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Distributed Generation Capacity Evaluation Using Combined Genetic Algorithm and OPF

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Distributed Generation Capacity Evaluation Using Combined Genetic Algorithm and OPF[*]

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Abstract

A range of techniques has been proposed to define the optimal locations and capacities of distributed generation (DG) as a means of ensuring that the maximum amount of DG can be connected to existing and future networks. However, there are limitations inherent in these methods, not least in finding the best combination of sites for connecting a predefined number of DGs. Here, a method combining optimal power flow and genetic algorithms aims to meet this requirement. Its use would be in enabling Distribution Network Operators to search a network for the best sites and capacities available to strategically connect a defined number of DGs among a large number of potential combinations. Some applications of the proposed methodology confirmed its effectiveness in sitting and sizing an assigned number of DG units.

KEYWORDS: distributed generation, power flow analysis, optimization methods, power generation planning

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I. INTRODUCTION

Connection of distributed generation (DG) fundamentally alters distribution network operation and creates a variety of well-documented impacts with voltage rise being the dominant effect, particularly in rural networks [1], [2]. Traditional options to mitigate adverse impacts remain costly for developers and Distribution Network Operators (DNOs). With the increasing levels of generation to be accommodated, planning and design of distribution networks will need to change to harness approaches that use information and communication technology to actively manage the network (e.g., network reconfiguration [3]). Further, current DNO policies of assessing DG connections on a first come-first served basis must be adapted to avoid ‘sterilizing’ parts of the network [4].

DG developments are driven by the potential to exploit renewable resources or combined heat and power (CHP). The need to mitigate DG-related effects occurs because of the mismatch between the location of these resources and the capability of the network to accept new generation. It is logical therefore to make best use of the existing network by DNOs encouraging development at the most suitable locations. As DNOs do not explicitly control the location of DG developments, this may be best achieved by the DNO issuing information to developers regarding the existence of spare connection capacity or from locational signals created by connection pricing. In order to do this, DNOs require a reliable and repeatable method of quantifying the capacity of new DG that may be connected to distribution networks without the need for reinforcement.

The challenge of identifying the best network locations for DG has attracted significant research effort, albeit referred to by several terms: optimal ‘capacity evaluation’ [4], ‘DG placement’ [5], or ‘capacity allocation’ [6], [7], [8]. While the literature suggests a wide range of objectives and a variety of constraints, two distinct approaches to the problem can be identified:

1. finding optimal locations for defined DG capacities, and
2. finding optimal DG capacities at defined locations.

The first approach aims to site DG of specified, discrete, capacities at the best sites. This problem has generally been tackled using genetic algorithms (GAs) [9]–[11] or other methods [5], [12] which can handle discrete formulations. For example, in [11] a GA was used to place generators of discrete capacities in order to minimize losses, costs and network disruption, while [12] adopted a heuristic approach where an investment-based objective function determines optimal DG site and size, assumed to be a multiple of a given capacity. In [13] an optimization technique, based on GAs and optimal power flow has been applied to minimize the active and reactive power generation costs together with the installation costs of DG. Simulation results pointed out that fixed capacities for DG units were defined by the GA, with optimal power flow being used to optimise the operating costs and points of the DGs rather than the capacities. The prejudging of capacity means that some opportunities that are smaller or larger than the standard will not be selected, resulting a non-optimal solution. Alternatively, when a large range of test capacities are to be examined this extends the field of search considerably.

The second approach requires the user to specify the network locations of interest and the algorithm will guide capacity growth at each location whilst respecting network constraints. The methods tend to use continuous functions of capacity solved using analytical approaches like optimal power flow [4]–[6], linear programming [7] or gradient search [14]. These approaches are robust, well defined and accepted and the outcome repeatable. A downside is that where a large number of locations are searched the perceived optimal solution may contain a number of sites with very small capacities. While this may be the case mathematically, the upfront costs of connection suggest the very small plant would not be economic. Specifying a minimum capacity at each location would unduly bias the analysis and potentially result in the algorithm being unable to find a feasible solution. As such, the major issue with these approaches is how to determine the best set of locations, given that the number of combinations of r locations in a network of n buses is given by ${}^{n}C_{r}$ which, even for a modest distribution network, represents a significant effort beyond the feasibility of manual searches [13].

