

MODIFIED PSO BASED STABLE POWER FLOW WITH RAMPING RENTS

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Abstract: This paper describes an application of Fitness Distance Ratio Particle Swarm Optimization (FDR PSO) algorithm to determine the optimal power dispatch of the Independent Power Producers (IPP) in deregulated environment. The loads and wheeling transactions are varying rapidly in the deregulated power market. Hence the power producers must respond quickly to those changes. In this paper, optimal production costs are computed with ramping cost for the power producers. Transient stability limits are also incorporated while solving the OPF problem. The effectiveness of the proposed algorithm has been demonstrated on practical IEEE 30 bus system for increased load conditions and Indian utility 62 bus system.

Key words: Optimal power dispatch, production cost, ramping cost, fitness distance ratio particle swarm optimization, transient stability limit.

I. INTRODUCTION

The restructuring of the electric power industry has involved paradigm shifts in real-time control activities of the power grids. Managing dispatch is one of the important control activities in a power system. Optimal Power Flow (OPF) has perhaps the most significant technique for obtaining minimum cost generation patterns in a power system with the existing transmission and operational constraints. Practically, the objective function of the OPF problem is non-convex in nature. Hence artificial intelligence methods have been recently proposed to solve the OPF problem. Abido solved the OPF problem using PSO technique. The global and local exploration capabilities of PSO are used to search for optimal settings of the control variables. The author demonstrated the PSO algorithm with different power system objectives on IEEE 30 bus system. [1]. Paranjothi *et al.* solved the OPF problem using Refined Genetic Algorithm (RGA) and demonstrated on IEEE 6 bus and 30 bus systems [2]. Yuchao Ma *et al.* have employed PSO algorithm to find the optimal supply function of the electricity producer with the objective of maximizing producer surplus in the market clearing. The authors have demonstrated the PSO algorithm with different simulation cases on IEEE 30 bus system [3]. All the above methods consider the OPF problem as convex in nature and assume that the IPP is operating between the minimum and maximum generation limits.

Though the solution of the OPF problem minimizes the fuel cost by satisfying the practical constraints like line flow, voltage limits etc., it has to be within the stability limits. The emergence of competitive power market makes the transient stability constrained OPF increasingly important because of the participation of many independent power producers. Hence the transient stability constraint is also incorporated in the OPF problem formulation.

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Zhang *et al.* have proposed an algorithm, which based on control variable parameterisation to solve the dynamic OPF problem on the 9 bus, 3 generator system [4]. David *et al.* have developed a transient security enhancement approach for deregulated power system by the corrected hybrid method [5].

In the deregulated power market, the loads and wheeling transactions are changing dynamically with respect to time. Hence IPPs have to respond to those changes and their new operating states have to be obtained. But the operating (elastic) range of the IPPs are restricted by their ramp rate limits [6]. When the operating range of the IPP is within the elastic range, the corresponding ramping process will not shorten life of the rotor and no ramping costs are incurred. When the operating range of the IPP violates the elastic range, the economic impact due to the rotor fatigue is expressed in terms of the ramping cost [7,8]. Shresha *et al.* derived the operating cost of the IPPs by considering ramping rate and time with conventional quadratic cost function [9] and demonstrated the same for a unit system. Tanaka described an extended form of real time pricing that achieves the optimal rate of change in quantity demanded by considering the ramping costs into account. The steepness of the load curve is controlled by the proposed optimal pricing policy, which reduced the ramping cost and the possibility of

large scale black out [10]. Wei Fan *et al.* solved the unit commitment problem with ramping constraints within lagrangian relaxation framework. The authors used a modified constructive dynamic programming method to determine the optimal generation levels of a commitment state without discretizing generation levels [11]. Morgan proposed Genetic Algorithm (GA) to solve Dynamic Economic Dispatch (DED) problem considering dynamic ramping rate constraints. The suitability and capability of GAs in dealing with the ramping rate constraints on the DED problem is demonstrated on 25 unit Northern Ireland Electricity system [12].

In this paper, the optimal production cost of the IPP is computed with ramping cost for IEEE 30 bus and Indian Utility 62 bus systems. The FDR PSO based algorithm is used to obtain the operating state of the IPPs with respect to change in load conditions. The ramping cost is calculated by taking into account of ramping rate and time with fuel cost function. Transient stability limits of the generators are also considered in the OPF problem formulation. Optimal production costs are obtained when contingency analysis is carried out on the 62 bus test system.

