Estimation of Strain Controlled Fatigue Properties of Steels Using Tensile Test Data

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***Abstract*—Aim of this study is to estimate various strain life fatigue parameters using tension test data. Monotonic tensile test properties, hardness and modulus of elasticity of various steel grades are extrapolated to predict various parameters of strain based fatigue approach. Artificial Neural Network (ANN) tool is used for prediction purpose. A neural network program is developed in MAT-LAB-2012 software. Four separate networks are developed to estimate four strain-life fatigue properties. These are stress at fracture in one stress cycle, true strain corresponding to fracture in one stress cycle, fatigue strength and ductility exponents. Tensile test results data, material hardness and modulus of elasticity is used as input for networks. The experimental fatigue test data available in literature for different grades of steel is used for training and test purpose. The results of neural network modeling indicated the close agreement with the real time values. The accuracy of predicted result is found to be approximately 87-98%. Finally, it is concluded that ANN is prominent tool to predict various properties of strain based fatigue approach which eliminates the need of actual experimentation.**
Keywords—Strain controlled fatigue properties; ANN; MAT-LAB; Fatigue; Tensile test.

I. INTRODUCTION

Normally, machine components are designed on the basis of mechanical properties obtained from monotonic tensile test. However, in service most of the components are subjected to cyclic loading. Hence it is important for design engineer to know fatigue properties of materials [1,2]. Often situation arises where knowledge about resistance to cyclic loading for specific material is required, but data is not available. On the other hand, tensile test properties, hardness, modulus of elasticity etc. are readily available for almost all materials [3-8]. This can be extrapolated to forecast various properties material under cyclic loading. The common practice to obtain the real time experimental values is challenged using ANN as prediction tool.

Analytical co-relations between tension test properties and strain-life fatigue parameters have been developed by many researchers [8, 9]. All these are based on certain assumptions, and some practical limitations associated with these. So, it is suggested to develop a robust approach which can provide solutions for fatigue problems on the basis of tension test data.

A. *Strain Based Fatigue Life*

Literature survey reveals that, strain based approach for fatigue life assessment is more powerful and accurate than traditional stress life approach [8]. Stress life approach to determine fatigue life is based on cyclic stress, referred as S-N approach. The relation between number of reversals to failure and stress amplitude is given by Basquin's equation [2] represented as equation (1).

$$\frac{\Delta s}{2} = \sigma_f'\left(2N_f\right)^b \quad (1)$$

Where, $\Delta s/2$ is stress amplitude and $2N_f$ is the number of reversals to failure. To determine life under cyclic loading input values required in eq.1 are fatigue strength coefficient,σ_f' and fatigue strength exponent, b.

Strain based fatigue life approach is based on local strain, also known as strain life (ε-N) method. This relates reversals to failure, $2N_f$, to the strain amplitude, Δε/2. The total strain is calculated as sum of elastic and plastic strain [2]. The relationship is referred as Coffin-Manson's equation, represented as Equation (2), (3).

$$\frac{\Delta\mathcal{E}}{2} = \left(\frac{\Delta\mathcal{E}e}{2}\right) + \left(\frac{\Delta\mathcal{E}p}{2}\right) \qquad (2) \qquad \{\text{elastic}\}$$

{plastic}

$$\frac{\Delta\mathcal{E}}{2} = \frac{\sigma_f'}{E}\left(2N_f\right)^b + \varepsilon_f'\left(2N_f\right)^c (3)$$

Where, $\Delta\mathcal{E}/2,\ \Delta\mathcal{E}e/2, \Delta\mathcal{E}p/2$ are total, elastic and plastic strain amplitudes, respectively, σ_f' is fatigue strength coefficient,b is fatigue strength exponent, ε_f' is fatigue ductility (strain) coefficient ,c is fatigue ductility (strain) exponent and $2N_f$ is number of reversals for failure. $\sigma_f', b,\ \varepsilon_f', c$ are influencing constants for strain-life behavior of material [1].