It is clear that while each of the broad approaches identified above offers advantages in terms of examining one of the problems, no approach in the literature can truly provide both optimal siting *and* sizing of DG across an entire network for a given number of DG units, without the requirement of predetermining capacities or locations. Here, a method is presented that combines the analytical accuracy of OPF with the ability of the genetic algorithm to efficiently search a large range of locational combinations. Although this comes at the expense of requiring predefinition of the number of DG units, this allows exploration of a range of interesting problems.

The paper is set out as follows: Section II sets out the basis for the hybrid DG capacity evaluation approach; Section III presents a case study using the tool which is discussed further in Section IV.

II. COMBINED GA-OPF OPTIMAL CAPACITY ALLOCATION

Optimal capacity allocation aims to define the optimal capacity of new generation that may be accommodated within the existing network, subject to a range of constraints imposed by statutory regulations (e.g., voltage limits), equipment specification (e.g., thermal limits on lines and transformers) or other operational or planning limits. In line with existing and traditional DNO practice in the UK these assessments are made assuming the worst case situation of maximum DG output at minimum load which provides the largest reverse power flows and voltage rise [1], [15]–[18].

The optimal DG capacity is deemed to be that of the DNO. Clearly, the attitude of the DNO is dependent on the actual or perceived benefits or costs associated with DG connection, and these will vary between systems. A significant driver of the costs and benefits will be the regulatory rules or incentives applicable to DG. Here the most general case in which the DNO is interested in simply maximizing connected capacity of DG, is described.

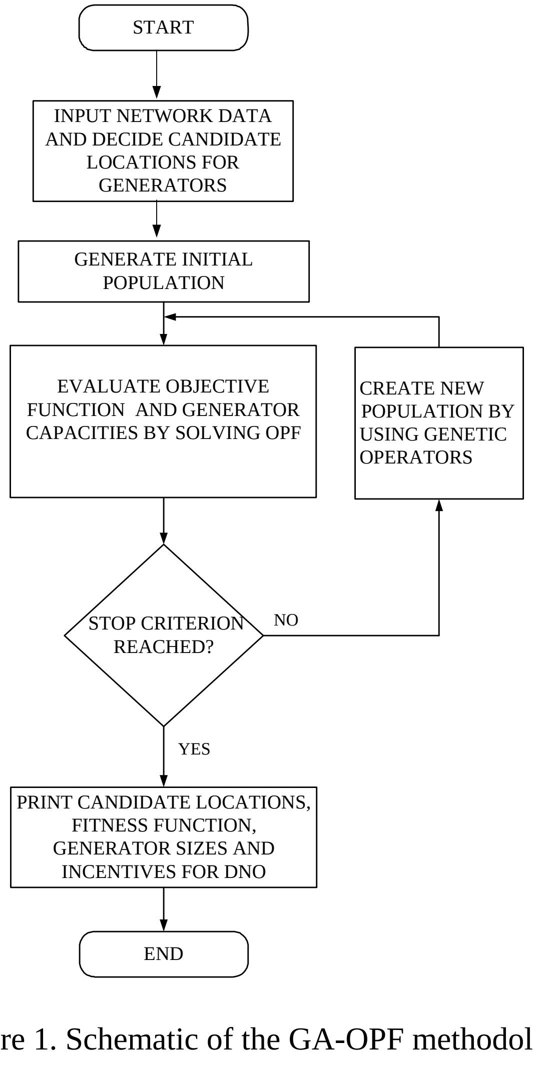

Figure 1. Schematic of the GA-OPF methodology.

This method requires the user to define the number of DG units to be connected rather than constraining the locations or unit size of generators. The Genetic Algorithm generates and optimizes combinations of locations from those possible for the network in question. For each combination of locations, an optimal power flow is used to define the capacity available for this combination: in essence the OPF is the GA's fitness function. This information is fed back to the GA which searches for the optimal connectable capacity as viewed by the DNO. As such, this combination method should deliver the best locations as well as the capacities available for a user-specified number of DG. The methodology is shown in Figure 1 and explained in more detail in the remainder of the section, beginning with the OPF component.

A. Optimal capacity allocation using OPF

For each set of locations provided by the GA, the maximum network capacity available for new DG (i.e., within the technical constraints) is found using the OPF. By returning the available capacity to the GA, the OPF acts as the fitness function for the GA.

