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Substation Expansion Planning Based on BFOA

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Abstract

In recent years, significant research efforts have been devoted to the optimal planning of power systems. Substation Expansion Planning (SEP) as a sub-system of power system planning consists of finding the most economical solution with the optimal location and size of future substations and/or feeders to meet the future demand. The large number of design variables, and combination of discrete and continuous variables makes the substation expansion planning a very challenging problem. So far, various methods have been presented to solve such a complicated problem. Since the Bacterial Foraging Optimization Algorithm (BFOA) has been proper results in studies of power systems, and has not been applied to SEP problem yet, this paper develops a new BFO-based method to solve the SEP problem. The technique discussed in this paper uses BFOA to simultaneously optimize the sizes and locations of both the existing and new installed substation and feeders by considering reliability constraints. To clarify the capabilities of the presented method a typical network is considered and the results of applying GA and BFOA on the network are compared. The simulation results demonstrate that the BFOA has the potential to find more optimal results than the other algorithm under the same conditions. Also, the fast convergence, consideration of real-world networks limitations as problem constraints and simplicity in applying to large scale networks are the main features of the proposed method.

Keywords: Bacterial Foraging Optimization Algorithm; Genetic Algorithm; Substation Expansion Planning.

1. Introduction

With electric power consumption growth, desired new transmission system elements are needed to overcome the possible lack of adequacy problems so that with the least costs, various operational constraints are met. In the so-called Substation Expansion Planning (SEP), the problem is to determine the required expansion capacities of the existing substations as well as the locations and the sizes of new substations together with the required availability times, so that the loads can be adequately supplied [1].

Usually, according to the geographic distribution of actual consumers, service areas of an electric power distribution system are divided into many small irregular areas, which are called “electrical domains”. Each domain has a load-point showing the power consumption of customers in this domain. Moreover, there are some candidate places for installing new substations as well as the possibility of expanding some of the existing ones.

Various constraints should also be observed during the optimization process. For example, the maximum permissible voltage drop, maximum allowable capacity of feeders, maximum permitted capacity of substation equipments, accessibility to upward and downward networks and considering enough space for possible future developments [2].

Prevalent cost indices are new substation installation cost, no-load and loading loss cost in substations’ transformers besides installation and loss costs of feeders. The solution that leads to the lowest total expansion and operational costs, which also satisfies the constraints, is considered as the optimal solution of SEP problem. So far, different algorithms have been developed by researchers for this purpose. Most existing methods can be categorized in two groups; numerical methods and heuristic methods.

Mixed integer linear programming (MILP) [3], nonlinear programming (NLP) [4], dynamic programming (DP) [5], ordinal optimization (OO) [6] and direct solution [7] are from numerical methods.

On the other hand, the second group consists of heuristic methods. Genetic Algorithm (GA) [8,9], Tabu search (TS) [10], Particle swarm optimization (PSO) [11, 12], Ant colony system (ACS) [13], Simulated annealing (SA) [14], Artificial bee colony (ABC) [15] and Bacterial foraging optimization (BFO) [16] are from heuristic methods.

By reviewing the above presented researches, advantages and disadvantages of the numerical and heuristic methods can be described.

The numerical methods have the following advantages: the optimal solution is usually accurate and the time to compute the optimal solution is low. On the other hand, the numerical methods have the following disadvantages: it is difficult to manage power system equations into an optimization model; in order to insert a new constraint, the optimization model has to be rearranged and new equations have to be added. Among the available numerical methods for SEP, the most efficient is the Mixed Integer Non Linear Programming (MINLP) method.

Heuristic methods are easy to use and they do not require the conversion of the power system model into an optimization programming model. Moreover, heuristic optimization methods are usually robust and provide near-optimal solutions for complex, large-scale SEP problems; however, there is no guarantee that they will find a global optimum solution. Generally, they require high computational effort; however, this is not necessarily critical in SEP applications. Among the available heuristic methods for SEP, the most efficient is the GA.

By reviewing the previous studies, it is concluded that heuristic methods have very applications to solve the SEP problem. GA is the most popular among them and usually its results are the best.