II. PROBLEM FORMULATION

Optimization of operating cost function F of generation has been formulated based on classical OPF problem with line flow constraints. For a given power system network, the optimization of operating cost of generation is given by the following equation.

$$F = \text{Min} \sum_{i=1}^n (f_i(P_i) + RC_i) \quad \$ / \text{hr} \quad \dots (1)$$

where F is the total operating cost of power producers, $f_i(P_i)$ is the fuel cost of the i^{th} power producer. RC_i is the ramping cost of the power producer and n is the total number of power producers connected in the network.

The fuel cost function of the i^{th} generator is given by

$$f_i(P_i) = a_0 + a_1 P_i + a_2 P_i^2 \quad \$ / \text{hr} \quad \dots (2)$$

where P_i is the real power output of an i^{th} power producer and a_0, a_1, a_2 are the fuel cost coefficients of the i^{th} power producer.

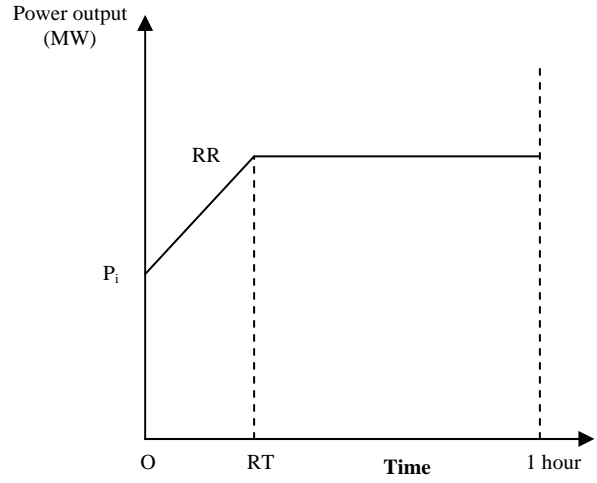


Fig. 1. Power delivery during a time interval

Fig.1 shows the variation of output during the ramping process. It consists of the ramping period $[0, RT]$ and a constant output period $[RT, 1 \text{ hr}]$. The power output of the power producer is given by

$$P_i = P_i + RR \cdot t \quad \text{when } t \in [0, RT] \quad \dots (3a)$$

$$= P_i + RR \cdot RT \quad \text{when } t \in [RT, 1] \quad \dots (3b)$$

where RR is the ramping (up/down) rate and RT is the ramping time of the i^{th} power producer.

The operating cost function of the power producer given in the Equation 1 is subjected to the following constraints.

$$\sum_{i=1}^n P_i = P_D + P_L \quad \dots (4)$$

where P_D is the total load of the system and P_L is the transmission losses of the systems.

* Ramp rate constraint

The ramp rate constraint restricts the operating range of the physical lower and upper limit to the effective lower limit \underline{P}_i and upper limit \overline{P}_i respectively. These limits are defined as

$$\underline{P}_i = \max [P_{\min}, P_i^0 - DR_i] \quad \dots (5a)$$

$$\overline{P}_i = \min [P_{\max}, P_i^0 + UR_i] \quad \dots (5b)$$

where P_i^0 is the power generation of unit i at previous hour and DR_i and UR_i are ramp rate limits of unit i as generation decreases and increases respectively. \underline{P}_i and \overline{P}_i are the physical lower and upper limits of the power producer and the area between these limits is known as elastic range, which is shown in Fig. 2.

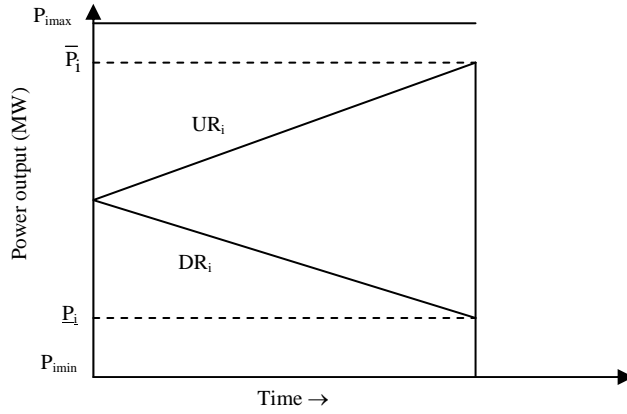


Fig. 2. Physical lower and upper limits of power producer

* The inequality constraint on real power generation P_i of each power producer i is given by

$$\underline{P}_i \leq P_i \leq \overline{P}_i \quad \dots (6)$$

Due to the change in load and credible contingencies, the power producers are adjusted to new setting values. If the power delivery of the power producer lies within the elastic range, no ramping cost is incurred, otherwise it is incurred.

