International Journal of Engineering Research and Development
e-ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 11, Issue 06 (June 2015), PP.30-37

Neuro-Genetic Optimization of LDO-fired Rotary Furnace Parameters for the Production of Quality Castings

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Abstract:- The rising demand for high quality homogenous castings necessitate that vast amount of manufacturing knowledge be incorporated in manufacturing systems. Rotary furnace involves several critical parameters like excess air, flame temperature, rotational speed of the furnace drum, melting time, preheat air temperature, fuel consumption and melting rate of the molten metal which should be controlled throughout the melting process. A complex relationship exists between these manufacturing parameters and hence there is a need to develop models which can capture this complex interrelationship and enable fast computation. In the present work, we propose a generic approach where the applicability and effectiveness of neural network in function approximation is used for rapid estimation of melting rate and they are integrated into the framework of genetic evolutionary algorithm to form a neuro-genetic optimization technique. A neural network model is trained with the experimental results. The results indicate that the heuristic converges to better solutions rapidly as it provides the values of various process parameters for optimizing the objective in a single run and thus assists for the improvement of quality in development of sound parts.

Keywords:- Rotary furnace, Neural networks (NN), Genetic algorithm (GA), Optimization, Neuro-genetic optimization

I. INTRODUCTION

A continuously rotating dome for getting homogeneous castings is the main idea of eco-friendly Rotary Furnace. This furnace consists of a cylindrical structure, which rotates continuously about its axis. The furnace can be run by a variety of fuels but at present we are considering a light diesel oil (LDO) fired furnace. This technique suits the conditions and requirements of the local foundries in terms of the cost of castings produced as well as their quality. Moreover, the pollutants emitted by the furnace are well within the range specified by the central pollution control board (CPCB) of India.

The Rotary furnace is the most versatile and economical mode of melting iron in ferrous foundries. But it is very strange that a very little information is available in the form of literature on this furnace.

There are a number of variables controllable to varying degrees which affect the quality and composition of the out-coming molten metal. These variables, such as excess air, flame temperature, rotational speed of the furnace drum, melting time, preheat air temperature, fuel consumption and melting rate play significant role in determining the molten metal's properties and should be controlled throughout the melting process. However, even an experienced operator may find it difficult to select the optimum input parameters which would yield ideal molten metal and often he may choose them by guessing which may not be effective and economical [1].

Process parameters are optimized to minimize the production cost in conventional manufacturing. In specialized manufacturing applications, such as production of high quality homogeneous castings in rotary furnace, achievement of specific goals in terms of improved casting quality and homogeneity may be the primary objective. Considering such requirements, it is imperative that the process parameters are chosen appropriately so as to ensure high quality castings and minimum possible production cost without violating any of the imposed constraints.

Thus, in order to optimize process parameters, variety of soft computing techniques is used. Genetic algorithm (GA) has been widely used for the selection of the operating conditions in several other applications. To simplify modeling, simulated annealing, fuzzy logic, and neural networks (NNs) have been used with the GAs. The GA finds the optimal solutions quickly when the analytical or empirical models are not available [2].

In this work, an effort is made to develop a neuro-genetic optimization technique, using a NN in tandem with genetic evolutionary algorithm (GEA) in determining the optimal process parameters. The optimization is performed using the GEA, which requires that, the fitness function, i.e., the value of melting rate for a set of process parameters, is easily computable for the method to be computationally tractable. An artificial neural network (ANN) model is used to provide the fitness function value in the technique. This technique has its own modeling and optimization tool to model the system from experimental data and to obtain the optimal operating conditions. This provides the value of process parameters in the form of result that correlate well with the experimental data. In this work operating conditions were selected to maximize the melting rate [3].