BFOA has been used in many studies of power systems [17-20]. The only paper that presents the BFOA in the planning studies is the Sing and others study [16] that is exactly in the field of feeder routing and its application is not sensible in the field of SEP. Since the Bacterial Foraging Optimization Algorithm (BFOA) has been proper results in studies of power systems, and has not been applied to SEP problem yet, this paper develops a new BFO-based method to solve the SEP problem. The results of the presented method are compared with GA as the most famous heuristic method to solve the SEP problem.

The paper is organized as follows: Section 2 provides the substation expansion planning problem. Section 3 introduces the BFO algorithm. The results of applying the proposed method on a typical and on a real network are presented in Section 4. And finally Section 5 concludes the paper.

1. Substation Expansion Planning

Power system planning studies consist of studies for the next 1–10 years or higher. Power system planning is a process in which the aim is to decide on new as well as upgrading existing system elements, to adequately satisfy the loads for a foreseen future [1]. The elements may be

- Generation facilities
- Substations
- Transmission lines and/or cables
- Capacitors/Reactors
- Etc.

The paper focuses on the case of substations. The aim of substation expansion planning is to determine a set of decision variables including substations' location, sizes and associated service areas with minimum expansion cost besides respecting technical constraints [21].

In mathematical terms, the problem may be defined as Equations (1) to (6).

Objective function of the SEP problem is presented in Equation (1), where the terms show expansion costs of the selected substations, total required costs for expanding the medium voltage feeders, total costs associated with medium feeder losses, substations no-load loss costs and substations loading loss costs respectively.

$$\begin{aligned} Fitness = & \sum_{i=1}^{n_s} C_i^S + \sum_{i=1}^{n_s}\sum_{j=1}^{n_l} C_{ij}^F .d_{ij} .\beta_{ij} \\ & + \sum_{h=1}^{n_y} PW^h \sum_{i=1}^{n_s}\sum_{j=1}^{n_l} \alpha.\gamma.\beta_{ij} .C^l .P_{ij}^{loss} \\ & + \sum_{h=1}^{n_y} PW^h . \sum_{i=1}^{n_s} \alpha.C^l .P_i^{iron} \\ & + \sum_{h=1}^{n_y} PW^h . \sum_{i=1}^{n_s} \alpha.\gamma.C^l .P_i^{cu} . \left(\frac{S_i^s}{CS_i} \right)^2 \end{aligned} \tag{1}$$

$$PW = \frac{1+\mathrm{inf\_}r}{1+\mathrm{int\_}r} \tag{2}$$

$$P_{ij}^{loss} = \frac{\left(S_j^l\right)^2 .d_{ij} .r_{ij}}{\left|V_n\right|^2}, \qquad \forall i \in \Omega^s, \qquad \forall j \in \Omega^l \tag{3}$$

$$S_i^s = \sum_{j=1}^{n_l} \beta_{ij} .\left(S_j^l + P_{ij}^{loss}\right), \qquad \forall i \in \Omega^s \tag{4}$$

$$\psi^{\min} .CS_i \le S_i^s \le \psi^{\max} .CS_i , \qquad \forall i \in \Omega^s \tag{5}$$

$$\left|\frac{S_j^l.\sum_{k=1}^{n_s}\left[\beta_{kj}.d_{kj}.z_{kj}\right]}{V_n}\right| \le \Delta V_{\max}, \qquad \forall j \in \Omega^l \tag{6}$$

Equations (5) and (6) guarantee the SEP constraints. Each feeder, regarding its conductor type, is able to transfer a certain amount of power. Also, due to the reliability considerations, substations should have less loading than the nominal capacity. These requirements are guaranteed by Equation (5). Finally, Equation (6) ensures that proper supplies to the electric consumers have been achieved with permissible voltage drop at load points [21].

The BFOA, as a powerful tool for solving the above complicated optimization problem, will be discussed in what follows.

2. Bacterial Foraging Optimization Algorithm

BFO method was invented by Kevin M. Passino [22] motivated by the natural selection which tends to eliminates the animals with poor foraging strategies and favor those having successful foraging strategies. The foraging strategy is governed basically by four processes namely Chemotaxis, Swarming, Reproduction, Elimination and Dispersal [23].

