OPTIMAL LOW-VOLTAGE DISTRIBITION NETWORK DESIGN USING GENETIC ALGORTIHMS

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ABSTRACT

In this paper, a new genetic algorithm (GA) has been developed for optimal distribution network design. Distribution transformer station location and size selection is evaluated together with feeder route and size selection in the study. The model used in the design includes realistic rules that are derived from actual networks.

I. INTRODUCTION

As energy consumption increases, the need to expand energy production and distribution is inevitable. To meet the increase timely, many studies have been made in this area. In this paper the optimum distribution network design is examined.

The goal of designing a new distribution network or the expansion of an existing distribution network is to provide the consumers with quality electrical energy while minimizing the cost. For this purpose, different algorithms and optimization techniques have been developed in this area.

Some of the researches in the past have focused only on distribution transformer location selection [1-4] or feeder route selection [2-5]. Others that included both distribution transformer location selection and feeder route selection have optimised these models separately, resulting in a two-step optimization and a lower chance in reaching the global optimum. Most of the algorithms developed optimize these two models simultaneously [6-13]. The inclusion of these two models in the same algorithm results in a greater chance in reaching the global optimum result. Few researches have included the reliability model and the cost of energy interruption into the algorithm [14-17]. This attains a better result. It is important that the distribution network should not experience long breaks of energy interruption. In other words, the distribution network should be reliable. Unfortunately, the data needed for reliability analysis has not been obtained by most countries, making it very hard to insert the reliability model in the algorithm.

In distribution network design, the selected optimization technique is nearly as important as the algorithm selected. The optimization techniques used for distribution networks can be categorized in two main headings:

i) Mathematical programming techniques
ii) Heuristic techniques (Includes evolutionary techniques)

Previous studies mainly used mathematical programming while recent studies mainly use heuristic techniques. Both techniques have their advantages and disadvantages.

Mathematical programming techniques have obtained global optimum with an acceptable fault. The main problems in this technique are to model real problems and the problems encountered in calculation. If too many variables are used, the mathematical programming takes too long computation time, forcing the programmer to neglect some of the variables. For this, the non-linear characteristics are linearized.

Evolutionary techniques are stochastic methods shaped according to the laws of nature or evolution. GAs is the most used evolutionary technique. The main problem in GA is defining the genetic operators in order to meet the global optimum. The power of GAscome from being able to model some features that classical mathematical programming methods would neglect. As a result, a more realistic result, which is nearer to the global optimum, is obtained. The ability to reach a realistic optimal result compared to other optimiziaton methods has made the selection of GA preferable.

Without violating the technical constraints, a GA optimization program developed in MATLAB which includes the model proposed for distribution network design is used for optimum distribution network design. The optimization process will be done using the site plan and load information provided in [18].

II. GENETIC ALGORTIHMS

GAs are stochastic search and optimization techniques shaped by the evolution theory. Goldberg [19] states the difference between GAs and classical optimisation and search methods in four ways:

1. GAs work with a coding of the parameter set, not the parameters themselves.
2. GAs search from a population of points, not a single point.
3. GAs use payoff (objective function) information, not derivatives or other auxiliary knowledge.
4. GAs use probabilistic transition rules, not deterministic rules.

GAs consist of an initial set of random solutions called *population*. Each individual in the population is called a *chromosome*, which is a string of symbols and represents a solution to the problem. The chromosomes *evolve* through successive iterations, called *generations*. During each generation, using some measures of *fitness*, the chromosomes are *evaluated*. The next generation is created by *offsprings*. These are created by either merging two chromosomes from the current generation using *crossover* operator or by modifying a chromosome using a *mutation* operator. A new generation is formed by selecting some of the parents (*reproduction*) and offspring according to the fitness values and by rejecting others so as to keep the population size constant [20]. A simple GA at work is shown in Figure 1.

Crossover is the main genetic operator. It combines two chromosomes features to generate an offspring. A simple crossover would be achieved by choosing a random cut-point and combining the segment of one parent to the left of the cut-point with the segment of the other parent to the right; generating an offspring. The crossover rate (p_c) is defined as the ratio of the number of offspring produced in each generation to the population size (pop_size). The number of chromosomes to undergo crossover would be pc*pop_size. A higher crossover rate allows a greater scaled exploration of the solution space, reducing the chance of a false optimum. Contrary, a high crossover rate increases the computation time greatly and results in wasting a lot of time in exploring unpromising regions of the solution space.