II. THEORETICAL BACKGROUND

Back propagation (BP) is one of the basic and most frequently used NNs. The user determines the number of inputs, outputs, hidden layers, and nodes of the hidden layers. In most applications, each node is connected to all the nodes of the next layer. The hidden and output layer nodes multiply the incoming values by weights and use a transfer function to determine their output. Sigmoid is the most commonly used transfer function. Linear, Gaussian, and various hyperbolic functions have also been used depending on the need. The network starts to process the incoming training signals with arbitrary weights. The error is calculated by comparing the output of the network with the corresponding values in the training file. All the weights are adjusted by back-propagating the errors through the network at each interaction. This process is repeated many times until the network's output errors are reduced to an acceptable level [4].

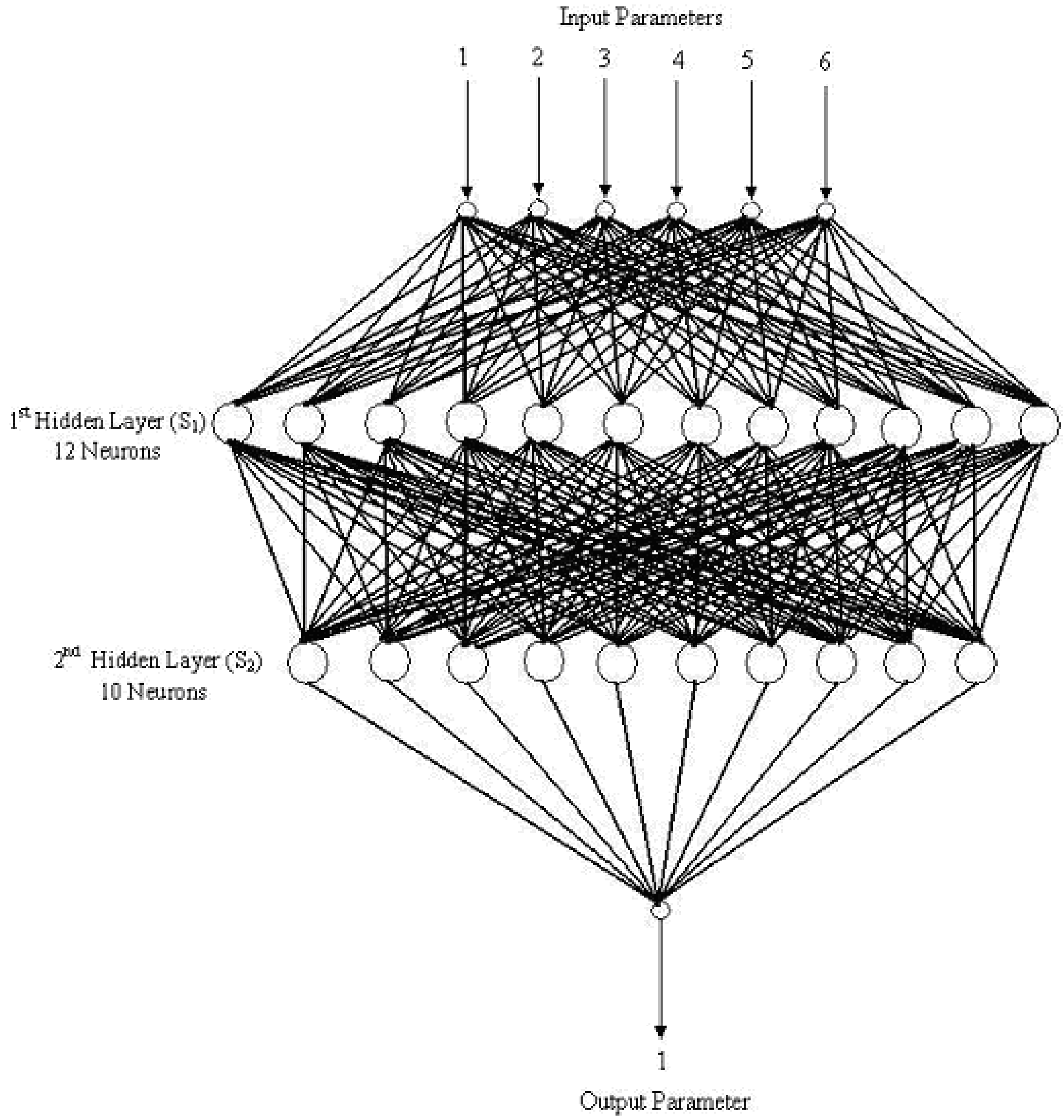

Fig.1: NN Architecture

ANNs are currently gaining wide popularity in manufacturing field. ANNs are proposed to represent the relationship between the operating conditions and the process-related variables because of their data driven approach i.e. they can capture and model extremely complex relationships even without the help of an explicitly stated mathematical model. This property of ANNs is extremely useful in situations where it is difficult to derive the mathematical model that links the various parameters.