* Power limit on transmission line is given by

$$MVA_{f_{p,q}} \leq MVA_{f_{p,q}}^{\max} \quad \dots (7)$$

where $MVA_{f_{p,q}}^{\max}$ is the maximum rating of transmission line connecting buses p and q .

* Transient stability constraint is expressed in terms of generator rotor angles which is given as follows:

$$\delta_{\min} \leq \delta_i \leq \delta_{\max} \quad \dots (8)$$

where δ_i is the relative rotor angle of the i^{th} power producer with respect to the reference.

When the ramping process is included in the power dispatch, the effective operating cost of a unit considering the change of the power output [9] is given by

$$F = f_1 + f_2 (1 - \frac{1}{2} * RT) * RT * RR + a_2 (1 - \frac{2}{3} * RT) * RT^2 * RR^2 \quad \dots (9)$$

where $f_1 = a_0 + a_1 P_i + a_2 P_i^2$ and $f_2 = a_1 + 2a_2 P_i$

III. OVERVIEW OF PARTICLE SWARM OPTIMIZATION

In 1995, Kennedy and Eberhart first introduced the PSO method which is motivated by social behavior of organisms such as fish schooling and birds flocking [13]. In a PSO system, particles fly around a 'd' dimensional problem space. During flight, each particle adjusts its position according to its own experience as well as by the best experiences of other neighboring particles. Let us consider $X_i = (X_{i1}, X_{i2}, \dots, X_{id})$ and $V_i = (V_{i1}, V_{i2}, \dots, V_{id})$ be the position and velocity of the i^{th} particle. Velocity V_{id} is bounded between its lower and

upper limits. The best previous position of the i^{th} particle is recorded and is given by $P_{\text{best}i} = (P_{i1}, P_{i2}, \dots, P_{id})$. Let $g_{\text{best}i} = (P_{g1}, P_{g2}, \dots, P_{gid})$ be the best position among all individual best positions achieved so far. Each particle's velocity and position is updated using the following two equations.

$$V_{id}^{k+1} = W * V_{id}^k + C_1 * \text{rand1} * (P_{id} - X_{id}) + C_2 * \text{rand2} * (P_{gid} -$$

$$X_{id}) \quad \dots (10)$$

$$X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1} \quad \dots (11)$$

where C_1 and C_2 are the acceleration constants, which represent the weighting of stochastic acceleration terms that pull each particle towards P_{best} and g_{best} positions. k represents the current iteration and rand1 and rand2 are two random numbers in the range $[0,1]$. Inertia weight W is a control parameter that is used to control the impact of the previous velocities on the current one. Hence, it influences the trade-off between the global and local exploration abilities of the particles. The search process will terminate if the number of iterations reaches the maximum allowable number.

IV. FDR PSO based Power Flow

In the literature, it has been proved that the particle positions in PSO oscillate in damped sinusoidal waves until they converge to points in between their previous P_{best} and g_{best} positions [14,15]. During this oscillation, if a particle reaches a point, which has better fitness than its previous best position, then the particle continues to move towards the convergence of the global best position discovered so far. All the particles follow the same behavior to converge quickly to a good local optimum. Suppose, if the global optimum of the problem does not lie on a path between original particle positions and such a local optimum, then the particle is prevented from effective search for the global value. In such cases, many of the particles are wasting their computational effort in seeking to move towards the local optimum already discovered. Better results may be obtained if various particles explore other possible search directions.

In the FDR PSO algorithm, in addition to the Socio-cognitive learning processes, each particle also learns from the experience of neighboring particles that have a better fitness than itself [16]. This approach results in change in the velocity update equation, although the position update equation remains unchanged. It selects only one other particle at a time when updating each velocity dimension and that particle is chosen to satisfy the following two criteria.