Mutation is a background operator, which produces spontaneous random changes in various chromosomes. Even though reproduction and crossover effectively search and recombine extant notions, occasionally they may become overzealous and lose some potentially useful genetic material. Mutation plays a crucial role because it recovers such lost genetic material, decreasing the error in finding the global optimum. Since mutation plays a secondary role in GAs, the mutation rate (p_m) is relatively low. If its too low, many genes that would have been useful are never tried out; but if its too high, the offsprings will start losing their resemblance to their parents resulting in the loss of fitter chromosomes.

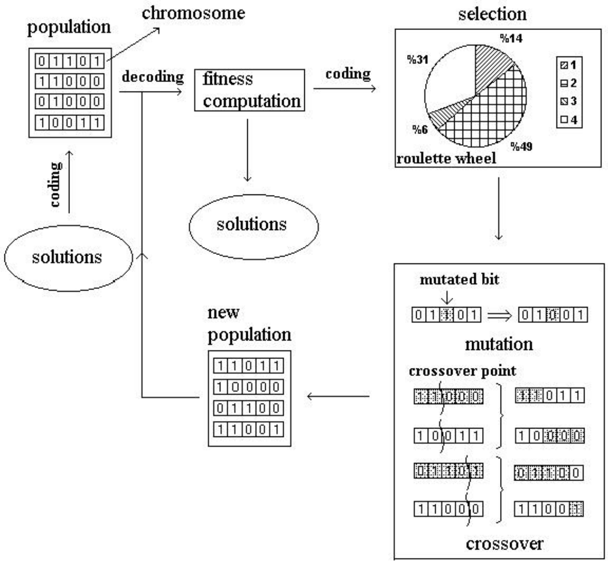

Figure 1. A simple GA at work is shown.

III. PROBLEM FORMULATION

Both distribution transformer station size and location, and feeder size and route selection is evaluated in this paper. Feeder and distribution transformer station investment and losses costs are also included in the model developed in the study. The model used in the design of a network through the optimization process includes the realistic rules which are performed from actual networks.

$$
\begin{aligned}
Z\min = {} & \sum_{k=1}^{m}\sum_{a\in N_a}\left[(K_{Tk})_a\right]+\sum_{k=1}^{m}\sum_{a\in N_a}\left[K_e\cdot(P_{dk})_a\cdot 8760\right] \\
& +\sum_{k=1}^{m}\sum_{a\in N_a}\left[K_e\cdot(P_{bk})_a\cdot\left(\frac{S_{\max}}{S_n}\right)^2\cdot F_k\cdot 8760\right] \qquad (1) \\
& +\sum_{l=1}^{n}\sum_{b\in N_b}(K_{Hl})_b\left[\cdot\, l_l\right] \\
& +\sum_{l=1}^{n}\sum_{b\in N_b}\left[K_e\cdot(r_l)_b\cdot l_l\cdot\frac{\left(P_l^2\right)}{\left|V_l^2\right|}\cdot F_k\cdot 8760\cdot 10^{-3}\right]
\end{aligned}
$$

K_e	energy cost coefficient [TL/kWh]
$(r_l)_b$	resistance per m of feeder section l to be built with size b [Ω/m]
P_l	active power in feeder section l [kW]

V_l	voltage at the beginning of feeder section l [kV]
$(K_{Hl})_b$	cost of feeder section l to be built with size b [TL/m]
l_f	length of feeder section l [m]
$(P_{bk})_a$	transformer copper loss associated with size a in substation site k [kW]
$(P_{dk})_a$	transformer core loss associated with size a in substation site k [kW]
$(K_{Tk})_a$	distribution transformer installation cost associated with size a in distribution transformer site k [TL]
8760	total hours in a year [h]
S_n	rated transformer power [kVA]
S_{max}	maximum power demand in transformer [kVA]
N_a	proposed transformer sizes
N_b	proposed feeder sizes
F_k	loss factor
n	number of feeder sections
m	number of transformers

The objective function is limited by the following technical constraints:

- Power-conservation limits,

$$\sum_{i=1}^{p}\left(P_{ij}-P_{ji}\right)\geq P_j \qquad (j=1,2,\ldots,n) \qquad (2)$$

- The feeder current must not be higher than the maximum current capacity of the cable,

$$\frac{P_l}{\left|V_l\right|}\leq\frac{P_l^{\max}}{\left|V_l\right|} \qquad (l=1,2,\ldots,n) \qquad (3)$$