The back propagation neural network (BPNN) is a multiple layer network with one input layer, one output layer and some hidden layers between input and output layers. Its learning procedure is based on gradient search with least sum squared optimality criterion. This algorithm can be expressed succinctly in the form of a pseudo-code as given below:

PSEUDO-CODE:

1. Pick a rate parameter *R*.
2. Until performance is satisfactory.
3. For each sample input, compute the resulting output.
4. Compute β for nodes in the output layer using: $\beta_z = D_z - O_z$; where *D* represents the desired output and *O* represents the actual output of the neuron.
5. Compute β for all other nodes using: $\beta_j = \sum_k W_{j \to k} O_k \left(1 - O_k\right) \beta_k$
6. Compute weight changes for all weights using: $\Delta W_{i \to j} = r O_i O_j \left(1 - O_j\right) \beta_j$
7. Add up the weight changes for all sample inputs and change the weights [5].

The standard BP algorithm suffers from the serious drawbacks of slow convergence and inability to avoid local minima. Therefore, BP with Levenberg-Marquardt (LM) approximation is used in this work. LM learning rule uses an approximation of the Newton's method to get better performance. This technique is relatively faster but requires more memory. The LM update rule is: $\Delta W = \left(J^T J + \mu I\right)^{-1} J^T e$; where *J* is the Jacobean matrix of derivatives of each error to each weight, μ is a scalar and e is an error vector. If the scalar is very large, the above expression approximates the Gradient Descent method and if it is small, the above expression becomes the Gauss–Newton method. The Gauss–Newton method is faster and more accurate near error minima. Hence, the aim is to shift towards the Gauss–Newton as quickly as possible. The μ is decreased after each successful step and increased only when the step increases the error [6-8].

GA uses the biological evolution principles including natural selection and survival of the fittest. All the parameters are represented with chromosomes. The algorithm tries to find the best 0 and 1 combination of this string either to minimize or to maximize the objective function [9]. The penalty functions might be used to force some of the parameters to stay in the selected range. The user generally selects the population size, the number of children for each set of the parents, and the probability of mutation [10]. The chromosomes are generated randomly for the first generation. GA has proved to be an effective tool for optimization of machining parameters as it converges to optimum solutions rapidly [11].

GA uses the biological evolution principles including natural selection, and survival of the fittest. The user determines the number of the binary digits to be assigned for each parameter and their boundaries. Additional bits can be assigned for switches. All the parameters and the switches are represented with chromosome. The algorithm tries to find the best 0 and 1 combination of this string either to minimize or to maximize the objective function. The penalty functions might be used to force some of the parameters to stay in the selected range. The user generally selects the population size, the number of children for each set of the parents, and the probability of mutation. The chromosomes are generated randomly for the first generation. Generally, GAs follows a five-step optimization procedure which includes:

a. Selection of the mating parents
b. Selection of the hereditary chromosomes from the parents
c. Gene crossover
d. Gene mutation, and
e. Creation of the next generation [12].

The general scheme of GA is shown in Fig.2.