Following the OPF approach of [4] and [6], the maximum DG capacity can be determined by modelling DG as generators with negative cost coefficients. By minimizing the (negative) cost of all these generators, the DG capacity and benefit resulting from it are maximized. The generator capacity cost function can take a range of forms depending on the situation including quadratics [6], [8] or linear forms [4]. Here, the simple linear function is assumed:

$$f_{OPF} = \sum_{g=1}^{n} C_g \cdot P_g \qquad (1)$$

where C_g represents the benefit the DNO derives from connecting generator g of capacity P_g. This is consistent with current UK practice where developers pay DNOs the sum of £2.50 per year for every kW of new DG connected. Incidentally, in the absence of any other objectives the value of the benefit is essentially arbitrary [6].

As DG capacity is inherently limited by the energy resource at any given location it is necessary to constrain capacity between maximum and minimum levels:

$$P_g^{\min} \le P_g \le P_g^{\max} \qquad (2)$$

A significant amount of research effort is being expended on active management of distribution networks wherein reactive power and voltage will be controlled to enhance DG penetration, e.g., [15], [19]. However, there are difficulties associated with this, not least in coordinating the action of DG and other network control elements. As such, it has been assumed that DG operates in power factor control mode, necessitating a constraint on power factor [19]:

$$\cos\phi_g = P_g \Big/ \sqrt{P_g^2 + Q_g^2} = const. \qquad (3)$$

The safe operation of power system equipment and quality of supply requires voltages to be maintained close to nominal:

$$V_b^{\min} \le V_b \le V_b^{\max} \qquad (4)$$

where $V_b^{\min}$ and $V_b^{\max}$ are the lower and upper bounds of the bus voltage V_b.

The thermal capacity, $S_t^{\max}$, of each line or transformer, t, also sets a limit to the maximum apparent power, S_t, transfer:

$$\left|S_t\right| \le S_t^{\max} \qquad (5)$$

For simplicity, other constraints on DG penetration such as the additional fault contributions from the DG are not considered here but could be included within the proposed methodology as described in [6] and [8].

B. Genetic Algorithm

The genetic algorithm is used to efficiently search the range of combinations of DG locations for a specified number of DG units. The GA will randomly generate the initial population of solutions (individuals) by defining a set of combinations of buses (defined by the population size). Each combination (chromosome) is represented by a vector of integers, each of which identifies an individual bus. As such, the location of DG units is expressed as a string of bus numbers. For each chromosome, defining locations for DG in the initial population, the OPF procedure nested in the GA algorithm determines the fitness of the combination by computing the optimal capacities considering the worst case of minimum load [1], [15]–[18], according to the objective function defined in (1).

At each generation, a new set of improved individuals is created by selecting individuals according to their fitness; the selection mechanism used here is the normalized geometric ranking scheme. After the new population is selected, each genetic operator is applied a discrete number of times to selected individuals These are: simple crossover, which randomly selects a cut-point dividing each parent into two segments and binary mutation that changes each of the bits of the parent based on the probability of mutation. An elitism mechanism, ensuring the best member of the population is not lost, is also adopted. The iteration process continues until the stop criteria are reached: the process stops when improvement of the best objective function value is below a threshold for a given number of generations or if the total number of generations is higher than a maximum number. It is worth noting that the requirement to pre-specify the number of locations allows DNOs to examine different opportunities when varying the number and locations of DG units to be installed. In this way DNOs could also be able to plan for DG connections in a desired order over a time horizon. In the case that DNO is not allowed to own its generation, DNO may however estimate additional credit that might be offered to private investors [9]. Further, an alternative chromosome representation of individuals, considering both the number and location of DG units, without the number constraint [13], suggests that the methodology should be entirely flexible.

C. Implementation

The methodology has been implemented in the Matlab®environment, incorporating some features of the approaches used in the MATPOWER suite [20]. Its use is illustrated in the following case study to identify the best combinations of a specified number of DG units within the network.