It is general practice to access resistance offered by material under cyclic loading using strain-life approach. This gives comprehensive description of fatigue behavior of material. This approach is more popular for design of automotive components [8].

B. Artificial Neural Network

The term "neural network" refers to a collection of neurons, their connections and strengths between them. The knowledge acquired during the training process is used to adjust weights and bias [10]. This is done so as to obtain linear co-relation between output response of network and known target values to maximum extent possible. Multi-layered feed forward neural network with back propagation is generally used [11]. Back propagation algorithm uses error minimization technique. Various non-linear activation functions such as sigmoidal, tanh or radial (Gaussian) are used to model the neuron activity [10-12].

The typical artificial neuron is given in *fig.1*. The scalar input X_i is transmitted through connections that multiply their strength by scalar weight w_i to form scalar product $W_i X_i$. All weighted inputs are then added to get $\sum WijXi$, to this scalar bias 'b_i' is added. The result is argument of transfer function f, which produces output 'a' (4). Note that w_i and b_i are adjustable scalar parameter of neuron. These can be adjusted in order to achieve desired performance of the network [10].

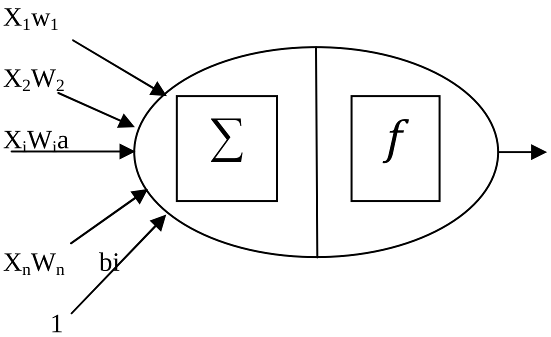


Fig.1.Schematic representation artificial neuron with one input and bias.

$$a_{=} f_{act}\left(\sum_{i=1} W_{ij}X_i + b_i\right) \qquad (4)$$

II. DEVELOPMENT OF NEURAL NETWORK

The main objective of this study is to develop and demonstrate the applicability of neural network to estimate various parameters of strain based fatigue approach on the basis of tension test data. Neural network is used as prediction tool. Experimental tensile and fatigue test data of 73 different steel grades as given in *Table.I*is used for network training and validation [8,9]. Neuralnetwork program is developed and written in MAT-LAB 2012 software. The program will estimate the known targets for known inputs and can generalize to accurately estimate the unknown targets for inputs that are not used to design the solution.The literature survey reveals that the model with more input and one output variables significantly improves the result accuracy [16]. Hencefour separate networks are examined to predict four strain-life fatigue properties: fatigue strength coefficient, σ'_f, fatigue ductility coefficient, b, fatigue strength exponent, ε'_f, and fatigue ductility exponent, c.Neural network approach comprises of three main stages: preparation of input-target data, design of network architecture, programming and training of ANN.

A. Preparation of Input-Target Dat:

Input output parameters are important and these are selected on the basis of physical processes to be investigated [10]. This step is performed outside the frame of neural network [11]. For this study monotonic tensile and fatigue test dataas given in *Table-I*is used for input and target matrix. Each column of input matrixhas five elements representing five tensile test properties (E, RA%, BHN,σ_y,σ_u) whose fatigue properties are already known. Similarly, data of 73 steel grades is used hence size of input matrix is 5x73.

Four target matrices are prepared to predict four strain life fatigue properties. Each corresponding column of target matrix has one element; representing one of the four strain-life fatigue properties.Hence size of target matrix is 1x73 which represents 73 known target values.

B. Design of Network Architecture

While designing ANN, selection of network architecture according to problem definition is important. For prediction problem input-output function fitting with feed forward neural network structure is the best [11-15]. The network structure is decided manually by trial and error.Structure of ANN architecture and its configuration designed for this study is given in fig.2.

