Chapter 6
Dynamic Scheduling of Energy Resources in Microgrid Using Grey Wolf Optimization

Salil Madhav Dubey, Hari Mohan Dubey, and Manjaree Pandit

Abstract Continuous and sustainable electricity is one of the major concerns in this modern world. This has led to the implementation of microgrid (MG) in order to establish an independent, efficient and cost-effective power supply system. The generation in MG can be conventional or non-conventional but due to increasing power demand, high fuel prices, scarcity of fossil fuels and degrading environment, there is a growing demand of using renewable energy sources (RS) for power generation. Solar PV units play an indispensable part in producing clean energy and coping with this modern-day power demand challenges. Grey wolf optimization (GWO), which is a metaheuristic technique inspired by the hierarchical hunting mechanism of grey wolves, is used in this chapter for solving a multi-objective problem in a dynamic environment of a microgrid. Dynamic dispatch is a more practical way which aims to provide an optimum solution in a scheduling horizon over twenty-four hours a day. A hybrid system comprising six conventional thermal plants and a solar farm containing thirteen solar PV units are discussed in this chapter. The performance and effectiveness of GWO are compared and validated with other two well-proven methods ABC and DE.

Keywords Microgrid · RS integration · GWO · Dynamic scheduling · Solar farm · Multi-objective scheduling

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Nomenclature

a_i, b_i, c_i	Fuel cost coefficients of i-th generating unit
P_i	Output power in MW of i-th generating unit
$\alpha_i, \beta_i, \gamma_i$	Emission coefficients of i-th generating unit
P_{rated}	Rated output of a solar plant
T_{ref}	Reference temperature taken (25 °C in this case)
T_{amb}	Ambient temperature of solar plant
μ	Temperature coefficient of solar plant (–0.50% in this case)
S_t	Incident solar radiation (W/m2) at t-th hour
P_L	Power loss
UR_i, DR_i	Up rate and down rate of ith generating unit, respectively
A, C	Coefficient vectors
$\mathcal{X}(t)$	Position vector of the prey
$\mathcal{X}$	Position vector of a grey wolf
$r1, r2$	Random vectors ∈[0, 1]
$\mathcal{X}_1, \mathcal{X}_2, \mathcal{X}_3$	Best position of alpha (α), beta (β) and delta (δ), respectively
$\mathcal{X}(t+1)$	Final position

1 Introduction

Sustainable, renewable, efficient and economical energy systems are the need of the hour for meeting the power demand of increased population. Implementation of microgrid (MG) has gained popularity as a solution to this increased power demand. However, MG has its own challenges for economic operations. Uncertainty in the output of renewable energy sources (RES), energy storage (ES) capacity management, optimization of MG operation with real-time electricity price in market, minimizing operational cost and emissions are some challenges faced when MG is incorporated in the power system [1]. Solutions to these problems like dynamic scheduling of MG using NSGA-II algorithm [2], use of approximate dynamic programming and deep recurrent neural network learning in MG energy management [3], short term generation scheduling [4], scheduling in a CHP-based MG for economic power sharing [5], etc., have evolved to fulfil the interests of all stakeholders in power market.

In recent years, a lot of researchers have been focusing on the operation of MG. Optimal scheduling has always been one of the most important functions in minimizing the net cost of MG [6]. Dynamic optimal scheduling is a good option for MG operation because it considers the lowest cost in scheduling as well as coordinates among different distribution generations (DERs) over many periods.

In India, more than 70% conventional sources of energy are thermal plants which use coal as major fuel. Burning of coal produces harmful gases which degrade our air quality. Also, the price of fuel used is increasing day by day. Under these conditions, sharing of demand by DERs is not only governed by the units' capability of minimizing the total fuel cost of system generation but also the capability of satisfying the emission requirements. Many optimization algorithms have been used for solving this problem of minimizing fuel cost and emissions. Metaheuristic optimization techniques have gained popularity within last two decades for solution of complex optimization problem. Grey wolf optimization (GWO) [7] is a recently developed metaheuristic technique which is inspired by the hierarchal arrangement in hunting mechanism of grey wolfs.

In this chapter, GWO is used for dynamic scheduling of energy resources considering environmental constraints. Remaining chapters are organized as follows: Problem formulation of this system is given in Sect. 2, the working of the optimization method is described in Sect. 3, results and discussion after using this model are explained in Sect. 4 and the conclusions drawn are compiled in Sect. 5.