Referring to [24], the four processes of the algorithm are as follows:

A) Chemotaxis

Chemotaxis process is the characteristics of movement of bacteria in search of food and consists of two processes namely swimming and tumbling. A bacterium is said to be 'swimming' if it moves in a predefined direction, and 'tumbling' if moving in an altogether different direction. Let *j* be the index of chemotactic step, *k* be the reproduction step and *l* be the elimination dispersal event. Let $\theta^i(j,k,1)$ is the position of *i*th bacteria at *j*th chemotactic step, *k*th reproduction step and *l*th elimination dispersal event, C is the size of the step taken in the random direction specified by the tumble, ϕ is the angle of the direction which is randomly generated in the range of [0, 2π). The position of the bacteria in the next chemotactic step after a tumble is given by

$$\theta^i(j+1,k,l)=\theta^i(j,k,l)+C\times\angle\phi \tag{1}$$

If the health of the bacteria improves after the tumble, the bacteria will continue to swim to the same direction for the specified steps or until the health degrades.

B) Swarming

Bacteria exhibits swarm behavior i.e. healthy bacteria try to attract other bacteria so that together they reach the desired location (solution point) more rapidly. The effect of Swarming is to make the bacteria congregate into groups and move as concentric patterns with high bacterial density. In mathematical terms, swarming behavior can be modeled as:

$$\begin{aligned}J_{cc}\left(\theta^i(j,k,l),\theta(j,k,l)\right)&=\sum_{i=1}^{s}J^t{}_{cc}\left(\theta^i,\theta\theta\right)\\&=\sum_{t=1}^{s}\left[-d_{attract}\exp\left(-\omega_{attract}\sum_{m=1}^{p}\left(\theta^i{}_m-\theta^t_m\right)^2\right)\right]\\&+\sum_{t=1}^{s}\left[-d_{repellant}\exp\left(-\omega_{repellant}\sum_{m=1}^{p}\left(\theta^i{}_m-\theta^t_m\right)^2\right)\right]\end{aligned} \tag{2}$$

Where $J_{cc}\left(\theta^i,\theta\right)$ is the cost function value to be added to the actual cost function to be minimized to present a time varying cost function. *s* is the total number of bacteria and *p* the number of parameters to be optimized which are present in each bacterium. $d_{attract}$, $\omega_{attract}$,$d_{repellant}$,$\omega_{repellant}$ are different coefficients that are to be chosen properly.

C) Reproduction

In this step, population members who have had sufficient nutrients will reproduce and the least healthy bacteria will die. The healthier half of the population replaces with the other half of bacteria which gets eliminated, owing to their poorer foraging abilities. This makes the population of bacteria constant in the evolution process.

D) Elimination and Dispersal

In the evolution process a sudden unforeseen event may drastically alter the evolution and may cause the elimination and/or dispersion to a new environment. Elimination and dispersal helps in reducing the behavior of stagnation i.e. being trapped in a premature solution point or local optima.

3. Numerical Results

In this section, a typical network is assumed and the results of substation expansion planning by the use of BFOA are obtained. In the horizon year (2020), the typical network consists of 31 load centers and 5 existing substations that are listed according to Tables I and II of Appendix. The network parameters, feeder parameters, investment cost of the existing substations, and new substations installation cost are presented according to Tables I through III.