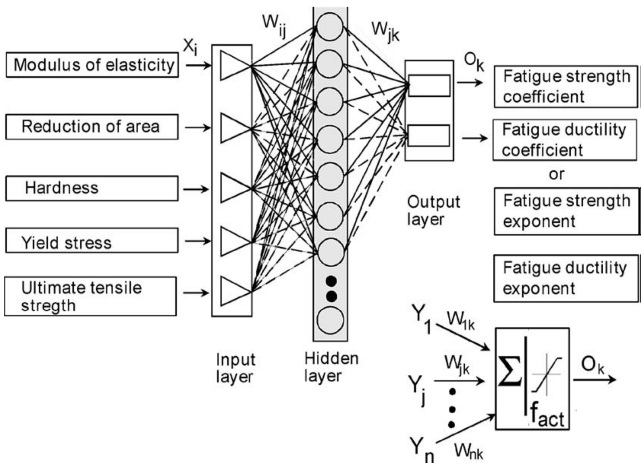


Fig.2.Structure ANN architecture used.

Three layered feed forward network with input layer, one hidden layer and output layer is used for this study. It is suggested that network with more input parameters and one output produces better results. Hence for this study network with five parameters at input layer and one output is designed as shown in fig.2.

'Xi' is receiving signal of node 'i' of input layer, 'W_{ij}' is the connection weight associated with node i of input layer and node j of hidden layer and 'b_i' is bias. Equation (5), gives net input Z_j to the hidden layer.

$$Zj = \left(\sum_{i=1} W_{ij}.X_i + b_i\right) \qquad (5)$$

Activation level of neuron in each layer depends on transfer function associated with it. [11].Generally, sigmoid, hyperbolic tangent or linear transfer functions are used.Equation (6), represents the hidden layer output (h) from neuron.

$$hj_{=} f_{act}\left(\sum_{i=1} W_{ij}.X_i + b_i\right) \qquad (6)$$

Equation (7), gives net input Z_k to node k of the output layer.

$$Z_k = \left(\sum_{i=1} W_{jk}.h_j + b_j\right) \qquad (7)$$

Each output unit applies activation function to compute its output signal; the output O_k of node k of the output layer is given (8).

$$O_{k=} f_{act}\left(\sum_{i=1} W_{jk}.h_j + b_j\right) (8)$$

Where, W_{jk} is the weight from hidden unit h_j to output unit O_k.

C. Programming

Neural network program to solve input-output function fitting problem with three layered feed forward network is developed. Flow chart for program development is given in *Fig 3*.

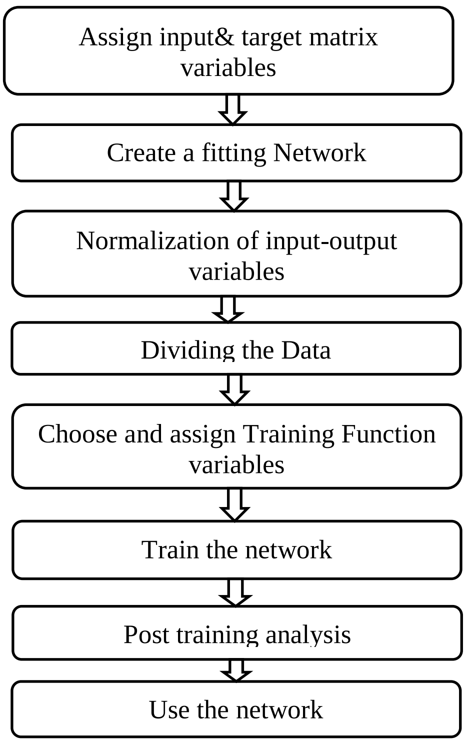


Fig.3: Flow chart showing programming steps.