2 Problem Formulation

The fuel costs of the conventional generators in a dynamic environment of 24 h which is a convex polynomial can be mathematically expressed as (in \$/h) [10]:

$$F(P) = \sum_{t=1}^{24} \sum_{i=1}^{6} \left\{ a_i \times P_i^2(t) + b_i \times P_i(t) + c_i \right\} \tag{1}$$

Similarly, emission dispatch function (in Kg/h) is also a convex polynomial and can be written as [10]:

$$E(P) = \sum_{t=1}^{24} \sum_{i=1}^{6} \left\{ \alpha_i \times P_i^2(t) + \beta_i \times P_i(t) + \gamma_i \right\} \tag{2}$$

Thus, the multi-objective economic emission dispatch problem can be mathematically stated as [10]:

$$C(P) = \sum_{t=1}^{24} \sum_{i=1}^{6} \left[\left\{ a_i P_i^2(t) + b_i P_i(t) + c_i \right\} + \text{ppf} \times \left\{ \alpha_i \times P_i^2(t) + \beta_i \times P_i(t) + \gamma_i \right\} \right] \tag{3}$$

where ppf is price penalty factor which is given by

$$\text{ppf} = \frac{\left\{ a_i P_{i\max}^2(t) + b_i P_{i\max}(t) + c_i \right\}}{\alpha_i \times P_i^2(t) + \beta_i \times P_i(t) + \gamma_i} \tag{4}$$

The power generated by each solar PV unit (in MW) at t-th hour in a solar farm is given by [11]:

$$P_{gs} = P_{rated}\left\{1 + \mu(T_{amb} - T_{ref}) \times \frac{S_t}{1000}\right\} \tag{5}$$

Cost of operation for the solar farm for 24 h is given as:

$$\sum_{t=1}^{24}\sum_{j=1}^{13} P_{gs} \times C_j \tag{6}$$

The multi-objective cost function of the hybrid system becomes [11]:

$$C(P) = \sum_{t=1}^{24}\left[w \times \left(\sum_{i=1}^{6}\left\{a_i P_i^2(t) + b_i P_i(t) + c_i\right\}\right) + \mathrm{ppf} \times (1-w) \times \left(\sum_{i=1}^{6}\left\{\alpha_i \times P_i^2(t) + \beta_i \times P_i(t) + \gamma_i\right\}\right) + \sum_{j=1}^{13} P_{gs} \times C_j\right] \tag{7}$$

2.1 Inequality Constraints

The power generated by the conventional thermal plants as well as the RS (Solar PV farm) must lie between maximum and minimum limits. Mathematically,

$$P_i^{\min} \le P_i \le P_i^{\max} \tag{8}$$

$$P_{gs}^{\min} \le P_{gs} \le P_{gs}^{\max} \tag{9}$$

The ramp rate limits for thermal unit power generation are considered in this problem. The power generation of thermal units is constrained by the ramp rate limits as follows:

$$P_i^t - P_i^{t-1} \le \mathrm{UR}_i \tag{10}$$

$$P_i^{t-1} - P_i^t \le \mathrm{DR}_i \tag{11}$$

2.2 Equality Constraints

The power generated at any instant of time by all the thermal plants and the RS (Solar PV farm) should satisfy the total desired load of the system which is mathematically described as:

$$P_{\text{Load}} = \sum_{i=}^{6} P_i + \sum_{j=1}^{13} P_{\text{gs}} + P_L \tag{12}$$

3 Grey Wolf Optimization

Grey wolf optimization (GWO) is belonging to the family of swarm intelligence [7]. Its analytical model mimics the intelligent, self-organized group behaviour of grey wolves for hunting prey in nature. Grey wolves live in a group of 5–15 members. They follow a proper hierarchy with four types of member represented as Alpha, Beta, Delta and Omega. The social hierarchy of grey wolves is illustrated in Fig. 1. Systematic organization and discipline are their main strength.

Group leader is male/female represented by Alpha. He or She is only the decision maker for hunting, walking and selection of place for sleeping. Beta wolf has second place in social hierarchy and helps group leader in decision making. Delta is the subordinates of alpha and beta but they dominate over omega. Delta has four subgroups: Scouts, Sentinels, Hunters and Caretakers. Scouts are responsible for watching boundary territory and warning the group members in case of any danger. Sentinels are responsible for the protection of group members. Hunters help alpha and beta in hunting and also responsible for arranging the food for the group members. Weak and wounded member are taken care by caretakers. Omega plays the role of scapegoat in the group and they generally eat at last only.

