BIG BANG–BIG CRUNCH OPTIMIZATION ALGORITHM FOR ECONOMIC DISPATCH WITH VALVE-POINT EFFECT

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ABSTRACT

The Big Bang–Big Crunch (BB–BC) optimization algorithm is a new optimization method that relies on the Big Bang and Big Crunch theory, one of the theories of the evolution of the universe. In this paper, a Big Bang–Big Crunch algorithm is presented for solving optimal power flow (OPF) problems with valve-point effects. The proposed algorithm has been tested with the IEEE 30-bus system with different fuel cost characteristics, quadratic cost curve model, and quadratic cost curve with valve-point effects model. Numerical results demonstrate the efficiency of the BB–BC algorithm compared to other heuristic algorithms.

Keywords: *Big Bang–Big Crunch, optimal power flow, Economic Dispatch, Valve-point effect*

1. INTRODUCTION

Economic dispatch is one of the most important problems to be solved in the operation of a power system. Improvements in scheduling the unit outputs can lead to significant cost savings. The primary objective of the economic dispatch problem (EDP) of electric power generation is to schedule the committed generating unit outputs so as to meet the required load demand at minimum operating cost while satisfying all unit and system equality and inequality constraints [1]. This makes the EDP a large-scale highly non-linear constrained optimization problem.

The input–output characteristics of large units are inherently highly non-linear because of valve-point loadings, generating unit ramp rate limits, etc. Furthermore they may generate multiple local minimum points in the cost function. In light of the non-linear characteristics of the units, there is a demand for techniques that do not have restrictions on the shape of the fuel-cost curves [2]. To obtain accurate dispatch results, approaches without restriction on the shape of incremental fuel-cost functions are needed. Whereas both lambda-iterative and gradient technique methods in conventional approaches to the problems are calculus-based techniques, and require a smooth and convex cost function and strict continuity of the search space. Dynamic programming (DP) [3] imposes no restrictions on the nature of the cost curves and therefore it can solve EDP with inherently nonlinear and discontinuous cost curves. This method, however, suffers from the "curse of dimensionality" or local optimality [1].

In the past decade, random search optimization methods, such as simulated annealing (SA) [4], evolutionary programming (EP) [5], genetic algorithms (GA) [6], [7], tabu search (TS) algorithm [8], [9] and particle swarm optimization (PSO) [10], which are probabilistic heuristic algorithms, have been successfully used to solve the dynamic ED problem.

A new optimization method relied on one of the theories of the evolution of the universe namely, the Big Bang and Big Crunch theory is introduced by Erol and Eksin [11] which has a low computational time and high convergence speed. According to this theory, in the Big Bang phase energy dissipation produces disorder and randomness is the main feature of this phase; whereas, in the Big Crunch phase, randomly distributed particles are drawn into an order. The Big Bang–Big Crunch (BB–BC) Optimization method similarly generates random points in the Big Bang phase and shrinks these points to a single representative point via a center of mass in the Big Crunch phase. After a number of sequential Big Bangs and Big Crunches where the distribution of randomness within the search space during the Big Bang becomes smaller and smaller about the average point computed during the Big Crunch, the algorithm converges to a solution. The BB–BC method has been shown to outperform the enhanced classical Genetic Algorithm for many benchmark test functions [11].

In this paper, the Big Bang–Big Crunch (BB–BC) Optimization method has been employed to solve economic dispatch problem with a valve point effects. The feasibility of the proposed method is to demonstrated and compared to those reported in the literature. The results are promising and show the effectiveness of the proposed method.

2. PROBLEM FORMULATION

2.1 Basic Economic dispatch Formulation

The total cost of operation of generators includes fuel, and maintenance cost but for simplicity only variable costs need to consider are fuel costs. The fuel cost is Important for thermal power plant. For the fuel costs, it is assumed that fuel cost curves for each generating unit is given [12].

Consider a system with n generators committed and that all the loads P_D, find P_{Gi} and V_i, P_L, δ_i. $i=1,2,..,n$. To minimize the total fuel cost

$$F=\sum_{i=1}^{N} C_i(P_{Gi})=\sum_{i=1}^{N} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (1)$$

Where N is the total number of generation units, a_i, b_i, c_i is the cost coefficients of generating unit and PGi is the real power generation of i_{th} unit. $i = 1, 2 \ldots$ to N.