For predicting four strain life fatigue properties, four separate network programs are developed. Each network program has same input and different targets. Programming syntax and various function selected for one of the network, which estimates fatigue strength coefficient is discussed below.

Step1: Input and targets matrix variable are assigned to the network. These matrices are created initially out of the frame of neural network. The script assumes that the input and target vectors are already loaded into the workspace.

```
inputs = I;
targets = fat_st_coe;
```

I- is Input matrix variable and fat_st_coe- is target matrix variable.

*Step2:*Three layered fitting network with input, output and one hidden layer is created transfer function .tan-sigmoid is used in the hidden layer and linear transfer function in the output layer. Considering training and test performance with various numbers of neurons in hidden layer, it is decided to keep ten neurons in hidden layer to achieve the optimum output. The network has one output neuron, because there is only one target valueassociated with each input vector.Mathematically,tan sigmoid activation function used for hidden layer is defined as (9)

$$fact(x) = \frac{1}{1+e^{-x}} \qquad (9)$$

Activation function used in output layer is purelin. Syntax for assigning input and output transfer functions ,hidden layer size is as given below.

```
purelin(y)= y
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize);
net.layers{1}.transferFcn = 'tansig';
net.layers{2}.transferFcn = 'purelin';
```

*Step3:*Normalization is done in order to reduce noise data of input and target vectors. This improves network processing time. The process functions, such as remove constant rows and map min-max are used, with this input/ target data falls in range [-1,1]. This is done before training the network.

```
net.inputs{1}.processFcns=
{'removeconstantrows','mapminmax'};
net.outputs{2}.processFcns=
{'removeconstantrows','mapminmax'};
```

removeconstantrows: Removes inputs/targets that are constant, mapminmax: Normalize inputs/targets to fall in the range [−1, 1].

*Step4:*The accuracy of network depends on training dataset. Input and target database are split in to three subgroups, training, validation and test dataset. 70% of data is used for training, 15% for validation and remaining 15% for test. Training set updates network weights and bias so as to obtain best fit between network response and known target values. Validation set is used to monitor

error during training process. Test set is used for comparing different models [10].
Following divide functions are used

```
net.divideFcn = 'dividerand';   %Divide data randomly
net.divideMode = 'sample';   %Divide up every sample
net.divideParam.trainRatio = 70/100;
```

70% of data is used for training.

```
net.divideParam.valRatio = 15/100;
```

15% of data is used for validation.

```
net.divideParam.testRatio = 15/100;
```

15% of data is used for test.

Step5: Now training function is assigned to the network. Selection of training function is important in order to enhance the performance of network. This optimizes the error function, by adjusting network weights and bias. Weights and bias are adjusted to improve the performance function when it declines rapidly. Selection of training function is most important and difficult task. It usuallydepends on a various factors such as the network structure,training time, memory usage etc. The Levenberg-Marquardt optimization algorithm (trainlm) is selected for this study. It was independently developed by Kenneth Levenberg and Donald Marquardt,this provides a numerical solution to the problem of minimizing a nonlinear function. It is fast and has stable convergence. In the artificial neural-networks field, this algorithm is suitable for training small- and medium-sized problems. The Levenberg–Marquardt algorithm is a blend of steepest descent method and the Gauss–Newton algorithm. It inherits the speed advantage of the Gauss–Newton algorithm and the stability of the steepest descent method [14].

```
net.trainFcn = 'trainlm'; %Levenberg-Marquardt
```

Step6: Once the network weights and biases are initialized, the network is ready for training. This involves optimization of network performance. Mean square error is used as performance function for this network. This is defined as average squared error between the network outputs O_i and the target outputs d_i. Mathematically it is represented as (10)

$$mse = \frac{1}{N}\sum_{i=1}^{N} ei^2 = \frac{1}{n}\sum_{i=1}^{n}(d_i - O_i)^2 \qquad (10)$$

```
net.performFcn = 'mse';  % Mean squared error
```