III. CASE STUDY

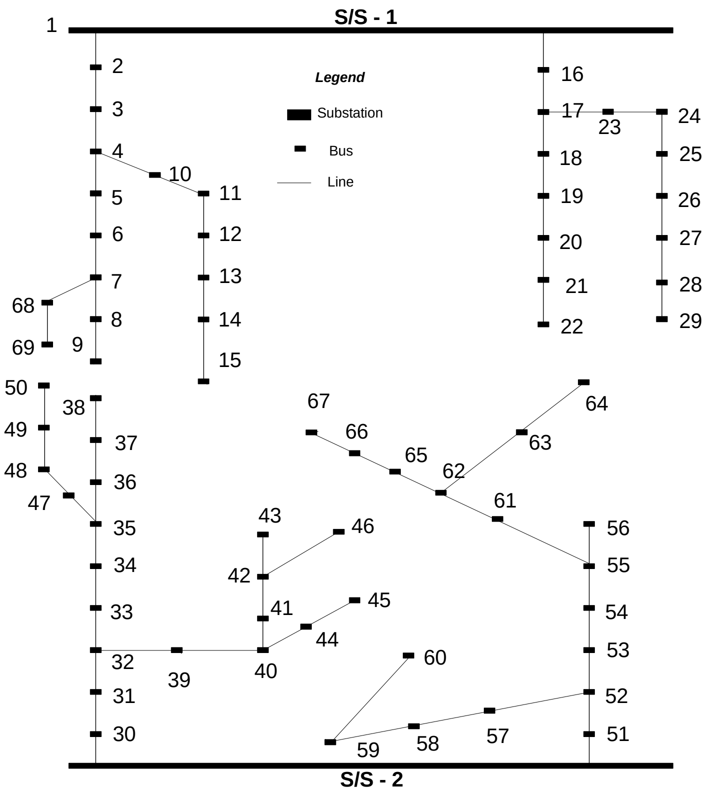

Figure 2. Radial distribution system.

A. Test System

Simulations were carried out on an 11-kV distribution system having two substations, four feeders, 69 nodes and 67 branches [21].

The network is shown in Figure 2 with detailed network data given in the Appendix. The system operates within voltages limits of ±6% of nominal and thermal limits of 3 MVA for all lines. All DG units were assumed to have fixed power factors of 0.9 lagging. The minimum aggregate active and reactive loadings are 4.47 MW and 3.06 MVA, respectively.

For illustration, the objective function assumes that the DNO benefits by £2.50 per year for every kW of new DG connected; this value is currently that applicable in the UK. Incidentally, in the absence of any other objectives the value of the benefit is essentially arbitrary as all locations will be favoured equally [4].

B. GA Setup

The GA uses a normalized geometric ranking scheme as a selection mechanism, while the simple crossover and the binary mutation are employed as genetic operators. A GA population size of 30 has been selected and the algorithm stops if the best solution does not improve by £100/year over 50 generations and if the number of generations reaches 300: these values were found to guarantee the convergence of the algorithm to a satisfactory solution.

C. Analyses

To demonstrate the approach, several analyses have been carried out to answer the following questions:

1. Where are the best positions and capacities available within the network to locate DG units?
2. What benefit, if any, accrues for greater numbers of DG?

A series of simulations were run to define the optimal connection points and capacities for a defined number of potential DG units. These were for the best set of 3, 5, 7 and 9 units located within the 67 possible sites, representing a search space of 4.79×10^{4}, 9.66×10^{6}, 8.70×10^{8} and 4.28×10^{10} combinations, respectively.

Each simulation is a fairly lengthy process, but given that this process is a strategic one, the duration is reasonable.

D. Results and Analysis

The optimal locations and capacities for the four DG cases are shown in Table 1 along with the values of the objective function, equating to the annual payments accruing to the DNO. The locations selected for the four cases are illustrated in Figure 3 with each circle representing an appearance in one of the optimal sets. In all cases the limiting factor on DG capacity is voltage rise.

There is a tendency for similar locations to be favoured across the four cases: Bus 38 appears in all four cases, while Bus 64 appears in three, with three other locations featuring in two of the assessments. In many of the cases the optimal locations appear to be towards the end of the feeders or close to branch points.

Bus	**Capacity Added [MW]**			
	3 DG	**5 DG**	**7 DG**	**9 DG**
8		1.769		
9			1.672	1.648
17		0.041	0.055	
18	2.634			
19		2.885		
20				2.402
22			1.801	
26				0.101
28				0.103
29			0.216	0.119
38	0.424	1.823	1.867	1.884
40			0.059	
42				0.060
52	4.028			
55				1.001
64		0.862	1.725	1.155
Total	**7.087**	**7.379**	**7.394**	**8.472**
Objective (£/year)	**17,716**	**18,447**	**18,486**	**21,180**

Table 1. Optimal DG Locations and Capacities

In the cases examined here, the network offers several times more potential sites than potential DG resulting in capacity being spread across different feeders.