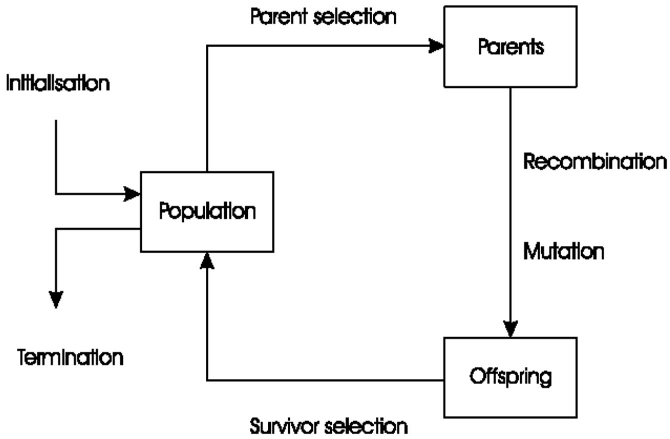

Fig.2: General scheme of GA.

III. PROPOSED OPTIMIZATION SYSTEM

The technique in this work used one BPNN and one GA. The NN had one output as melting rate to have the best possible accuracy. The inputs of the NN were the flame temperature, preheat air temperature, rotational speed of the furnace, excess air percentage, melting time and fuel consumption. The NN was trained to estimate the melting rate by using the experimental results in Appendix. The architecture of the proposed optimization system is shown in Fig.3.

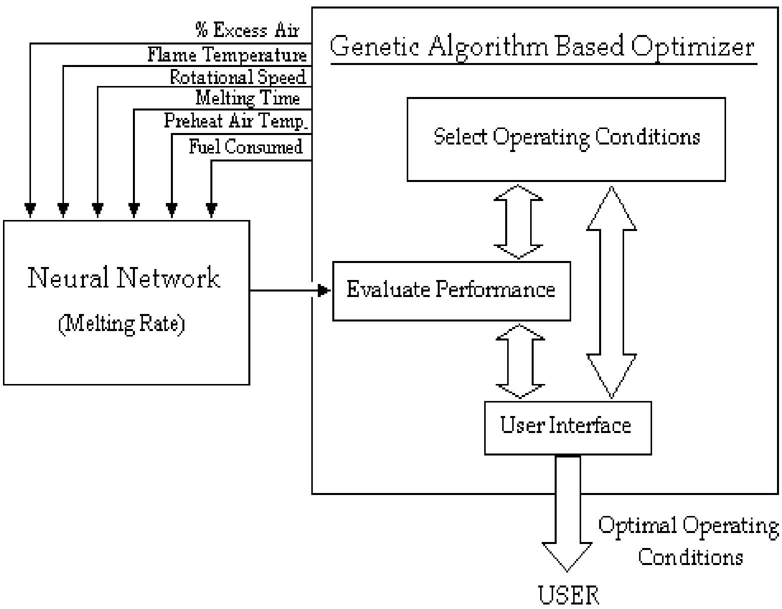

Fig.3: The Architecture of the proposed optimization system.

The pseudo-code of the proposed algorithm can be expressed concisely as under:

PSEUDO-CODE:
1) Initialize:
a) Randomly select '*N*' parent strings,
b) Determine number of children to be generated by each parent,
c) Initialize Pareto-optimal Set (PS).
2) For each parent '*i*', generate '*m (i)*' children using crossover.
3) Perform mutation with a probability 'p_m'.
4) Find the best child for each parent, based on fitness evaluated with the NN model.
5) Select the best child as the parent for the next generation.
6) Repeat step 7 to step 10 for each family.
7) Count=0.
8) Repeat step 9 for each child; go to step 10.

9) Increase count as per pseudo-code given in the explanation of steps 6-9.
10) Acceptance number of the family is equal to count (A).
11) Sum up the acceptance number of all the families (S).
12) For each family '*i*', calculate the number of children to be generated in the next generation according to the following formula: *m(i)=(T×A)/S*; where *T*=Total number of children generated by all the families.
13) Update PS.
14) Repeat step 2 to step 14 until a certain number of iteration has been reached.

The NN model is used to provide the fitness function value by incorporating in the above mentioned algorithm. This approach of using a NN model, in tandem with GEA is quite novel.

IV. EXPERIMENTAL SETUP AND DATA COLLECTION

The rotary furnace data used to train the ANNs have been extracted from the experiments conducted on self-designed and developed furnace (see Fig.4) at Foundry Shop, Faculty of Engineering, DEI, Dayalbagh, Agra, India.