Subject to the satisfaction of the power flow equations and the following inequality constraints on generator power, voltage magnitude and line power flow.

A. Equality Constraints As

$$P_{gi} - P_{di} - \sum_{j=1}^{N} |Vi||Vj||Yji| \cos(\delta i - \delta j - \theta ij) = 0$$

$$Q_{gi} - Q_{di} - \sum_{j=1}^{N} |Vi||Vj||Yji| \sin(\delta i - \delta j - \theta ij) = 0 \quad (2)$$

$$\sum P_{gi} - P_D - P_L = 0$$

Where P_D is the demand power and P_L is the total transmission network losses.

B. Inequality Constraints As

Branch flow limits:

$$|Si| \le S_i^{\max} \qquad i=1,\ldots n_l \qquad (3)$$

Where n_l is the number of lines.

Voltage at load buses

$$|S_D|^{\min} \le |Si| \le |S_D|^{\max} \qquad i=1,\ldots n_d \qquad (4)$$

Where n_d is the number of load buses.

Generator MVAR

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad i=1,\ldots N \qquad (5)$$

Slack bus MW

$$P_G^{\min} \le P_G \le P_G^{\max} \qquad (6)$$

Transformer tap setting

$$t_k^{\min} \le t_k \le t_k^{\max} \qquad (7)$$

Upper and lower bounds with bus voltage phase angles:

$$\delta_i^{\min} \le \delta_i \le \delta_i^{\max} \qquad (8)$$

2.2. valve-point effects

The generating units with multi-valve steam, turbines exhibit a greater variation in the fuel cost functions. Since the valve point results in the ripples as show in fig. 1, a cost function contains higher order nonlinearity [13]. Therefore, the equation (1) should be replaced as the equation (9) to consider the valve point effects. Here, the sinusoidal functions are thus added to the quadratic cost function as follows.

The incremental fuel cost function of the generation units with valve-point loading is represented as follows.

$$Fi(P_{gi}) = a_i + b_i P_{Gi} + c_i P_{Gi}^2 + |e_i \times \sin(f_i \times (P_{Gi\min} - P_{Gi}))| \quad (9)$$

Where ei and fi are the coefficients of generator i reflecting valve point effects.

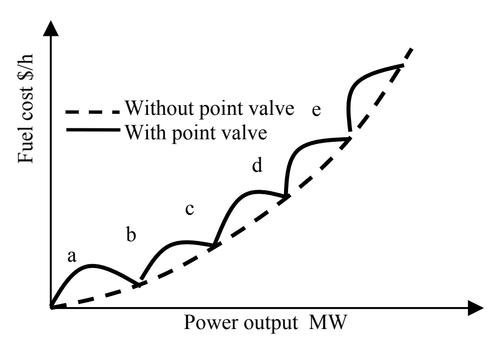

Fig. 1 : Fuel cost versus power output for 6 valve steam turbine unit.

3. BIG BANG–BIG CRUNCH (BB–BC) OPTIMIZATION ALGORITHM

The BB–BC method developed by Erol and Eksin [11] consists of two phases: a Big Bang phase, and a Big Crunch phase. In the Big Bang phase, candidate solutions are randomly distributed over the search space. Similar to other evolutionary algorithms, initial solutions are spread all over the search space in a uniform manner in the first Big Bang. Erol and Eksin [11] associated the random nature of the Big Bang to energy dissipation or the transformation from an ordered state (a convergent solution) to a disorder or chaos state (new set of solution candidates).

Randomness can be seen as equivalent to the energy dissipation in nature while convergence to a local or global optimum point can be viewed as gravitational attraction. Since energy dissipation creates disorder from ordered particles, we will use randomness as a transformation from a converged solution (order) to the birth of totally new solution candidates (disorder or chaos) [11].

The proposed method is similar to the GA in respect to creating an initial population randomly. The creation of the initial population randomly is called the Big Bang phase. In this phase, the candidate solutions are spread all over the search space in an uniform manner [11].