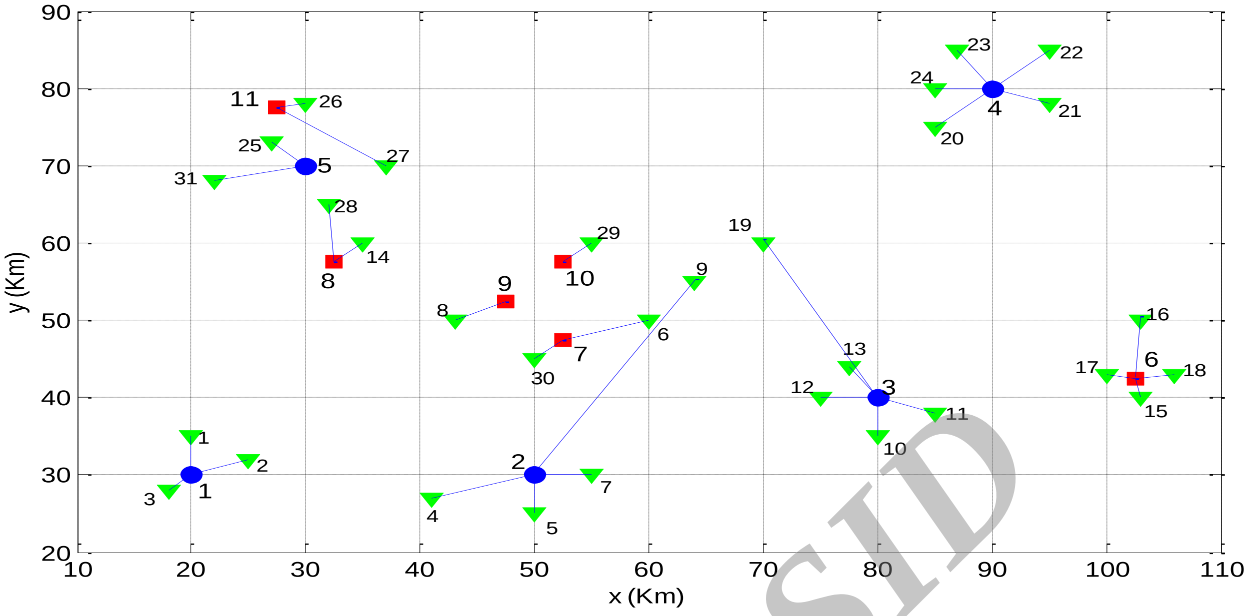

Fig. 1. Results of applying GA to solve the SEP problem on the typical network(▼: Load Centers, ●: Existing and, ■: New Substations)

Table.1.
Parameters of the typical network

Losses Cost(M$/ MWhr)	Permitted voltage drop	Power factor	Loss factor	reserve factor
0.9	5%	0.85	0.36	0.3

Table.2.
Characteristics of the feeders of the typical network

Feeders capacity (MVA)	5	10
Feeders installation cost ($/Km)	8000	11000
Feeder resistance (Ω/Km)	0.068	0.034
Feeder reactance (Ω/Km)	0.04	0.08

Table.3.
Expansion and installation cost of the substations of the typical network

Capacity of substations (MVA)	45	30	15
Installation cost of substations (M$)	4.5	3	1.5
Cost of expansion to higher capacity (M$)	-	0.7	0.430
No load losses (MW)	0.041	0.027	0.013

In this paper, the candidates are acquired by dividing the area under study into a number of small squares and the center of each square is considered as the candidate point.

In order to compare the performance of the proposed algorithm with other methods, SEP results for the proposed network is obtained by GA, as a famous method in SEP, at first.

In order to make sure that GA and BFOA have really found the best solution, the simulations are executed many times and the best results are considered as the optimum solution.

Fig. 1 depicts the results of applying GA on the typical network. After running the program, all of the loads are fed by substations in the horizon year. Six new substations have been installed in the shown positions and four substations have been expanded. Table IV provides more details. Fig. 2 shows the convergence curve of the GA. The curve depicts that the algorithm is converged after about 560 iterations during 327 seconds.