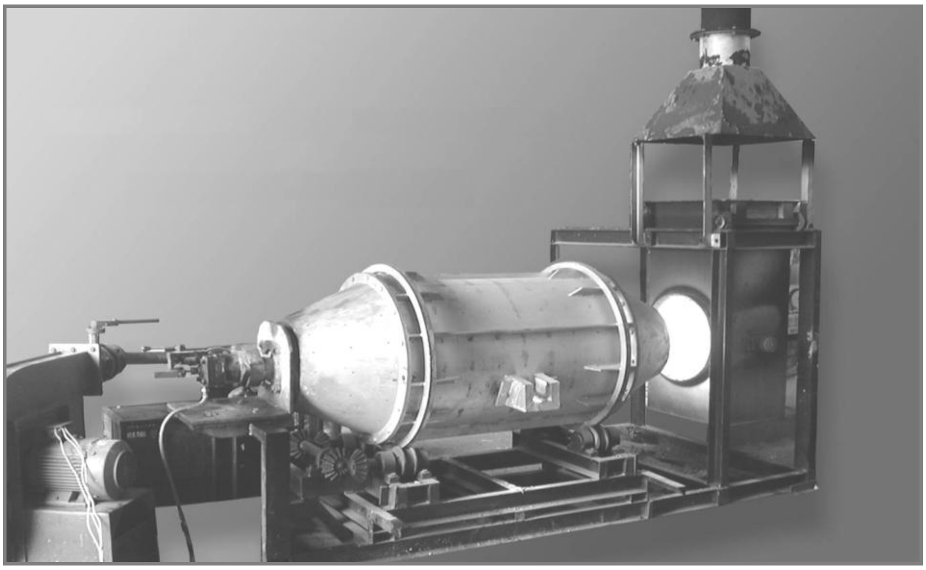

Fig.4: Self-designed and developed Rotary furnace at Faculty of Engineering DEI, Agra

In the experimentation, 200 *kg* of the charge is melted in the rotary furnace. A circular burner is used for burning light diesel oil (LDO) as fuel. Due to the heat transfer by conduction, when refractory material comes in contact with the molten charge, to have better heat transfer, the maximum time is given to refractory to be in contact with the charge. The quantity of fuel consumed is reduced in subsequent heats and normally it is found to be almost constant in third heat onwards.

Numbers of experiments were conducted at different percentage of excess air varying from 10% to 50% and amount of air preheat from 200°C to 400°C.

It was observed that it is difficult to achieve the rotation below 0.8 RPM from the fabricated rotary furnace so, keeping this in view the experiments were carried out at rotational speed ranged from 0.8 to 2.0 RPM and the following results were obtained.

While conducting experiments, it was observed that rate of melting varies with change of rotational speed. The charge of 200 *kg* when melted at 2 RPM takes 45 *min*, the rate of melting (*MR*) is given by:

$$MR = \frac{\text{Quantity of charge in } MT \times 60}{\text{Time taken for complete melting}} = \frac{0.2 \times 60}{45} = 0.266 MT \,(\text{Metric Ton}) / hr$$

Under similar conditions, the total time taken for complete melting from third heat onwards was reduced to 35 *min*, when the rotational speed is reduced to 1 RPM. The *MR* is given by:

$$MR = \frac{\text{Quantity of charge in } MT \times 60}{\text{Time taken for complete melting}} = \frac{0.2 \times 60}{35} = 0.343 MT / hr$$

From above, it can be interpreted that the rate of melting is high at slower rotational speed. During experimentation it was observed that the fuel consumption varies with rotational speed percentage of excess air and air preheat temperature. Charge of 200 *kg*, when melted in the furnace at 2 RPM with 20% excess air and 300°C air preheat, takes 47 *min* and consumed 85 *liters* of LDO.