- The power demanded from the distribution transformer must not be higher than the distribution transformers rated maximum power,

$$P_t \leq P_t^{\max} \qquad (4)$$

- The voltage drop must not be higher than the maximum voltage drop limit ($e_{\max}$=%3),

$$\Delta U_l \leq \Delta U_{\max} \qquad (l=1,2,\ldots,n) \qquad (5)$$

- The distribution system must be radial,

$$\sum_{i=1}^{p}\left(P_{ij}+P_{ji}\right)\leq 1 \qquad (j=1,2,\ldots,n) \qquad (6)$$

IV. THE PROPOSED ALGORİTHM

By considering the technical constraints, a GA optimization program developed in MATLAB is used for optimum distribution network design. The optimization process will be done using the site plan and load information provided in [18].

Binary coding which includes distribution transformer size and location, and feeder size and routes is used. Normal crossover and a mutation operator, which starts at a high level but quickly drops exponentially than rises slowly, is used together with e*litism* and *plague* operators. High mutation rate in the beginning forces the population to quickly improve itself. Since mutation is a background operator, its rate should not be high until the best individual in the population does not change for a long time. Elitism makes sure that the best result is never lost, and plague operator randomly kills the individuals in the population and creating new random individuals. Plague operator makes sure that the population doesn't become dominated by the best results, thus evading local optimum results. Selection is done with roulette wheel selection and tournament selection.

V. RESULTS

The program has been tested on a PIII personal computer.

The optimal genetic operators have been found as 0.7 crossover rate, 0.004 constant mutation rate and 0.005 plague rate. The mutation rates droped from 0.394 to 0.008 in the first ten generations, then rises logarithmically up to 0.0304. It has been observed that a population of 40 individuals was enough to obtain the optimum result.

The optimization has been done using the purchasing and installation costs provided by TEDAŞ (2002), the technical data from manufacturers, and site plan, shown in Figure 2, and load information provided in [18]. Table 1 and Table 2 include the technical data and costs of the distribution transformer and feeder costs, respectively. The load data is given in Table 3.

Table 1. Distribution transformer technical data and costs

Power [kVA]	Losses		Cost [TL]
	Load	No Load	
800	1.520	9.700	12.539.548.000
1000	1.600	12.200	13.968.871.000
1250	1.950	14.000	15.720.859.000
1600	2.350	16.500	18.951.672.000

Table 2. Feeder technical data and costs

No.	Cable	Resistance [Ω/km]	Current carrying capacity [A]	Cost [TL]
I	3*70/35	0.268	228	19.154.000
II	3*95/50	0.193	275	23.779.000
III	3*120/70	0.153	313	28.593.000
IV	3*150/70	0.124	353	33.528.000
V	3*185/95	0.0991	399	39.752.000
VI	3*240/120	0.0754	464	49.970.000
VII	2*(3*150/70)	0.0620	706	67.056.000
VIII	3*(3*240/120)	0.02513	1392	149.910.000

Table 3. Load data

Load Point	Load [kW]	Load Point	Load [kW]	Load Point	Load [kW]
3	45.8	21	36.64	39	20
4	36.64	22	36.64	40	36.64
5	36.64	23	36.64	41	45.8
6	36.64	24	36.64	42	52
7	36.64	25	40	43	47.8
8	45.8	26	25	44	55
9	20	27	36.64	45	25
10	29.872	28	36.64	46	36.64
11	29.872	29	47.8	47	36.64
12	37.340	30	36.64	48	10
13	10	31	45.8	49	36.64
14	36.64	32	36.64	50	36.64
15	36.64	33	36.64	51	36.64
16	10	34	10	52	45.8
17	36.64	35	36.64	53	36.64
18	36.64	36	36.64	54	10
19	52	37	52	55	36.64
20	47.3	38	45.3	56	36.64
				57	10

Using these information supplied in Tables1-3, the distribution network in Figure 2 has been optimized. After 2000 generations, the optimum total cost has been found as 103.310.000.000 TL. Total distribution transformer station costs were found as 36.958.000.000 TL and total feeder costs were found as 66.351.000.000 TL. The optimal distribution network plan is shown in Figure 3. The optimal distribution transformer sizes have been found as 1000kVA for 1 and 1250kVA for 2. Figure 4 shows the best results throughout the generations.