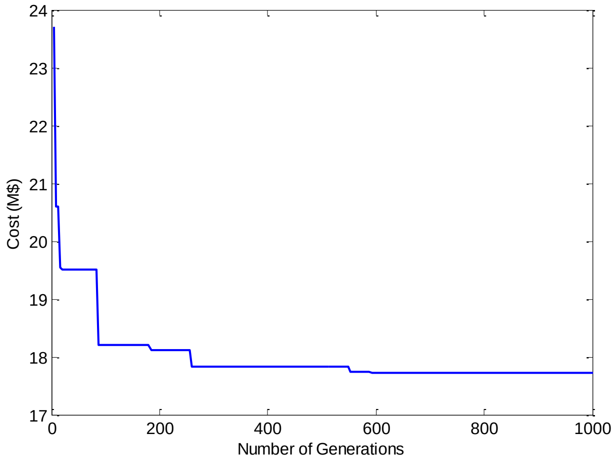

Fig. 2. Convergence curve of GA

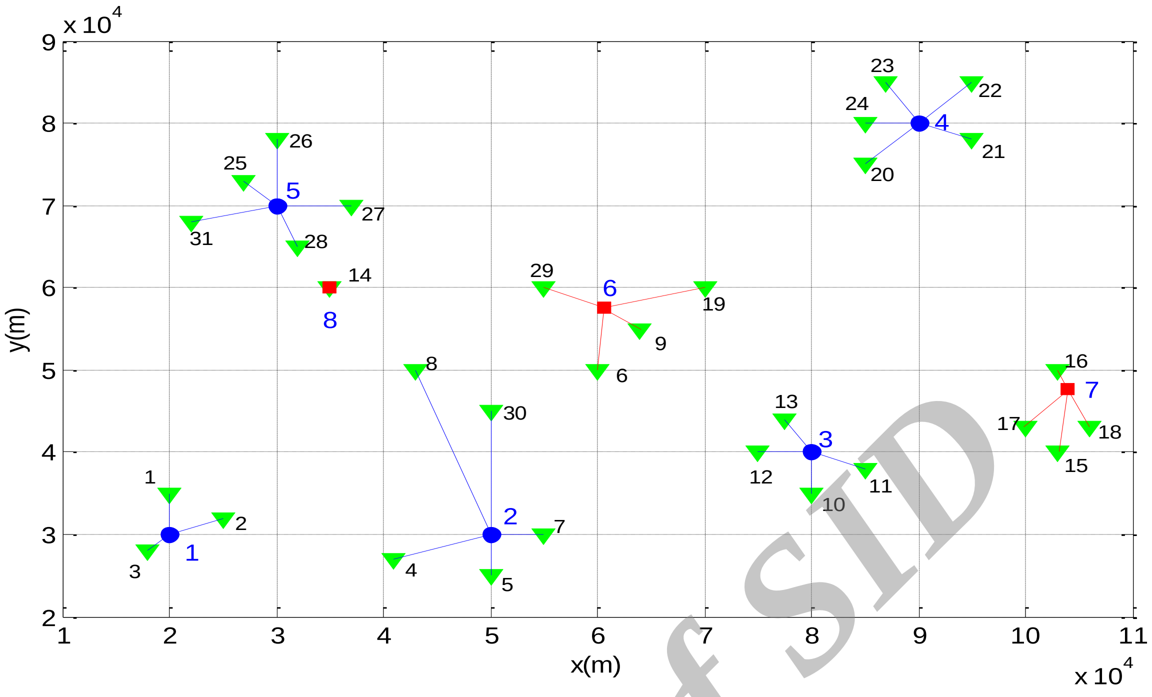

Fig. 3. Results of applying BFOA to solve the SEP problem on the typical network, ▼: Load Centers, ●: Existing and ■: New Substations

In the following, the results of applying BFOA on the typical network are presented. Fig. 3 and Table V show the results, it is clear that by installing three new substations in the shown positions and by expanding one existing substation, the loads will be adequately supplied in the horizon year.

For more details see Table V.Fig. 4 shows the convergence curve of the BFOA. The curve depicts that the algorithm is converged after about 480 iterations during 263 seconds. By comparing the Tables IV and V it is clear that the expansion cost of the network by the BFOA is lower.

Thus, the solution presented by the BFOA is preferable. By comparing the results of Tables IV and V and the convergence curves of GA and BFOA it is clear that GA falls in local minima and is not as able as BFOA at solving SEP problem. In other words, BFOA is more able than GA to find an optimal solution to SEP. Table VI presents the control parameters of the GA and the BFOA.