$$\text{Rate of fuel consumption} = \frac{\text{Fuel consumed}\left(liters\right)}{\text{Quantity of charge}\left(kg\right)} = \frac{85}{200} = 0.425\, {liters}/{kg}$$

Under similar conditions, the fuel consumption for complete melting of charge at the rotational speed of 1 RPM with 20% excess air and 300°C air preheat is 81 *liters*.

$$\text{Rate of fuel consumption} = \frac{\text{Fuel consumed}\left(liters\right)}{\text{Quantity of charge}\left(kg\right)} = \frac{81}{200} = 0.405\, {liters}/{kg}$$

From the above discussion it can be interpreted that the rate of fuel consumption is high at higher rotational speed.

Large numbers of heats were taken from the rotary furnace with the variations of the above mentioned parameters and finally a set of 201 heats was obtained from the furnace. This data was used to train the artificial NN and to find optimum operating conditions for maximizing melting rate in the proposed technique. Here, a set of 50 readings is presented.

V. RESULTS AND DISCUSSIONS

A two layer feed forward network with six input neurons, twelve neurons in the first hidden layer (S_1), ten neurons in the second hidden layer (S_2), and one output neurons in the output layer was designed and trained with NN. The logarithm of sigmoid function is used in the first hidden layer, tangent of sigmoid in the second hidden layer and the output layer has pure linear neurons.

The input parameters were:

1. Percentage of Excess Air (in %)
2. Flame Temperature (in °C)
3. Rotational Speed (in RPM)
4. Melting Time (in Minutes)
5. Preheat Air Temperature (in °C)
6. Fuel Consumed (in Liters)

Melting Rate is taken as single output parameter.

The training parameters are as follows:

Frequency of progress displays (in epochs) = 100

Maximum number of epochs to train = 10000

Sum-squared error goal = 10^{-10}

Neurons in layer 1, S_1 = 12

Neurons in layer 2, S_2 = 10

Number of epochs = 1567.

While performing optimization, the technique was asked to maximize the melting rate. The population size, child number, cross-probability, mutation-probability and creep-probability were selected as 100, 10, 0.2, 0.1, and 0.05, respectively, during the optimization process. Optimum values were found in less than 50 iterations. GA was stopped after 50 iterations were completed. The range of the parameters in the optimization study is shown in Table I and the optimization results are presented in Table II.

The operating conditions were optimized to obtain the best maximized value of melting rate. Flame temperature, preheat air temperature, rotational speed of the furnace, excess air percentage, melting time and fuel consumption were kept in the desired range and the technique was asked to maximize the melting rate for a set of process parameters. A series of alternatives were provided to the user. The results obtained correlated well with the experimental data.

VI. CONCLUSION

The technique was proposed for selection of the optimal operating conditions in rotary furnace operations from the experimental data without developing any analytical or empirical models. NNs were trained by using a series of experimental results to represent the relationship between the process parameters such as flame temperature, preheat air temperature, rotational speed of the furnace, excess air percentage, melting time and fuel consumption. The technique determined the optimal process parameters while maximizing the melting rate. The tendency of the estimations of the technique agreed with the theoretical expectations.

The technique has proved to be effective for constrained optimization as it provides the values of various process parameters in a single run and so assists in achieving in energy and material saving.

Table I: Range of process parameters given to the proposed technique

Excess air (%)	**Flame temperature** (°C)	**Rotational speed** (RPM)	**Melting time** (*Min*)	**Preheat air temperature** (°C)	**Fuel consumed** (*Liters*)
10–50	1690–2300	0.8–2.0	32–50	200–400	74–88

Table II: Optimization results

Parameter maximization	**Melting rate** (*MT./ hr.*)	**Operating conditions**					
		Excess air (%)	**Flame temperature** (°C)	**Rotational speed** (RPM)	**Melting time** (*Min.*)	**Preheat air temperature** (°C)	**Fuel consumed** (*Liters*)
Melting Rate	0.3751	10	2290	0.8	32	400	74

The results indicate that the proposed heuristic converges to better solutions rapidly thereby assisting in the improvement of quality in development of sound parts. This methodology ensures quality, precision, economy and flexibility in agile manufacturing.