On the basis of above-disciplined group behaviour, the analytical model of GWO is described by three phases during hunting which are described as below.

(a) **Entrapment of prey**

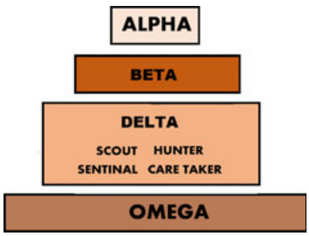

Fig. 1 Social hierarchy of grey wolves in nature

In its first phase, model is based upon assumption that grey wolves update their position one with respect to other in n-dimensional search space as below [7].

$$\mathcal{D} = |\mathcal{C} \times \mathcal{X}_P(t) - \mathcal{X}(t)| \tag{13}$$

$$\mathcal{X}(t+1) = \mathcal{X}_P(t) - \mathcal{A} \times \mathcal{D} \tag{14}$$

$$\mathcal{A} = 2ar_1 - a \tag{15}$$

$$\mathcal{C} = 2r_2 \tag{16}$$

$$a = 2 - (t)\left(\frac{2}{T}\right) \tag{17}$$

The value 'a' is linearly decreased from 2 to 0 over the course of iterations and Fig. 2 illustrates this phase

(b) **Hunting of Prey**

In order to simulate self-organized and group behaviour of grey wolves, alpha, beta and gamma are considered as three best solutions. Alpha is assumed to be closest to the best solution followed by the solution of beta and gamma. Therefore, during optimization process, first three solutions are considered as the best and remainders are considered as omega. The position is updated with respect to the position of

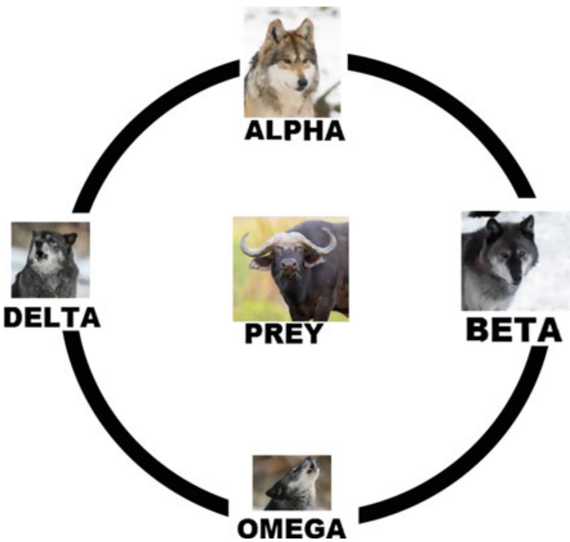

Fig. 2 Entrapment of prey phase

omega. The position of omega (ω) will vary as per the current best position in algorithm. The final position is defined with respect to position of alpha, beta and delta in search space as below.

$$\mathcal{D}_\alpha = |\mathcal{C}_1.\mathcal{X}_\alpha - \mathcal{X}|,\ \mathcal{D}_\beta = \left|\mathcal{C}_2.\mathcal{X}_\beta - \mathcal{X}\right|,\ \mathcal{D}_\delta = |\mathcal{C}_3.\mathcal{X}_\delta - \mathcal{X}| \tag{18}$$

$$\mathcal{X}_1 = \mathcal{X}_\alpha(t) - \mathcal{A}_1 \times \mathcal{D}_\alpha, \mathcal{X}_2 = \mathcal{X}_\beta(t) - \mathcal{A}_2 \times \mathcal{D}_\beta, \mathcal{X}_3 = \mathcal{X}_\delta(t) - \mathcal{A}_3 \times \mathcal{D}_\delta \tag{19}$$

$$\mathcal{X}(t+1) = \frac{1}{3} \times (\mathcal{X}_1 + \mathcal{X}_2 + \mathcal{X}_3) \tag{20}$$

(c) **Attacking the Prey**

In the last stage, grey wolf attacks the prey. In the analytical model, it can be realized by shrinking value of "*a*" from 2 to 0 as iteration progresses and hence $\mathcal{A}$ reduces. The last stage in hunting is attacking the prey when the prey has stopped. This can be achieved mathematically by reducing the value of a gradually from 2 to 0, consequently, $\mathcal{A}$ is varied randomly in range [−1, 1].