The Big Bang phase is followed by the Big Crunch phase. The Big Crunch is a convergence operator that has many inputs but only one output, which is named as the ‘‘center of mass”, since the only output has been derived by calculating the center of mass. Here, the term mass refers to the inverse of the merit function value [14]. The point representing the center of mass that is denoted by x_c is calculated according to:

$$\vec{x}^{c} = \frac{\sum_{i=1}^{N} \frac{1}{f^{i}} \vec{x}^{i}}{\sum_{i=1}^{N} \frac{1}{f^{i}}} \tag{10}$$

where x_i is a point within an n-dimensional search space generated, f_i is a fitness function value of this point, N is the population size in Big Bang phase. The convergence operator in the Big Crunch phase is different from ‘exaggerated’ selection since the output term may contain additional information (new candidate or member having different parameters than others) than the participating ones, hence differing from the population members. This one step convergence is superior compared to selecting two members and finding their center of gravity. This method takes the population members as a whole in the Big-Crunch phase that acts as a squeezing or contraction operator; and it, therefore, eliminates the necessity for two-by-two combination calculations [11].

After the Big Crunch phase, the algorithm must create new members to be used as the Big Bang of the next iteration step. This can be done in various ways, the simplest one being jumping to the first step and creating an initial population. The algorithm will have no difference than random search method by so doing since latter iterations will not use the knowledge gained from the previous ones; hence, the convergence of such an algorithm will most probably be very low. An optimization algorithm must converge to an optimal point; but, at the same time, in order to be classified as a global algorithm, it must contain certain different points within its search population with a decreasing probability. To be more precise, we mean that, large amount of solutions generated by the algorithm must be around the 'so-called' optimal point but the remaining few points in the population bed must be spread across the search space after certain number of steps. This ratio of solution points around the optimum value to points away from optimum value must decrease as the number of iterations increases; but, in no case, it could be equal to zero, which means the end of the search. This convergence or the use of the previous knowledge (center of mass) can be accomplished by spreading new off-springs around this center of mass using a normal distribution operation in every direction where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases. This convergence can be formulated as below, where the space boundary is the sum of the Euclidian distances of all members:

space boundary in the k_{th} iteration/space boundary in the $(k+1)_{th}$ iteration > 1

After the second explosion, the center of mass is recalculated. These successive explosion and contraction steps are carried repeatedly until a stopping criterion has been met. The parameters to be supplied to normal random point generator are the center of mass of the previous step and the standard deviation. The deviation term can be fixed, but decreasing its value along with the elapsed iterations produces better results.

After the Big Crunch phase, the algorithm creates the new solutions to be used as the Big Bang of the next iteration step, by using the previous knowledge (center of mass). This can be accomplished by spreading new off-springs around the center of mass using a normal distribution operation in every direction, where the standard deviation of this normal distribution function decreases as the number of iterations of the algorithm increases [14]:

$$x^{new} = x^c + l.r / k \qquad (11)$$

where x^c stands for center of mass, l is the upper limit of the parameter, r is a normal random number and k is the iteration step. Then new point xnew is upper and lower bounded.

The BB–BC approach takes the following steps [11]:

Step 1 Form an initial generation of N candidates in a random manner. Respect the limits of the search space.

Step 2 Calculate the fitness function values of all the candidate solutions.

Step 3 Find the center of mass according to (10). Best fitness individual can be chosen as the center of mass.

Step 4 Calculate new candidates around the center of mass by adding or subtracting a normal random number whose value decreases as the iterations elapse of using (11).

Step 5 Return to Step 2 until stopping criteria has been met.

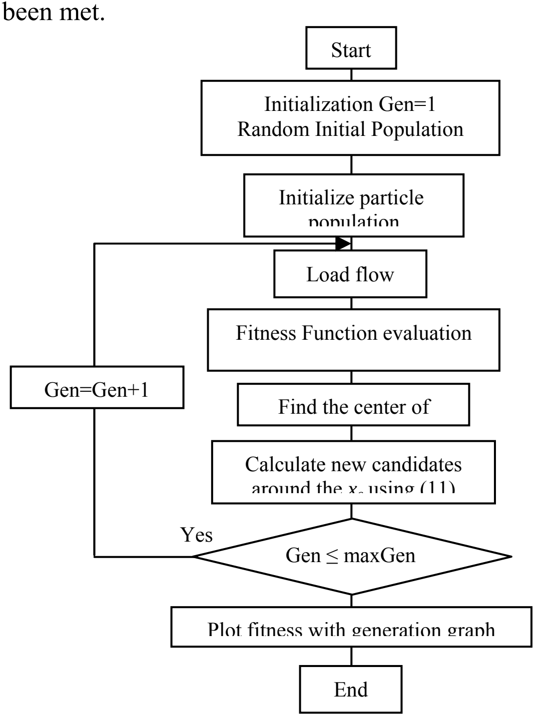

Fig. 2 BB–BC-OPF computational procedure.