4. Conclusion

Substation expansion planning is one of the important parts of the power system expansion planning studies. The diversity of decision variables in the SEP problem has made the solution process more difficult. This paper introduced a new method for solving the SEP as an optimization problem. Optimization method was based on BFOA. To demonstrate the capabilities of the BFOA, GA was used as the benchmark method for assessing validity. A typical and a real network were assumed and the results of SEP by the use of GA and BFOA were obtained. The results showed that BFOA was more efficient than GA in finding the solutions. The results of applying BFOA on the real network showed the functional capabilities of the presented method.

Other features of this method are the capability to apply to sub-transmission and transmission networks, high speed of convergence, quality of solutions, consideration of real-world networks limitations as SEP constraints, and simplicity in applying to real networks.

Table.4.
Detailed results of applying GA to solve the SEP problem on the typical network

Number of new installed substations	6
Sum of loads	152 (MW)
Sum of the new substations capacity	105 (MVA)
Installation cost of the new substations	10,500,000($)
Expanded substations	1,2,3,4
Sum of the old substations expansion capacity	90 (MVA)
Expansion cost of the old substations	6,755,000($)
Low voltage expansion cost	1,125,000 ($)
Total expansion cost	17,705,000($)

Table.5.
Detailed results of applying BFOA to solve the SEP problem on the typical network

No. of new installed substations	3
Sum of the loads	152 (MW)
Sum of the capacity of new substations	105 (MVA)
Installation cost of the new substations	10,500,000($)
Expanded substations	1,2,3,4,5
Sum of the expansion capacity of the old substations	120 (MVA)
Expansion cost of the old substations	4,900,000($)
Low voltage expansion cost	1,575,000($)
Total cost of expansion	16,975,000($)

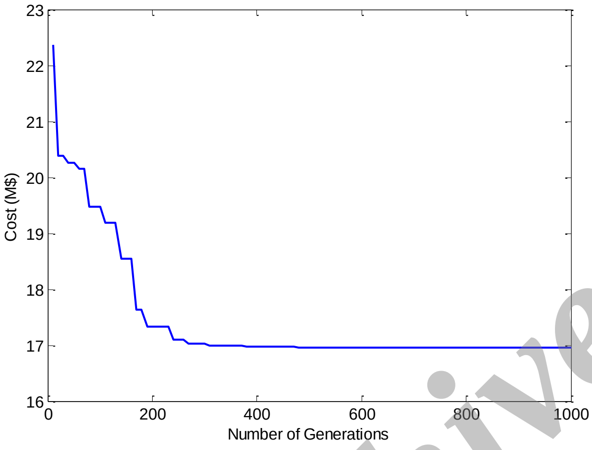

Fig. 4. Convergence curve of BFOA

Table.6.
Control parameters of GA and BFOA

BFOA Parameters		GA Parameters	
number of bacteria	8	population size	30
number of swimming steps	6	mutation rate	0.8
number of chemotaxis steps	20	cross over rate	0.2
number of reproduction	5		
number of elimination and dispersal	5		
probability index of elimination and dispersal	0.4		
step size for each bacterium	0.05		

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Appendix

Table.1.
Load centers profiles of the typical network

Load Center No.	Position		Load (MW)
	X (Km)	Y (Km)	
1	20	35	5
2	25	32	3
3	18	28	2
4	41	27	3
5	50	25	7
6	60	50	4
7	55	30	5
8	43	50	6
9	52	28	2
10	80	35	5
11	85	38	5
12	75	40	3
13	77.5	44	10
14	80	46	7
15	103	40	3
16	103	50	10
17	100	43	5
18	106	43	5
19	55	55	10
20	85	75	2
21	95	78	5
22	95	85	4
23	87	85	4
24	85	80	5
25	27	73	5
26	30	78	4
27	37	70	4
28	32	65	4
29	15.5	67.5	8
30	25	45	4
31	22	68	3

Table.2.
Existing Substations specifications of the typical network

No.	Position		Allocated Loads	Existing Capacity	Expandable Capacity
	X	Y			
1	20	30	1	15	15,30
2	50	30	4	15	15,30
3	80	40	10,11,12	30	15,30
4	90	80	20	15	15,30
5	30	70	25	15	15,30