1. It must be near the current particle.
2. It should have visited a position of higher fitness.

The simplest way to select a nearby particle which satisfies the above mentioned two criteria is that maximizes the ratio of the fitness difference to the one-dimensional distance. In other words, the d^{th} dimension of the i^{th} particle's velocity is updated using a particle called the n_{best} , with prior best position P_j . It is necessary to maximize the following Fitness Distance Ratio which is given by

$$\frac{\text{Cost}(P_j) - \text{Cost}(X_{id})}{|P_{jd} - X_{id}|} \dots (12)$$

In the FDR PSO algorithm, the particle's velocity update is influenced by the following three factors:

1. Previous best experience i.e. P_{best} of the particle.
2. Best global experience i.e. g_{best} , considering the best P_{best} of all particles.
3. Previous best experience of the "best nearest" neighbor i.e. n_{best} .

Hence, the new velocity update equation becomes:

$$V_{id}^{k+1} = W * V_{id}^k + C_1 * \text{rand1} * (P_{id} - X_{id}) + C_2 * \text{rand2} * (P_{gid} - X_{id}) + C_3 * \text{rand3} * (P_{nd} - X_{id}) \dots (13)$$

where P_{nd} is the nearby particle that have better fitness.

The position update equation remains the same as in Equation (11). The step by step algorithm is given in Fig.3.

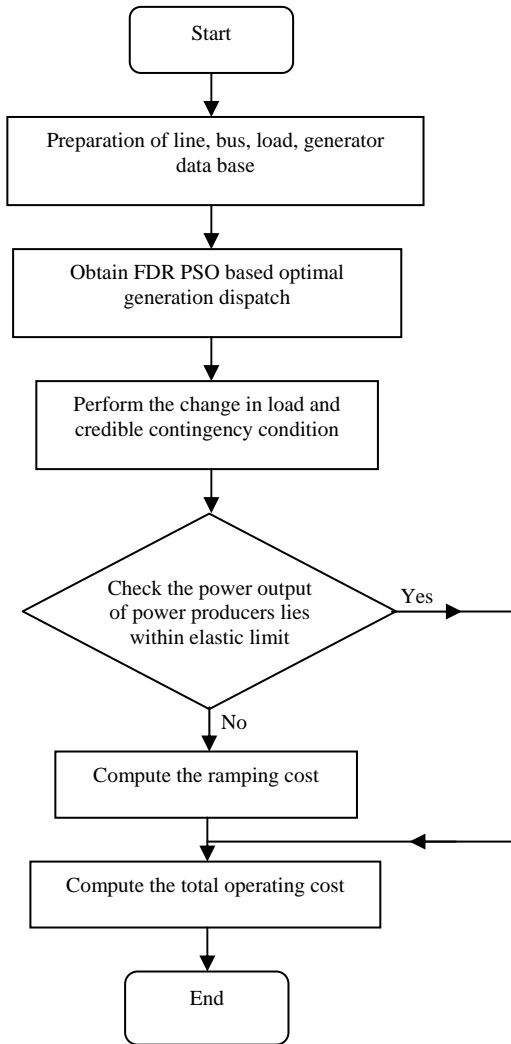


Fig. 3. Step-by-Step algorithm

V. SIMULATION RESULTS AND DISCUSSION

In the proposed approach, the optimal power dispatch and minimum production cost of the IPPs were obtained using swarm intelligence algorithms by satisfying the transmission line constraints. When the ramping process was included in the power dispatch, the effective ramping cost of the power producer was computed due to the change in their power output corresponding to load changes. The step-by-step algorithm for computing the production cost is given in Fig.3.

The swarm intelligence algorithms were tested on IEEE 30 bus and an Indian utility 62 bus test systems. In the swarm intelligence methods, the population size, the number of generations and the acceleration constants decide the execution time of the algorithm and their details are given in Appendix A. A linearly decreasing inertia weight W , which varies from 0.9 to 0.2, was used for the convergence characteristics. The line flows were computed using Newton Raphson method and their derated limits were incorporated.

The transient stability limits of the generators were incorporated in the OPF problem formulation and security of the system is ensured. The simulation studies were carried out on P IV, 3 GHz system in MATLAB environment. The following case studies were carried to obtain the transient stability based OPF solution.