This occurs as the voltages at buses on the same feeder are strongly interdependent, with DG capacity at one bus tending to crowd out that of others ([4] explores this aspect in detail). As such, with the low numbers of generators, the method will connect maximum generation at locations that are relatively far apart, electrically. It would be expected that as the number of DG increases the greater the likelihood of two or more DG being located on the same feeder with consequent voltage interdependence.

The overall connectable capacity increases with the number of DGs, with capacity increasing by 20% between the 3 and 9 unit cases. This is reflected in the value of the objective function (nominally representing the DG benefit) which rises as more capacity is connected, increasing from almost £18k to above £21k over the range of cases identified here. As described in [4] the maximum connectable capacity will continue to rise until DG is sited at every location.

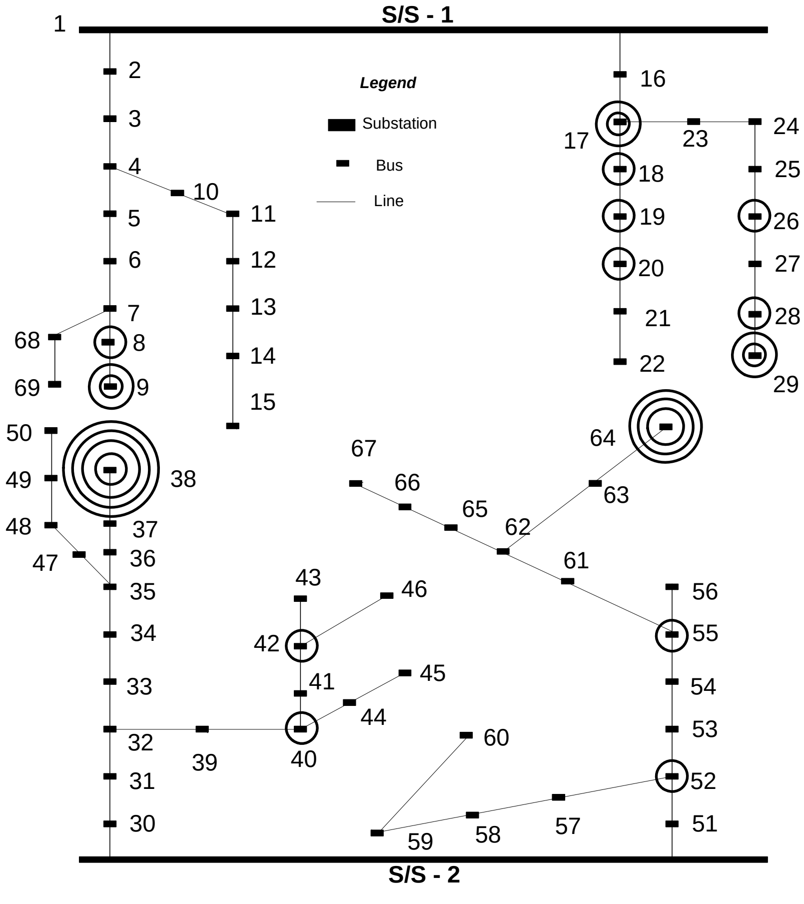

Figure 3. Optimal location of DG across all 4 cases (one circle per case)

IV. DISCUSSION

The method presented here attempts to overcome limitations to determining optimal DG capacity within existing approaches described in the literature. The combination of OPF and GA techniques provides a means of finding the best combination of sites within a distribution network for connecting a predefined number of DGs.

As such, it would allow DNOs to search a given network for the best sites to strategically connect specified number of DG among a large number of potential combinations. DNOs could use this information to plan for DG connections in a desired order over a given time horizon thus overcoming difficulties with current first come-first served connection policies.

This paper concentrates on the technical constraints on DG development. As such, it does not deal explicitly with the issue of DG impacts on losses, although this is an area that is being extensively researched at present. Although modest penetrations of DG tend to reduce losses, the maximization of DG capacity as developed in this paper tends to promote reverse power flows and raise losses; this effect is demonstrated in [19] and [22].

The impact of the incentive offered to the DNO by loss reduction on optimal placement of DG is briefly covered in [19] while in [23] the authors discuss the implications of this and other potential DG benefits in terms of the behaviour of DNOs and developers.

