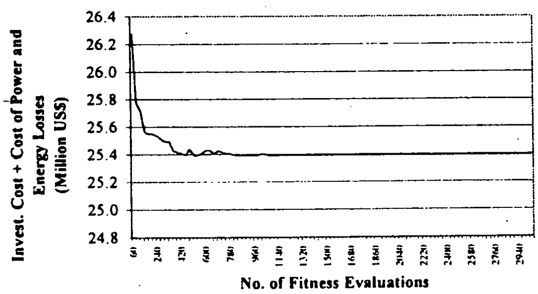

Figure 6. Convergence of the algorithm

4.2 Sri Lanka Transmission Network

The Model Developed was applied to the Sri Lanka Transmission network in order to carry out two- (02) stage optimal capacitor placement study. The planning stages were considered as year 2001 and 2004. It was assumed that the network at the beginning of each planning stage remains the same during that stage. The main network details are as summarised in Table 5. Furthermore, it was assumed that 0 to 70 Mvar reactive power compensation is possible at pre-identified bus points at any planning stage. The unit cost of a capacitor bank and LRMC values of power and energy were assumed as same as those used in the 6-bus example.

	2001	2004
Total No of busses	138	176
Total no of branches	202	264
Total no of voltage controlled busses*	40	54
Reactive power compensated busses	21	17

Table 5

* Voltage controlled bus nodes, using reactive power compensation (33 kV load bus bars)

The solution obtained with the above algorithm is given in Table 6. However, it should be clearly mentioned that this answer might be too optimistic since the problem was handled totally from a planning viewpoint. This means that the algorithm did not consider voltage adjustments made by the tap-changers at grid substations, since it was considered as an operational practice than a planning technique. Therefore all the transformers were assumed at their nominal tap positions.

Bus Name (No-2001/No-2004)	2001 Mvar	2004 Mvar
Amp-3 (69/91)	10	20
Kelan-3A (75/15)	10	-
Kelan-3B (76/15)	10	-
Avis-3 (78/105)	30	-
Thul-3 (81/108)	30	-
Koln-3A (83/110)	50	-
Koln-3B (84/110)	30	-
Panni-3 (85/112)	40	0
Kotug-3 (87/115)	30	-
Bolaw-3 (88/116)	20	0
Galle-3 (92/121)	30	20
Kurun-3 (94/124)	0	-
Habar-3 (95/125)	0	-
Kirib-3 (98/129)	-	40
Ratma-3A (100/131)	30	10
Matug-3 (101/132)	40	0
Put-3 (102/133)	0	10
Pand-3 (104/137)	3	-
Chill-3 (105/138)	2	0
Kollu-11 (109/146)	30	-
Fort-11 (110/147)	10	-
Kuliya-3 (-/94)	-	30
Kelan-TT (-/99)	-	0
Panni-C (-/113)	-	0
Badul-3 (89/118)	-	10
Deniy-3 (91/120)	-	10
N-Galle-3 (-/122)	-	10
Trinc-3 (97/127)	-	0
Ambal-3 (-/140)	-	10

Table 6

Table 6 shows the optimal capacitor placements for two-stage network planning study, with minimum investment cost, power and energy losses and minimum voltage deviations at load busbars. The network diagrams corresponding to above solution are given in Fig.7 and Fig.8.

5 Conclusions

The optimal reactive power compensation (capacitor placement) problem is a combinatorial optimization problem, in which the number of combinations to be analyzed increases exponentially with the increase of the network size. Therefore time dimension of the problem become a considerable factor when the network size becomes larger. However, proposed GA based approach provides a set of time-ordered investment decisions, which are very useful in dynamic network planning. Furthermore, this Paper clearly implies that the GA approach to multi-stage reactive power planning problem is both feasible and advantageous.