Case 1: IEEE 30 bus system

The test system consists of 6 power producers, 41 transmission lines, 4 tap changing transformers and 2 injected VAR sources. The base load of the test system is 283.4 MW. In this paper, ramp rate limits are also included in the generator real power limits to meet the change in load demand. The fuel cost coefficients, the operating state of the generators and their corresponding ramp rate limits are given in Appendix B. The optimal production cost obtained through the PSO and FDR PSO methods for the base load condition is given by 829.33 \$/hr and 813.49 \$/hr respectively. The optimal power dispatch and minimum production costs were obtained using the swarm intelligence algorithms for increased load conditions and the results are given in Table 1. From this table, it is observed that the proposed FDR PSO algorithm gives better results than PSO algorithm. The voltage magnitude plot corresponding to 130% of load condition is shown in Fig. 4. From this figure, it is inferred that the OPF solution obtained by the algorithm satisfies the voltage limits even at the large load change condition.

Table 1: Optimum results obtained in different cases

% of load	PSO				FDR PSO			
	FC	RC	PC	P_L	FC	RC	PC	P_L
110	908.9	24.66	933.56	8.69	904.6	21.99	926.59	6.511
120	999.43	28.63	1028.06	11.32	992.14	25.11	1017.25	12.55
130	1105.37	24.79	1130.16	13.47	1100.86	21.54	1122.4	12.59

FC–Fuel Cost(\$/hr) RC–Ramping Cost(\$/hr) PC– Production Cost (\$/hr)
 P_L – Loss (MW)

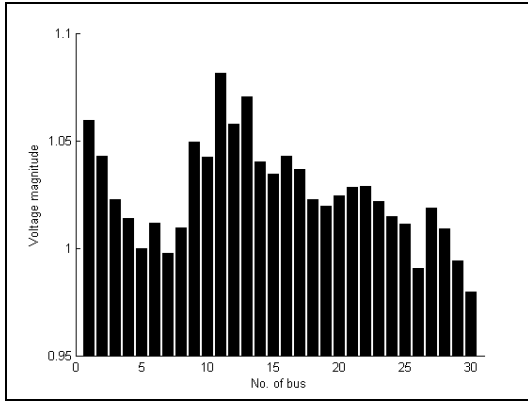


Fig.4: Voltage magnitude plot at 130% load condition

In the above OPF solution, the transient stability limit has been incorporated by the following procedure: A three phase to ground fault was assumed in the transmission line connected between buses 1 and 2. The above fault was cleared by opening the contacts of the circuit breakers by 100 ms. The obtained OPF solution satisfies transient stability limit and the corresponding relative rotor angles of the generators are shown in Fig.5.

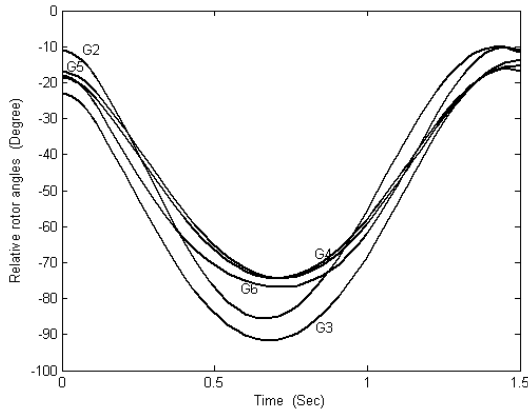


Fig.5: Relative rotor angle curves at 130% load condition

Hence the obtained OPF solution satisfies the voltage, line flow, ramp rate and transient stability limits of the generators.

Case 2: Indian Utility 62 bus system

To validate the proposed algorithm, a practical Indian Utility system with a major contingency analysis is described in this section. The test system consists of 62 buses, 19 power producers, 89 (220KV) lines with 11 tap changing transformers have been considered. The ramping rate coefficients of the power producers of the Indian utility system are given in Appendix C. The base load of the system is 2909 MW. The optimal production cost obtained through PSO and FDR PSO methods for the base case is 14709.35 \$/hr and 14423.87 \$/hr respectively. The practical test system is subjected to the dynamic load changes with respect to 24 hours and it is illustrated in Fig. 6.