ACKNOWLEDGMENT

The authors gratefully acknowledge the inspiration provided by Most Revered Prof. P.S. Satsangi Sahab, Chairman, Advisory Committee on Education, Dayalbagh, Agra.

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Appendix: Comparison of Melting Rate obtained by Experimentation on Rotary Furnace & by ANN Model

S. No.	**Excess air** (%)	**Flame temperature** (°C)	**Rotational speed** (RPM)	**Melting time** (*Min.*)	**Preheat Air temperature** (°C)	**Fuel consumed** (*Liters*)	**Experimental values of melting rate** (*MT/hr.*)	**NN Values of melting rate** (*MT/hr.*)
1.	10	2190	0.8	35	200	76	0.343	0.343
2.	10	2185	0.8	35	200	75	0.343	0.342
3.	10	2190	0.8	35	200	76	0.343	0.343
4.	10	2195	0.8	36	200	75	0.330	0.329
5.	10	2200	0.8	34	300	75	0.353	0.353
6.	10	2215	0.8	34	300	75	0.353	0.352
7.	10	2215	0.8	35	300	76	0.343	0.342
8.	10	2220	0.8	34	300	75	0.353	0.353
9.	10	2280	0.8	32	400	74	0.375	0.375
10.	10	2290	0.8	32	400	74	0.375	0.375
11.	10	2300	0.8	32	400	74	0.375	0.374
12.	10	2290	0.8	32	400	74	0.375	0.375
13.	10	2180	1.0	37	200	78	0.324	0.324
14.	10	2175	1.0	37	200	78	0.324	0.323
15.	10	2175	1.0	38	200	79	0.315	0.315
16.	10	2195	1.0	35	300	76	0.343	0.343
17.	10	2200	1.0	35	300	76	0.343	0.342
18.	10	2215	1.0	36	300	79	0.330	0.330
19.	10	2265	1.0	34	400	75	0.343	0.342
20.	10	2270	1.0	34	400	75	0.343	0.343
21.	10	2270	1.0	34	400	76	0.343	0.343
22.	10	2160	1.2	38	200	79	0.315	0.314
23.	10	2165	1.2	38	200	78	0.315	0.315
24.	10	2160	1.2	37	200	79	0.324	0.323
25.	10	2180	1.2	37	300	77	0.324	0.324
26.	10	2185	1.2	37	300	78	0.324	0.324
27.	10	2190	1.2	37	300	77	0.324	0.323
28.	10	2250	1.2	36	400	76	0.330	0.330
29.	10	2245	1.2	36	400	75	0.330	0.329
30.	10	2245	1.2	36	400	76	0.330	0.329
31.	10	2150	1.4	38	200	80	0.315	0.315
32.	10	2155	1.4	38	200	80	0.315	0.314
33.	10	2160	1.4	37	200	79	0.324	0.324
34.	10	2175	1.4	36	300	80	0.330	0.330
35.	10	2180	1.4	36	300	81	0.330	0.330
36.	10	2170	1.4	36	300	81	0.330	0.329
37.	10	2230	1.4	34	400	80	0.353	0.353
38.	10	2240	1.4	34	400	79	0.353	0.352
39.	10	2240	1.4	34	400	79	0.353	0.352
40.	10	2145	1.6	38	200	81	0.315	0.315
41.	10	2150	1.6	38	200	80	0.315	0.315
42.	10	2150	1.6	37	200	81	0.324	0.323
43.	10	2170	1.6	36	300	79	0.330	0.330
44.	10	2178	1.6	36	300	79	0.330	0.329
45.	10	2170	1.6	36	300	80	0.330	0.330
46.	10	2220	1.6	35	400	78	0.343	0.343
47.	10	2215	1.6	35	400	78	0.343	0.342
48.	10	2210	1.6	35	400	79	0.343	0.343
49.	10	2100	2.0	39	200	80	0.307	0.307
50.	10	2110	2.0	38	200	80	0.315	0.315