The intention here was to provide a means of analyzing the optimal connection of broadly deterministic energy sources (e.g., CHP) within applicable deterministic network constraints. The approach could be adapted to cope with variable energy sources and probabilistic network constraints to allow a cost-benefit approach to be taken.

V. CONCLUSIONS

A method combining optimal power flow and genetic algorithms aims to provide a means of finding the best combination of sites within a distribution network for connecting a predefined number of DGs. In doing so it overcomes known limitations inherent in current available techniques to optimize DG capacity. Its use would be to enable DNOs to search a network for the best sites to strategically connect a small number of DGs among a large number of potential combinations.

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VII. APPENDIX: 69-BUS SYSTEM DATA

n.line	s-bus	r-bus	R (Ω)	X (Ω)	P (r-bus) (kW)	Q (r-bus) (kVAr)
1	1	2	1.0970	1.0740	100	90
2	2	3	1.4630	1.4320	60	40
3	3	4	0.7310	0.7160	150	130
4	4	5	0.3660	0.3580	75	50
5	5	6	1.8280	1.7900	15	9
6	6	7	1.0970	1.0740	18	14
7	7	8	0.7310	0.7160	13	10
8	8	9	0.7310	0.7160	16	11
9	4	10	1.0800	0.7340	20	10
10	10	11	1.6200	1.1010	16	9
11	11	12	1.0800	0.7340	50	40
12	12	13	1.3500	0.9170	105	90
13	13	14	0.8100	0.5500	25	15
14	14	15	1.9440	1.3210	40	25
15	7	68	1.0800	0.7340	100	60
16	68	69	1.6200	1.1010	40	30
17	1	16	1.0970	1.0740	60	30
18	16	17	0.3660	0.3580	40	25
19	17	18	1.4630	1.4320	15	9
20	18	19	0.9140	0.8950	13	7
21	19	20	0.8040	0.7870	30	20
22	20	21	1.1330	1.1100	90	50
23	21	22	0.4750	0.4650	50	30
24	17	23	2.2140	1.5050	60	40
25	23	24	1.6200	1.1100	100	80
26	24	25	1.0800	0.7340	80	65
27	25	26	0.5400	0.3670	100	60
28	26	27	0.5400	0.3670	100	55
29	27	28	1.0800	0.7340	120	70
30	28	29	1.0800	0.7340	105	70
31	1	30	0.3660	0.3580	80	50
32	30	31	0.7310	0.7160	60	40
33	31	32	0.7310	0.7160	13	8
34	32	33	0.8040	0.7870	16	9
35	33	34	1.1700	1.1450	50	30
36	34	35	0.7680	0.7520	40	28
37	35	36	0.7310	0.7160	60	40
38	36	37	1.0970	1.0740	40	30
39	37	38	1.4630	1.4320	30	25
40	32	39	1.0800	0.7340	150	100
41	39	40	0.5400	0.3670	60	35
42	40	41	1.0800	0.7340	120	70
43	41	42	1.8360	1.2480	90	60
44	42	43	1.2960	0.8810	18	10
45	40	44	1.1880	0.8070	16	10
46	44	45	0.5400	0.3670	100	50
47	42	46	1.0800	0.7340	60	40
48	35	47	0.5400	0.3670	90	70
49	47	48	1.0800	0.7340	85	55
50	48	49	1.0800	0.7340	100	70
51	49	50	1.0800	0.7340	140	90
52	1	51	0.3660	0.3580	60	40
53	51	52	1.4630	1.4320	20	11
54	52	53	1.4630	1.4320	40	30
55	53	54	0.9140	0.8950	36	24
56	54	55	1.0970	1.0740	30	20
57	55	56	1.0970	1.0740	43	30
58	52	57	0.2700	0.1830	80	50
59	57	58	0.2700	0.1830	240	120
60	58	59	0.8100	0.5500	125	110
61	59	60	1.2960	0.8810	25	10
62	55	61	1.1880	0.8070	10	5
63	61	62	1.1880	0.8070	150	130
64	62	63	0.8100	0.5500	50	30
65	63	64	1.6200	1.1010	30	20
66	62	65	1.0800	0.7340	130	120
67	65	66	0.5400	0.3670	150	130
68	66	67	1.0800	0.7340	25	15