4. LOAD FLOW CALCULATION

Once the reconstruction operators have been applied and the control variables values are determined for each candidate a load flow run is performed. Such flows run allows evaluating the branches active power flow, the total losses and voltage magnitude this will provide updated voltages angles and total transmission losses. All these require a fast and robust load flow program with best convergence properties; the developed load flow process is upon the full Newton Raphson algorithm [15].

5. SIMULATION RESULTS AND DISCUSSION

The proposed BB–BC algorithm is tested on standard IEEE 30 bus system and a comparison with other heuristic algorithms reported in [16], [17]. The test system consists of 6 thermal units (Table 1), 24 load buses and 41 transmission lines of which four of the branches (6-9), (6-10), (4-12) and (28-27) are with the tap setting transformer. The total system demand is 283.4 MW

All methods are performed with ten trials under the same evaluation function and individual definition in order to compare their solution quality, convergence characteristic and computation efficiency. In these examples. The software was implemented by the MATLAB language, on a Pentium 4, 2.4 GHz personal microcomputer with 1GB DDR RAM under Windows XP.

According to simulation, the following parameters in the BB–BC algorithms methods are used :

- The number of generation is 100 iterations and Size of population 50 individuals (candidates).

- The individual having minimum cost value is chosen for Big-Crunch phase.

- New population (Big Bang phase) is generated by using normal distribution principle with (11):

$$P_{Gi}^{k} = Pest_i + (P_{GiMax} - P_{GiMin}).rand / it \qquad (12)$$

Where k number of candidates, i number of parameters, $Pest_i$ value which falls with minimum cost, P_{GiMax} and P_{GiMin} are parameter upper and lower limits and it number of iterations.

5.1. Case 1: The OPF with quadratic fuel cost functions

In this case the units cost curves are represented by quadratic function. The generator cost coefficients are given in Table A.1. The proposed BB–BC based OPF algorithm is applied to standard IEEE 30 bus system.

The best solutions, which are shown in Table 1, satisfy the system constraints. The statistical results obtained with ten trials, such as the generation cost, computational time and Standard deviation are shown in Table 2.

Table 1 : Best solution of standard IEEE 30 system

Unit power output	Methods		
	IEP [16]	SADE_ALM [17]	BB–BC
P_1 (MW)	176.2358	176.1522	175.8299
P_2 (MW)	49.0093	48.8391	48.6122
P_5 (MW)	21.5023	21.5144	21.1692
P_8 (MW)	21.8115	22.1299	22.6083
P_{11} (MW)	12.3387	12.2435	12.5263
P_{13} (MW)	12.0129	12.0000	12.0000
Total Pg (MW)	292.9105	292.8791	292.7460
P_{loss} (MW)	9.5105	9.4791	9.346
Total cost ($/h)	802.465	802.404	802.0207

Fig. 3 shows the cost convergence of BB–BC based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 100 generations. Hence it is clears from the Fig. 3 That the solution is converged to a high quality solution at the early iterations (45 iterations).

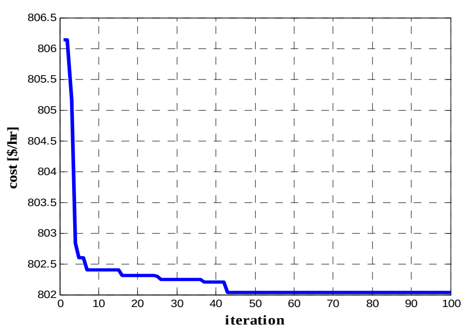

Fig. 3 Convergence characteristic of system (Case 1).