Step7: After the training is completed, training record, (tr) is checked. This contains information related to network training. During training, tr structure generates information about several variables such as value of the performance function, the magnitude of the gradient, etc. The training record can be used to plot the performance progress by using the plotperfcommand. The next step in post training analysis is network validation. This does regression analysis, which gives relation between network response and known targets. When output and target values matches exactly, the training is said to be perfect [10,11]. This rarely happens in practice.

```
net.plotFcns = {'plotperform','plottrainstate','ploterrhist', ...
'plotregression', 'plotfit'};
% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs);
% Recalculate Training, Validation and Test Performance
trainTargets = targets .* tr.trainMask{1};
valTargets = targets  .* tr.valMask{1};
testTargets = targets  .* tr.testMask{1};
trainPerformance = perform(net,trainTargets,outputs)
valPerformance = perform(net,valTargets,outputs)
testPerformance = perform(net,testTargets,outputs)
```

*Step 8:*After the network is trained, validated and better regression plot is obtained. The network is ready to be used for predicting outputs of which real time target values are not available.For example, to predict fatigue ductility coefficient of steel 1038, as given in 5th row of *Table I.*

a = net(I(:,5))

a =1054 (Predicted value of Fatigue ductility coefficient,σ_f')

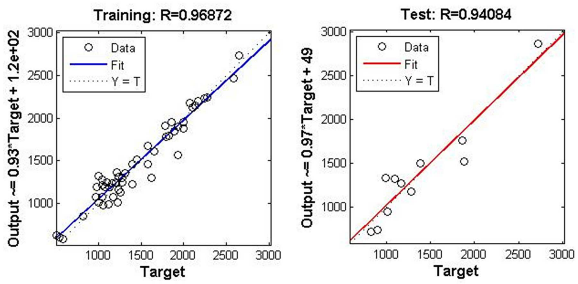
Actual value is 1043; hence predicted value is reasonably close to the actual. Similar prediction can be done for any inputs which are not used while designing the network.

III. RESULTS AND DISCUSSIONS

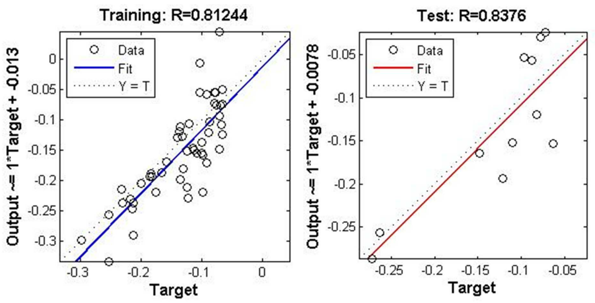
The main objective of the present study is to develop and demonstrate a robust approach using neural network tool, which estimates strain based fatigue properties of material by using readily available tension test data. Four neural networks for predicting four strain-life fatigue properties are developed. The neural network training is conducted by varying number of neurons in hidden layer in order to achieve optimum performance of each network. The performance of the networks was evaluated by calculating MSE errors. For fastest convergence Optimum learning rate and momentum coefficient values are determined in each network. The regression analysis is performed between network response and corresponding target values. This assesses the validity and accuracy of network. *TableII*, gives values network parameters, number of hidden nodes in testing for individual networks.

The performance of the network is better when network response and corresponding targets are closer.
The slopes of theelastic and plastic plots are assumed to be equal to 0.12 and -0.6, respectively [3]. This assumption gives satisfactory agreement between calculated and experimental fatigue values.