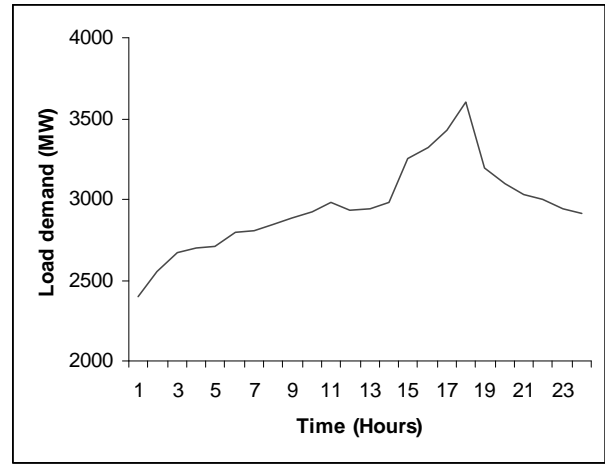


Fig.6: Daily load curve – Indian utility 62 bus system

For the corresponding load changes, the proposed FDR PSO algorithm was applied to obtain the optimal power dispatch and ramping cost of the generators. In this case, contingency analysis was also carried out on the test system along with the load changes. The 4th generator is made out of service to incorporate major contingency. The operating cost of the test system with dynamic load constraints in the horizon of 24 hours were evaluated and given Fig. 7. It infers that the proposed algorithm is capable to obtain the minimum solution with load changes and contingency by satisfying the power flow constraints.

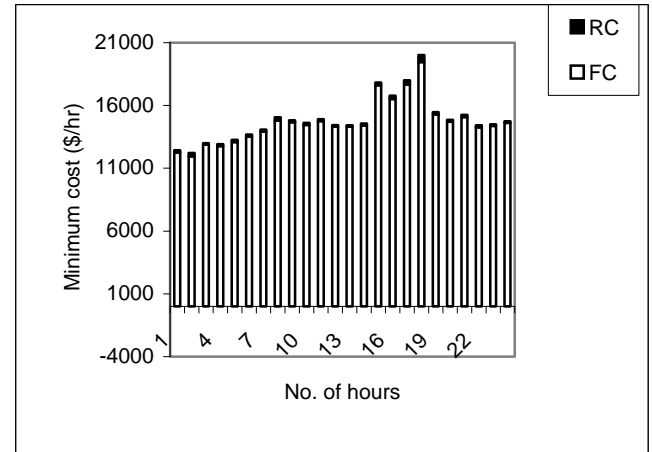


Fig.7: Minimum cost Analysis

VI. CONCLUSION

This paper has presented the FDR PSO based algorithm for the computation of production cost of the power producers. The production cost including the ramping cost was obtained from conventional fuel cost and ramping rate functions. The obtained solution satisfies voltage, line flow and transient stability limits. The optimal power dispatch and ramping rents for the practical test systems were obtained for dynamic load changes. The solutions are quite useful to carry out the accurate pricing scheme in the present deregulated environment.

VII. Appendix

A: Simulation parameters –PSO and FDR PSO methods

Algorithm	C ₁	C ₂	C ₃	Population size	Maximum No. of generations
PSO	1.0	1.0	---	20	750
FDR PSO	1.0	1.0	2.0	20	750

B: Fuel cost coefficients and ramp rate limits

Gen No.	a ₀	a ₁	a ₂	P _{1 min}	P _{1 max}	Operating Power (MW)	RR (MW/hr)		RT (Min)
							UR _i	DR _i	
1	0	2.0	0.00375	50	200	135	42	60	45
2	0	1.75	0.01750	20	80	65	12	15	40
3	0	1.00	0.06250	15	50	35	12	13	35
4	0	3.25	0.00834	10	35	25	08	16	30
5	0	3.00	0.02500	10	30	20	06	09	30
6	0	3.00	0.02500	12	40	30	08	12	30

C: Ramping rate coefficients – 62 bus system

Gen No.	Bus No.	P _{1 min} (MW)	P _{1 max} (MW)	Operating Power (MW)	RR (MW/hr)		RT (Min)
					UR _i	DR _i	
1	1	0	300	250	104.5	135	35
2	2	50	450	300	152	162	20
3	5	50	450	300	55	180	25
4	9	8	25	20	5	12	20
5	14	50	300	120	88	81	35
6	17	50	450	300	110	135	25
7	23	50	200	130	30	63	30
8	25	50	500	600	440	450	20
9	32	0	600	500	220	270	35
10	33	0	100	30	11	14	25
11	34	50	150	100	60.5	77	20
12	37	0	100	50	2705	40	35
13	49	50	300	120	40	87	25
14	50	0	150	50	30	41	30
15	51	0	250	125	182	85.5	35
16	52	0	100	55	30	36	20
17	54	0	100	55	5.5	36	25
18	57	50	300	150	40	90	30
19	58	100	600	550	110	198	20

VIII. ACKNOWLEDGEMENT

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