Or the IEEE 30 bus system, the best solutions of the seven methods are given in Table 1 after performing ten trials. The results of the BB–BC based OPF algorithm are compared with those obtained by the EP, TS, TS/SA, ITS, IEP, and SADE_ALM algorithms in terms of Worst, Average, Best generation cost, the Standard deviation and Average computational time as shown in Table 2. Obviously, all methods have succeeded in finding the near optimum solution presented in [16], [17] with a high probability of satisfying the equality and inequality constraints.

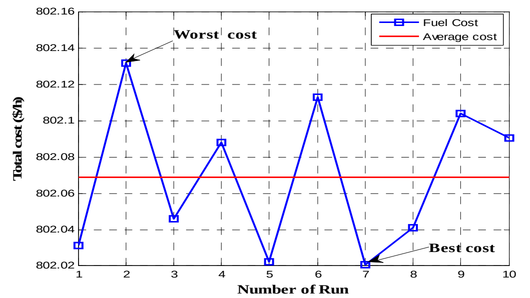

Fig. 4 Distribution of generation cost for IEEE 30 bus system (Case 1).

Fig. 4 shows distribution the generation cost of the best solution for each run in the case of 283.4 MW load demand.

5.1. Case 2: The OPF for units with valve-point effects

In this case, the generator fuel cost curves of generator at bus 1 and 2 are represented by quadratic functions with rectified sine components using (10). Bus 1 is selected as the slack bus of the system to allow more accurate control over units with discontinuities in cost curves. The generator cost coefficients of those two generators are given in Table A.2.

The best solutions, which are shown in Table 3, satisfy the system constraints.

TABLE 2 : COMPARISON OF BB–BC PERFORMANCE WITH OTHER METHODS

Methods	Fuel Cost ($/hr.)				Average computational time (minutes)
	Best cost	Average cost	Worst cost	Standard deviation	
EP [16]	802.907	803.232	803.474	0.226	66.693
TS [16]	802.502	802.632	802.746	0.080	86.227
TS/SA [16]	802.788	803.032	803.291	0.187	62.275
ITS [16]	804.556	805.812	806.856	0.754	88.495
IEP [16]	802.465	802.521	802.581	0.039	99.013
SADE_ALM [17]	802.404	802.407	802.411	0.003	15.934
BB–BC	802.020	802.069	802.132	0.041	04.418

The statistical results obtained with ten trials, such as the generation cost, computational time and Standard deviation are shown in Table 4.

Table 3 : Best solution of standard IEEE 30 bus system

Unit power output	Methods		
	IEP [16]	SADE_ALM [17]	BB–BC
P_1 (MW)	149.7331	193.2903	199.6127
P_2 (MW)	52.0571	52.5735	20.0000
P_5 (MW)	23.2008	17.5458	21.7407
P_8 (MW)	33.4150	10.0000	26.2079
P_{11} (MW)	16.5523	10.0000	13.9545
P_{13} (MW)	16.0875	12.0000	12.0000
Total Pg (MW)	291.0458	295.4096	293.5158
P_{loss} (MW)	7.6458	12.0096	10.1158
Total cost ($/h)	953.573	944.031	920.5089

Fig. 5 shows the cost convergence of BB–BC based OPF algorithm for various numbers of generations. It was clearly shown that there is no rapid change in the fuel cost function value after 100 generations. Hence it is clears from the Fig. 5 That the solution is converged to a high quality solution at the early iterations (45 iterations).

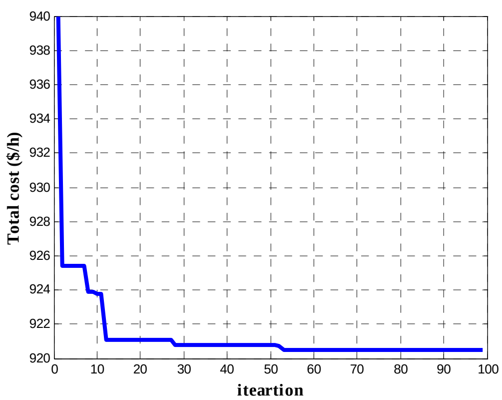

Fig. 5 Convergence characteristic of the IEEE 30 bus system (Case 2).

For this case, the results from ten test runs of BB–BC do not violate any constraints. Table 4 shows that worst, average, best generation cost, the standard deviation and average computational time of BB–BC are lower than those obtained by TS, TS/SA, ITS, EP, IEP and SADE_ALM.