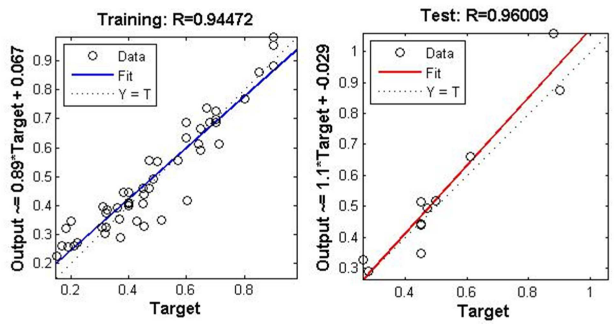
Fig. 4 shows results of regression analysis. Horizontal axis represents known target values and vertical axis represents output response obtained from network. The quality of neural network dependents on prediction its accuracy for unseen target data. Looking at the network performance for each fatigue properties as given in *Fig.4*,the prediction accuracy is found to bereasonably good. To evaluate the network stability training tests are done five to six times by using randomly selected training and test dataset. For every fatigue property, training and test regression graphs are obtained. Results of regression analysis for training data gives 95-98% accuracy of network. Furthermore regression results of test data also indicated the better prediction, R=80 to 85%. In addition unseen test data is also predicted with close accuracy.



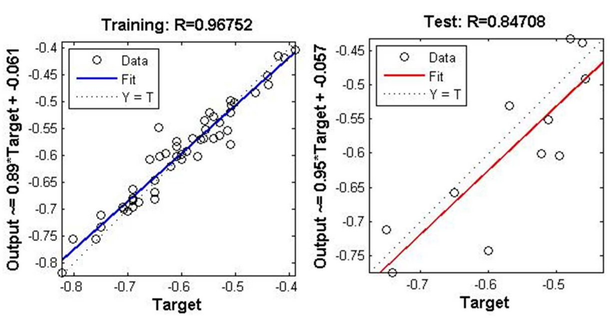
a. Fatigue strength coefficient, σ_f'



b. Fatigue strength exponent, b



c. Fatigue ductility coefficient, ε_f'



d. Fatigue ductility exponent, c

Fig.4: Predicted Fatigue Properties from neural network Vs experimental target data for training and test.

TABLE II: Network details and testing results of neural networks

Network Parameters	Output Parameters			
	σ'_f	ε'_f	b	c
Hidden Neuron Number	5	6	5	7
Learning rate-momentum coefficient	0.75-0.9	0.8-0.9	0.85-0.9	0.7-0.85

IV. CONCLUSIONS

The study reveals that ANN can be used as robust approach for prediction of strain-life fatigue properties. Network design with multiple neurons at input layer and one neuron at output layer gives best prediction quality. Fatigue strength coefficient and fatigue ductility coefficients which primarily characterizes strain amplitude vs life reversal curve are predicted with high accuracy. Hence actual experimentation required to get fatigue properties can be eliminated completely. This will save the time and huge cost involved in experimentation. To establish the stable network it is require to perform some permutations and combinations of various associated parameters. Good sampling of data and proper selection of input parameters for training may improve the prediction performance and training time.It can be concluded that ANN approach should be used to get best prediction quality.

V. FURTHER SCOPE

The scope of this study is limited to development and demonstration of ANN as prediction tool for strain life fatigue properties. Further, comparison between developed neural network prediction and prediction on the basis other analytical methods [8] can be carried out. On the basis of investigation results, comments can be made on robustness of ANN as prediction tool.

In order to investigate the dependence of input parameters on result accuracy, networks with various permutations and combinations of input parameters can be developed for regression and MRE analysis.

Since,output results of network for various strain based fatigue properties are closer to known target data, fatigue life is not calculated. Because it is obvious that fatigue life if calculated by using network results will show satisfactory results when compared with real time data.