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Appendix 1: Loading and Generation Levels (Net injected power)

Bus No.	Stage-1		Stage-2		Stage-3	
	P (MW)	Q (Mvar)	P (MW)	Q (Mvar)	P (MW)	Q (Mvar)
0 (Existing)	Selected as the slack bus					
1 (Existing)	+225/-100	-30	+200	-	+300	-
2 (Existing)	-200	-100	-264	-110	-300	-170
3 (Existing)	-160	-110	-176	-121	-200	-140
4 (Existing)	-240	-140	-264	-154	-290	-170
5 (Existing)	-50	-30	-100	-60	-220	-160
6 (New site)	-	-	+200	+100	+350	

Appendix 2: Transmission Line Details

Line No.	Starting Bus	Ending Bus	G_{sht}	B_{sht}	R_{ser}	X_{ser}	Capacity MVA
0	0	2	0.000	0.006	0.008	0.030	400
1	0	3	0.000	0.006	0.008	0.030	400
2	1	4	0.000	0.004	0.005	0.020	400
3	1	2	0.000	0.004	0.005	0.020	400
4	3	2	0.000	0.008	0.010	0.040	200
5	2	5	0.000	0.008	0.010	0.040	200
6	3	5	0.000	0.012	0.015	0.060	200
7	4	5	0.000	0.004	0.005	0.020	200
8	3	6	0.000	0.008	0.010	0.040	400
9	6	5	0.000	0.008	0.010	0.040	400