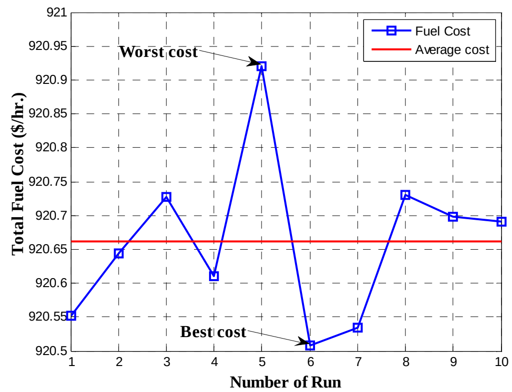

Fig. 6 Distribution of generation cost for IEEE 30 bus system (Case 2).

Fig. 6 shows distribution the generation cost of the best solution for each run in the case of 283.4 MW load demand.

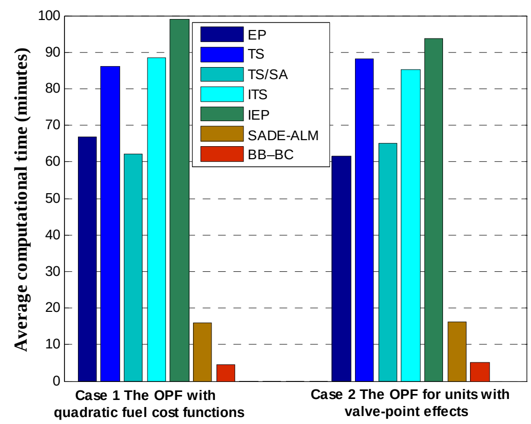

Fig. 7 Comparison of computation performance.

The comparisons of computational time of the seven methods in the two cases are shown in Fig. 7. Clearly, the computational time of the MTS algorithm method is lowest in comparison to those of the other methods.

Table 4 : Comparison of BB–BC performance with other methods

Methods	Fuel Cost ($/hr.)				Average computational time (minutes)
	Best cost	Average cost	Worst cost	Standard deviation	
EP [16]	955.508	957.709	959.379	1.084	61.419
TS [16]	956.498	958.456	960.261	1.070	88.210
TS/SA [16]	959.563	962.889	966.023	2.146	65.109
ITS [16]	969.109	977.170	985.533	6.191	85.138
IEP [16]	953.573	956.460	958.263	1.720	93.583
SADE_ALM [17]	944.031	954.800	964.794	5.371	16.160
BB–BC	920.508	920.661	920.920	0.121	5.0472

The simulation results in the IEEE 30 bus system demonstrate the feasibility and effectiveness of the proposed method BB-BC in minimizing cost of the generator. It is useful for obtaining high quality solution in a very less time compared to other methods EP, TS, TS/SA, ITS, IEP and SADE_ALM.

6. CONCLUSION

A Big Bang-Big Crunch optimization (BB-BC) is developed for the optimal power flow (OPF) problems. This method consists of a Big Bang phase where candidate solutions are randomly distributed over the search space, and a Big Crunch phase working as a convergence operator where the center of mass is generated.

The comparison of numerical results of optimal power flow (OPF) problems with valve-point effects using the BB–BC method with the results obtained by other heuristic approaches are performed to demonstrate the robustness of the present algorithm.

The BB-BC optimization has several advantages over other evolutionary methods: Most significantly, a numerically simple algorithm and heuristic methods with relatively few control parameters; and the ability to solve problems that depend on large number of variables.

APPENDIX

Table A.1 : Generator cost coefficients in case 1

Bus No.	Real power output limit (MW)		Cost Coefficients		
	Min	Max	a	b	c
1	50	200	0.00375	2.00	0
2	20	80	0.01750	1.75	0
5	15	50	0.06250	1.00	0
8	10	35	0.00834	3.25	0
11	10	30	0.02500	3.00	0
13	12	40	0.02500	3.00	0

Table A.2 : Generator cost coefficients in case 2

Bus No.	Real power output limit (MW)		Cost Coefficients				
	Min	Max	a	b	c	e	f
1	50	200	0.00160	2.00	150	50	0.063
2	20	80	0.01000	2.50	25	40	0.098

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