Table.3.
Specifications of the load centers of the real network

No. of load centers	X (km)	Y (km)	Load (MW)	Feeding sub no.	No. of load centers	X (km)	Y (km)	Load (MW)	Feeding sub no.
1	616.97	3839.29	1.45	18	47	750.04	3560.93	0.001	13
2	771.46	3701.35	2.33	2	48	531.1	3756.57	1.76	4
3	762.62	3658.31	2.03	12	49	708.04	3641.32	2.12	5
4	803.41	3696.85	0.82	1	50	768.51	3629.40	1.86	1
5	790.96	3759.38	0.99	6	51	703.59	3715.31	3.76	19
6	531.05	3711.72	3.11	4	52	615.75	3764.66	0.79	18
7	631.32	3804.81	3.83	11	53	685.76	3667.38	2.97	10
8	541.43	3795.6	3.28	4	54	632.71	3742.98	3	11
9	759.69	3783.94	6.88	2	55	601.86	3768.59	4.98	14
10	696.66	3795.18	5.61	19	56	531.91	3741.91	1.5	4

11	613.22	3738.70	0.92	18	57	699.37	3639.02	0.69	5
12	722.81	3585.92	1.67	12	58	687.01	3636.73	0.41	8
13	684.64	3674.55	1.25	8	59	703.79	3604.29	3.67	8
14	614.99	3740.40	0.16	18	60	543.14	3748.38	3.15	4
15	705.19	3619.16	1.55	10	61	783.95	3498.88	4.39	16
16	720.52	3620.20	0.55	10	62	562.95	3791.10	1.51	14
17	707.29	3699.59	9.21	5	63	784.39	3589.82	5.42	12
18	621.89	3736.17	0.99	18	64	695.73	3638.59	4.38	5
19	648.06	3607.20	2.66	8	65	642.69	3740.64	4	11
20	614.71	3751.60	0.1	14	66	720.13	3744.58	4.18	15
21	842.61	3466.57	1.36	16	67	719.94	3690.32	2.05	10
22	707.37	3698.72	10.14	5	68	676.81	3755.76	3.44	7
23	701.34	3790.80	3.92	19	69	699.41	3713.00	5	19
24	664.656	3716.48	1	7	70	677.66	3716.67	2.11	15
25	667.27	3791.98	2.21	7	71	540.34	3748.74	2.23	4
26	659.98	3796.83	3.86	11	72	698.77	3638.74	0.87	5
27	611	3746.12	2.48	14	73	770.11	3651.45	4	1
28	676.78	3568.45	5.83	8	74	758.76	3704.17	4	2
29	760.08	3417.60	3.91	16	75	540.73	3742.55	2	4
30	641.48	3712.68	0.38	11	76	708.75	3637.79	2	5
31	676.67	3650.90	1.28	8	77	708.78	3637.88	2	5
32	719.21	3693.89	12.02	17	78	694.85	3639.34	7	5
33	764.59	3601.82	4.91	1	79	780.28	3723.06	4	6
34	642.93	3797.19	2.55	11	80	667.51	3764.98	4	7
35	607.99	3704.20	3.49	14	81	688.92	3519.53	1.9	0
36	669.58	3717.56	2.24	7	82	707.91	3691.02	4	10
37	704.44	3697.42	11.52	5	83	640.85	3716.46	4	11
38	715.42	3696.98	3.15	5	84	631.35	3748.78	4	11
39	741.22	3694.93	4.17	12	85	758.75	3614.46	2	12
40	624.34	3709.33	1.94	14	86	739.11	3621.54	4	12
41	787.13	3493.81	4.06	16	87	614.91	3771.07	6	14
42	708.07	3637.01	4.15	17	88	701.39	3743.07	30	15
43	803.36	3721.71	3.32	6	89	783.47	3529.32	4	16
44	785.88	3522.17	3.87	16	90	825.84	3576.61	14.7	0
45	725.46	3706.14	1.55	15	91	735.62	3558.52	2.14	0
46	807.15	3616.75	1.32	1	92	767.35	3563.80	1.83	0