4 Results and Discussion

The main objective of this chapter is to find the impact of renewable integration on operating cost of fuel and quantity of emissions released, which is discussed in two cases. First case involving only thermal units and second case is a hybrid arrangement of thermal plants with solar PV integration.

4.1 Description of Test Cases

Case 1 This test system contains six thermal power units; its fuel cost, minimum and maximum power limits and emission coefficients which are adapted from [10] and listed in Table 1.

Case 2 It is a hybrid test case having six thermal units similar to Case 1 and a solar PV farm comprising of 13 PV units. The required data of the solar PV farm are adapted from [11] and illustrated in Fig. 3 and listed in Table 2. Figure 4 provides the data of temperature (°C) and solar radiation (W/m^2) of PV on a single day for 24 h. Table 2 gives data of rated power and per unit cost of thirteen PV units in the solar farm.

Table 1 Data related to six conventional thermal power plants

Unit	1	2	3	4	5	6
a_i ($/MW^{2}h)	0.007	0.0095	0.009	0.009	0.008	0.0075
b_i ($/MWh)	7	10	8	11	10.5	12
$c_i(\$/h)$	240	200	220	200	220	190
Pmin	100	50	80	50	50	50
Pmax	500	200	300	150	200	120
α_i(Kg/MW^{2}h)	0.00419	0.00419	0.00683	0.00683	0.00461	0.00461
β_i (Kg/MWh)	0.32767	0.32767	-0.54551	-0.54551	-0.51116	-0.51116
γ_i(Kg/h)	13.8593	13.8593	40.2669	40.2669	42.8955	42.8955
UR (MW/h)	80	50	65	50	50	50
DR(MW/h)	120	90	100	90	90	90

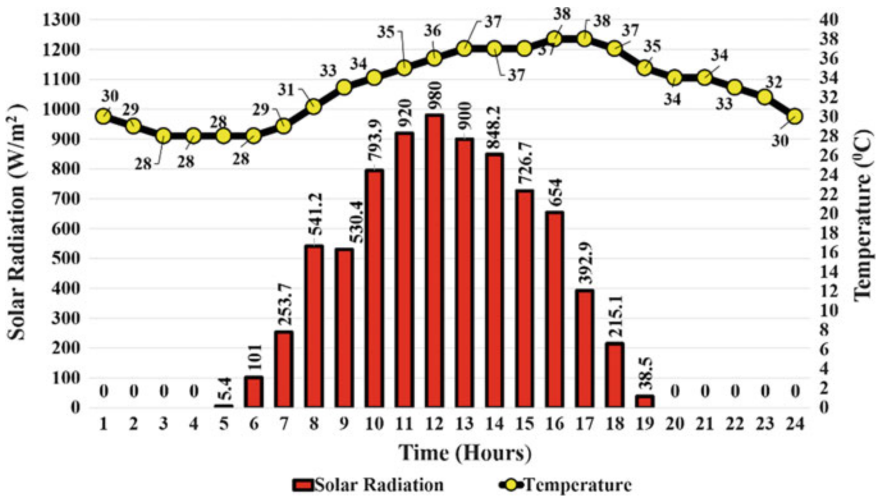

Fig. 3 Solar PV data of temperature (°C) and radiation (W/m^2)

4.2 Simulation Results

GWO is implemented for solution of ELD, EED and CEED problem in MATLAB R2013a environment. For each case, GWO algorithm was run for 30 times and best results are tabulated in Tables 3, 4, 5, 6 and 7.

The performance of GWO with recent methods like artificial bee colony (ABC) [8] and differential evolution (DE) [9] is given in Table 3. Table 4 tabulates the optimum scheduling of the six thermal units for CEED. The parameters considered in implementing the algorithms are given in Table 5. Here, it is observed that the optimum results in terms of minimum cost and least emissions obtained by GWO

Table 2 Rated power and per unit price of solar PV units in the solar farm

Unit	1	2	3	4	5	6	7	8	9	10	11	12	13
P_{rated}	20	25	25	30	30	35	35	40	40	40	40	40	40
UR	0.22	0.23	0.23	0.24	0.24	0.25	0.26	0.27	0.275	0.28	0.28	0.28	0.28