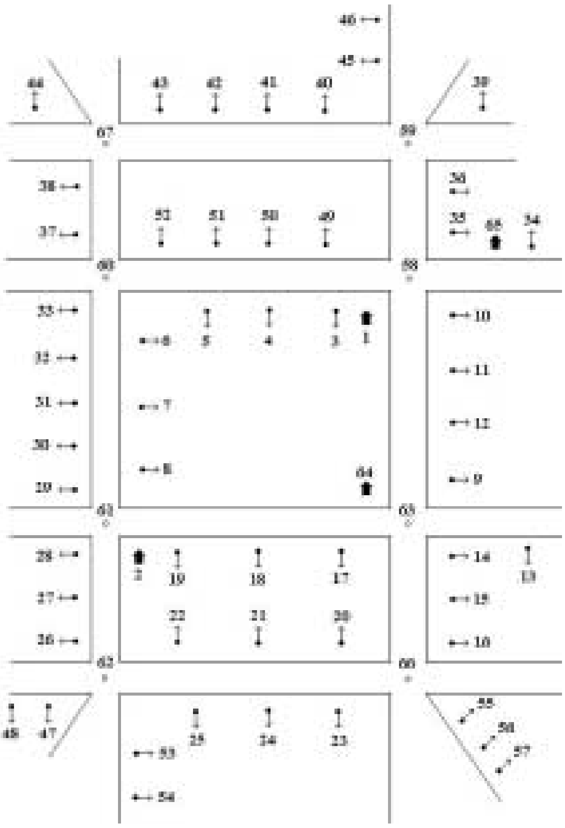

Figure 2. Site plan

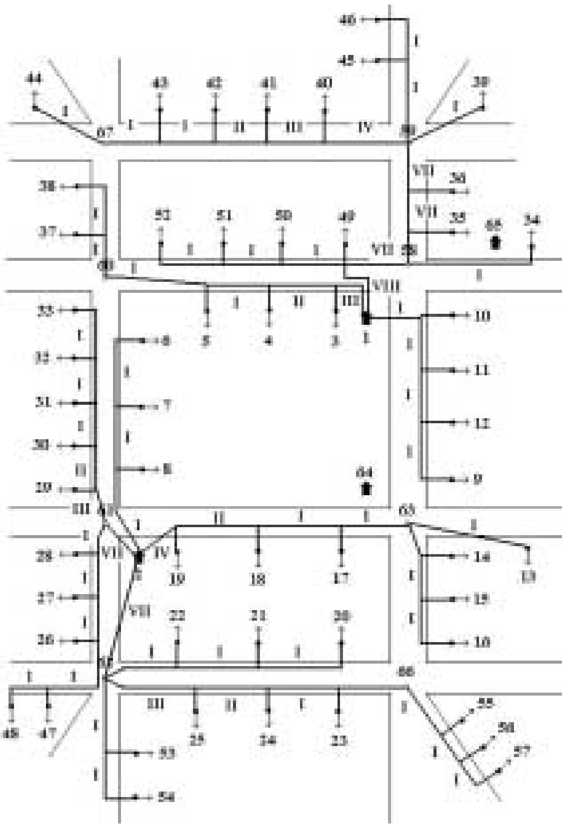

Figure 3. Optimal distribution network

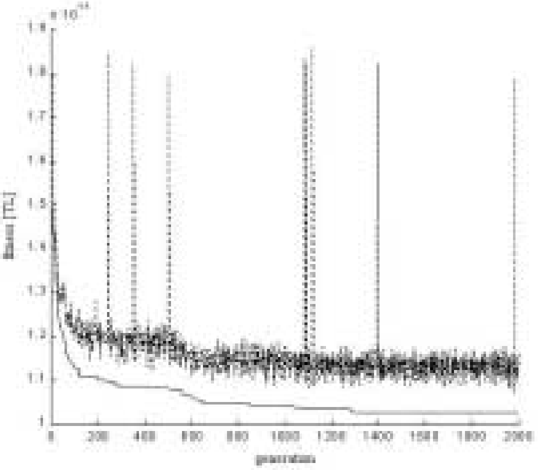

Figure 4. Evolution of the GA.

VI. CONCLUSIONS

As energy consumption and component price increases, the need for optimal planning is becoming more and more important. To achieve this goal, the planner cannot rely only on his planning abilities but must use powerful optimization techniques.

This study has examined the power of GAs used as an optimisation technique in distribution planning. The results show clearly that GAs can optimize distribution networks successfully and can be a good alternative to other optimization techniques. Furthermore, this study has shown that using GA in considerably large distribution networks makes it more likely to reach the global optimal solution.

GAs can handle non-linear relations with easily, allowing the planner to insert characteristics which could have been neglected classical optimisation techniques, giving a more realistic result.

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