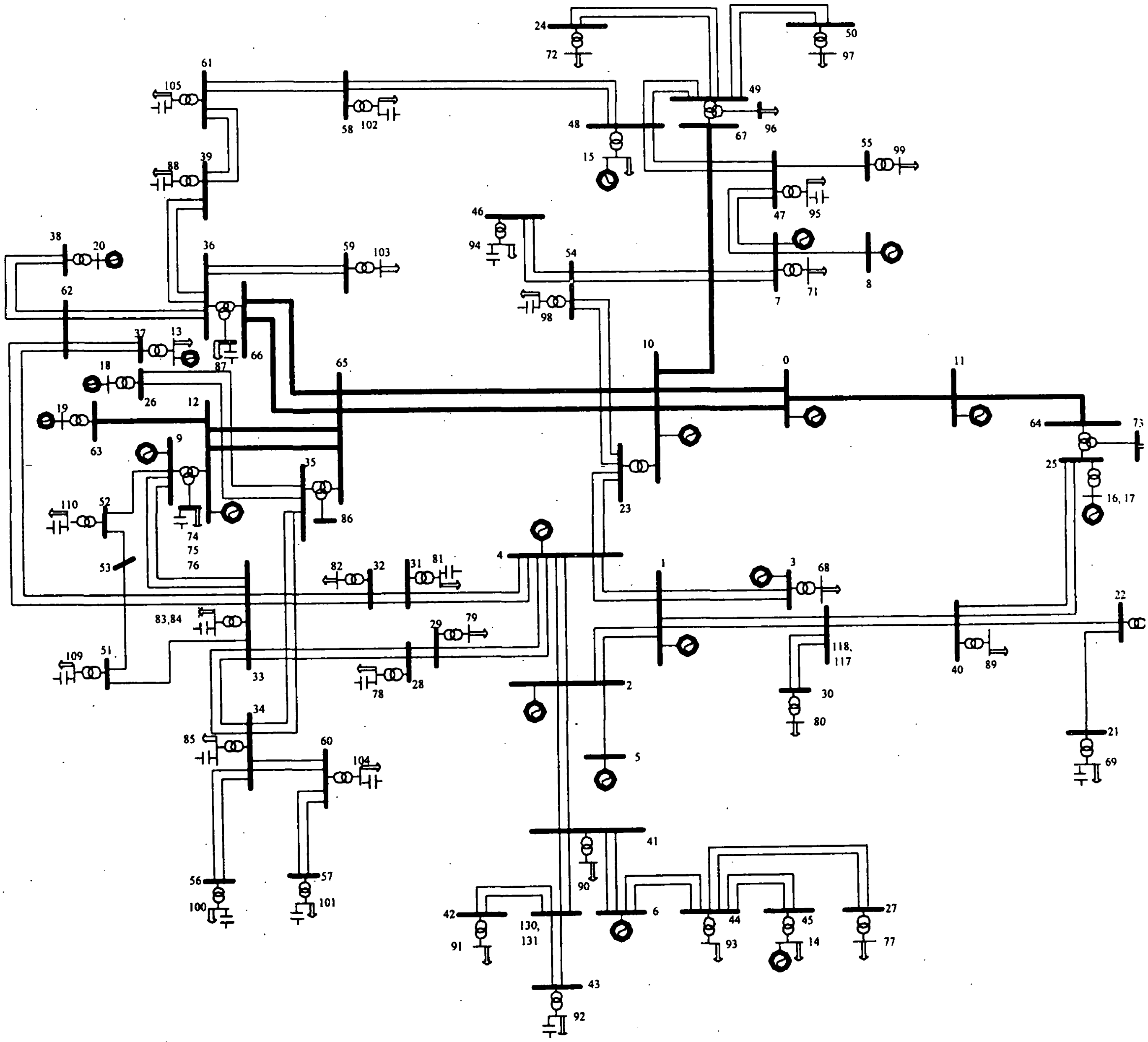

Fig.6 Network Diagram at year 2001

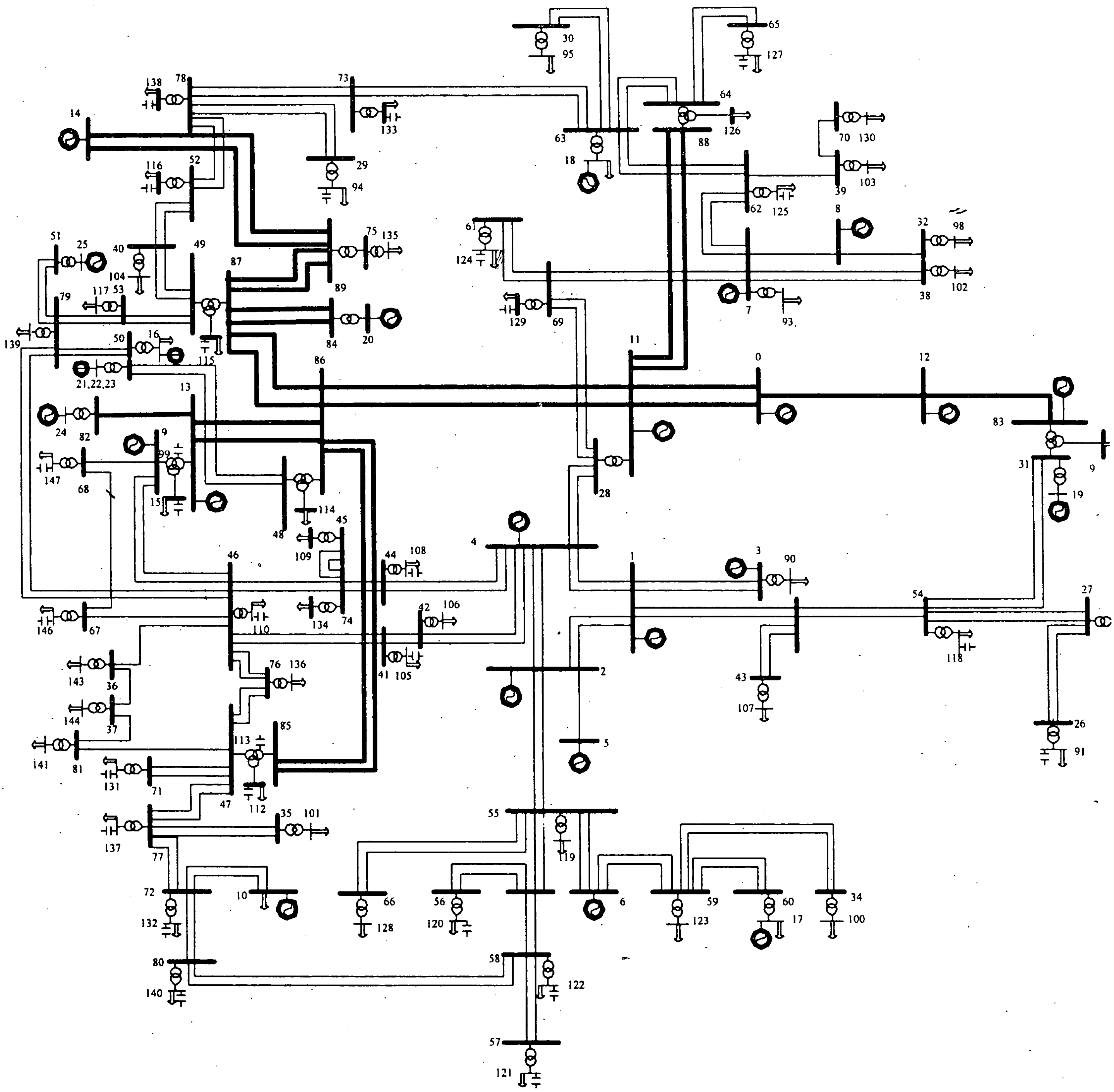

Fig. 7. Network diagram at year 2004