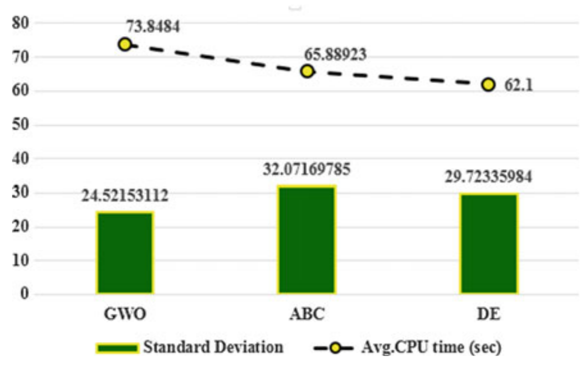

Fig. 4 Statistical and computational comparison of Case 1

Table 3 Comparison of cost and emissions for different algorithms (Case 1)

Method used	Thermal cost (\$/h)	Total emission (Kg/h)
Economic load dispatch		
GWO	308039.0700	34101.0440
ABC	309591.6145	33901.0262
DE	308078.0118	33297.0680
Economic emission dispatch		
GWO	316174.2286	25577.1096
ABC	316172.2100	25579.5970
DE	316172.5736	25606.2910
Combined economic emission dispatch		
GWO	313504.6600	26594.1923
ABC	309361.6796	32703.8763
DE	309569.9413	33492.4277

are lowest as compared to the results obtained by simulation using ABC [8] and DE [9]. The statistical comparison in Fig. 4 illustrates that though the average CPU time in computation is more for GWO than ABC and DE, the standard deviation obtained in results by GWO is lowest than the other two methods.

The optimal solution in terms of cost and emission for hybrid thermal–PV system is listed in Table 6. By comparing results, it can be observed that the total cost for hybrid system is found to be lowest for GWO as compared to other two metaheuristic methods for all three objective functions taken into consideration. The optimal generation scheduled for CEED obtained using GWO is tabulated in Table 7. Here, it is observed that all associated operational constraints (8)–(11) are fully satisfied.

Table 4 Optimum generation schedule (CEED) obtained by GWO (Case 1)

Hour	P1	P2	P3	P4	P5	P6	Load (MW)
1	259.5374	149.3329	125.9369	109.1559	195.7285	115.3084	955
2	208.8734	123.3427	147.2819	148.8409	196.8753	116.7858	942
3	181.6658	155.7335	200.0944	131.9412	168.2502	115.3149	953
4	224.8678	102.1668	145.7005	143.4121	197.0021	116.8507	930
5	236.0181	138.2135	163.1357	105.9371	173.6471	118.0485	935
6	252.2066	120.3990	197.5179	148.2297	146.3651	98.2817	963
7	277.2475	125.9615	145.4991	148.2154	176.7064	115.3701	989
8	266.3530	148.9245	199.5718	122.3128	170.4414	115.3965	1023
9	310.7137	194.4492	153.4075	149.3816	199.5837	118.4643	1126
10	281.0990	198.1337	204.9100	148.3168	199.5668	117.9737	1150
11	350.3692	166.2672	219.3761	146.1391	198.8513	119.9971	1201
12	335.4002	175.6566	260.9748	149.5477	197.1420	116.2786	1235
13	369.6719	170.7951	187.6973	147.0773	197.3182	117.4401	1190
14	348.9233	198.5079	238.5792	148.1412	197.9208	118.9275	1251
15	404.2717	196.3962	237.2358	113.5441	192.9023	118.6499	1263
16	354.7831	198.6413	242.3785	146.6850	190.4917	117.0203	1250
17	394.5981	157.5716	203.4344	149.6969	198.7658	116.9333	1221
18	319.0318	197.9201	260.4055	109.1597	197.6255	117.8574	1202
19	389.6461	159.2299	219.9534	122.7978	149.4363	117.9365	1159
20	307.3071	134.1719	221.9858	147.3151	164.8292	116.3909	1092
21	242.0499	160.1049	176.4222	149.5229	177.4241	117.4760	1023
22	243.2312	106.4994	171.2364	145.3539	198.5802	119.0989	984
23	189.3753	153.2756	215.8568	148.1036	150.9817	117.4069	975
24	227.2540	166.6708	147.5936	148.4603	167.8862	102.1351	960

Table 5 Parameters used for different algorithms

Optimization	Population size (PS)	Food number	Limit	Max cycle	F1	F2	CR
GWO	100	–	–	100	–	–	–
ABC	100	PS/2	100	100	–	–	–
DE	150	–	–	100	0.2	0.2	0.8

5 Conclusion

This chapter focuses on using recently evolved nature-inspired technique named as grey wolf optimization (GWO) for solution of a hybrid thermal–PV system working

Table 6 Comparison of cost and emissions for different algorithms (Case 2)

Algorithms	Thermal cost ($/h)	PV cost ($/h)	Total cost ($/h)	Total emission (Kg/h)
Economic load dispatch				
GWO	268606.9160	856.4677	269463.3836	24453.7943
ABC	269214.9327	856.4677	270071.4004	24015.6247
DE	269492.3920	856.4677	270348.8597	24049.3635
Economic emission dispatch				
GWO	269135.3267	856.4677	269991.7944	23677.4826
ABC	269648.7819	856.4677	270505.2496	23756.6617
DE	269647.1498	856.4677	270503.6175	23759.0086
Combined economic emission dispatch				
GWO	269007.5291	856.4677	269955.7506	23939.7894
ABC	269451.6499	856.4677	270308.1176	23801.7434
DE	269648.1603	856.4677	270504.6279	23758.5261

as power producers in a microgrid in island mode. After analysing the illustrations above, it can be concluded that GWO provides better results as compared to two other well-proven optimization techniques which are ABC and DE. In dynamic environment, the GWO algorithm converged in an efficient manner for solution of environmental/economic dispatch problem in dynamic environment without violating any constraint.

In Case 1, GWO optimizes the minimal cost (ELD) and gives least emissions (EED) as compared to ABC and DE. In Case 2, the microgrid using thermal–PV units as DERs have lesser cost of operation, lower fuel cost and lesser emissions than in Case 1. Thus, using renewable sources of energy will economically and ecologically make the existing microgrid more efficient.

Microgrid using the proposed hybrid thermal–PV system implementing GWO as optimization methodology will be an economic and efficient way to solve the modern-day multi-objective power scheduling problems.

Table 7 Optimum generation schedule (CEED) obtained by GWO (Case 2)

Hour	P1	P2	P3	P4	P5	P6	PV output (MW)
1	291.6677	128.3787	226.496	96.4727	122.8774	89.1075	0
2	308.716	128.2172	200.563	102.6369	122.6878	79.1791	0
3	333.0985	117.9031	209.3775	95.4665	114.0431	83.1113	0
4	301.2931	127.0684	201.1006	83.5105	137.4587	79.5687	0
5	310.3517	137.8202	183.8572	94.0479	125.8481	80.7345	2.34036
6	287.9521	137.5316	198.416	103.5973	111.5374	80.1922	43.7734
7	285.7395	112.1214	168.3167	98.5323	131.7926	83.1021	109.39544
8	236.4054	77.2908	167.7723	95.6519	127.8353	87.0601	230.98416
9	288.7889	106.2189	183.7551	97.3922	146.7348	79.0691	224.04096
10	200.9361	111.4404	198.5657	91.0967	132.4942	81.8701	333.59678
11	213.1547	124.5768	200.5624	97.1991	86.8663	94.0807	384.5600
12	242.4135	117.6926	168.4934	99.1394	113.769	86.0081	407.4840
13	261.721	118.4019	150.4681	93.4949	112.4729	81.2012	372.24 00
14	272.2764	109.4945	205.7171	93.4321	143.2713	75.9931	350.81552
15	313.3497	129.3932	209.7549	99.4467	126.4515	84.041	300.56312
16	324.11	114.4542	194.7587	113.0236	137.8464	96.7515	269.0556
17	348.7288	138.4968	199.6722	109.6982	163.7378	99.0271	161.63906
18	358.7244	184.5096	237.4808	105.422	142.4219	84.4759	88.96536
19	437.3826	125.3974	207.0658	107.7161	185.8632	79.4819	16.0930
20	366.19	140.0392	243.4533	96.4065	149.4269	96.4841	0
21	361.6952	139.283	217.7123	111.0116	101.233	92.0649	0
22	324.2422	133.4168	191.4634	115.4422	134.5866	84.8488	0
23	333.5948	120.1099	219.0381	74.4675	148.1716	79.6181	0
24	304.34	124.8371	202.8644	99.884	134.9458	93.1287	0

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