TABLE I: Monotonic Fatigue and tension test properties of Steels used in this study. [8],[9]

Steel	E(Gpa)	RA [%]	BHN	Sy	Su	S'f	b	E'f	c
1141	217	54	241	602	802	1080	-0.079	0.361	-0.508
1141	214	49	217	450	725	1255	-0.102	0.43	-0.529
1141	215	58	252	610	797	1162	-0.086	0.534	-0.555
1141	220	47	229	493	789	1326	-0.103	0.602	-0.58
1038	201	54	163	331	582	1043	-0.107	0.309	-0.48
1038	219	53	185	359	652	1004	-0.098	0.202	-0.44
1038	219	67	195	410	649	1009	-0.097	0.225	-0.46
1541	205	55	180	475	783	1622	-0.135	0.515	-0.548
1541	205	42	195	475	906	1044	-0.083	0.513	-0.557
1050	211	50	205	465	821	989	-0.126	0.433	-0.512
1050	203	34	220	460	829	1094	-0.075	0.309	-0.502
1090	203	14	259	735	1090	1310	-0.091	0.25	-0.496
1090	217	22	309	650	1147	1878	-0.12	0.7	-0.6
1090	203	14	279	760	1251	1928	-0.12	0.734	-0.642
1141	216	57	223	457	771	1168	-0.097	0.257	-0.464
1141	227	59	277	814	925	1127	-0.066	0.309	-0.514
1141	220	53	199	418	695	1117	-0.096	0.264	-0.462
A538Aa	185	67	405	1482	1515	1655	-0.065	0.3	-0.62
A538Ba	185	56	460	1793	1860	2135	-0.071	0.8	-0.71
1541F	206	49	290	889	951	1276	-0.076	0.68	-0.65
1541F	206	60	260	786	889	1276	-0.071	0.93	-0.65
A538Ca	180	55	480	1931	2000	2240	-0.7	0.6	-0.75
AM-350b	180	20	496	1861	1905	2690	-0.102	0.1	-0.42
H-11	205	33	660	2034	2585	3170	-0.077	0.08	-0.74
RQC-100b	205	43	290	896	940	1240	-0.07	0.66	-0.69
RQC-100b	205	67	290	883	930	1240	-0.07	0.66	-0.69
10B62	195	38	430	1510	1640	1780	-0.067	0.32	-0.56
1005-1009	205	73	90	269	360	580	-0.09	0.15	-0.43
1005-1009	205	66	125	448	470	515	-0.59	0.3	-0.51
1005-1009	200	64	125	400	415	540	-0.073	0.11	-0.41
1005-1009	200	80	90	262	345	640	-0.109	0.1	-0.39
1015	205	68	80	228	415	825	-0.11	0.95	-0.64
1020	205	62	108	262	440	895	-0.12	0.41	-0.51
1040	200	60	225	345	620	1540	-0.14	0.61	-0.57
1045	200	65	225	634	725	1225	-0.095	1	-0.66
1045	200	51	410	1365	1450	1860	-0.073	0.6	-0.7
1045	205	59	390	1276	1345	1585	-0.074	0.45	-0.68
1045	205	55	450	1517	1585	1795	-0.07	0.35	-0.69
1045	205	51	500	1689	1825	2275	-0.08	0.25	-0.68
1045	205	41	595	1862	2240	2725	-0.081	0.07	-0.6
4130	220	67	258	779	895	1275	-0.083	0.92	-0.63
4130	200	55	365	1358	1425	1695	-0.081	0.89	-0.69
4142	200	29	310	1048	1060	1450	-0.1	0.22	-0.51
4142	205	48	380	1379	1415	1825	-0.08	0.45	-0.75
4142	200	42	450	1586	1760	2000	-0.08	0.4	-0.73
4142	200	37	450	1862	1930	2105	-0.09	0.6	-0.76
4142	205	35	475	1724	1930	2170	-0.081	0.09	-0.61
4142	205	27	560	1689	2240	2655	-0.089	0.07	-0.76

4142	200	47	400	1448	1550	1895	-0.09	0.5	-0.75
4142	200	20	475	1896	2035	2070	-0.082	0.2	-0.77
4340	195	43	243	634	825	1200	-0.095	0.45	-0.54
4340	200	38	409	1372	1470	2000	-0.091	0.48	-0.6
4340	195	57	350	1172	1240	1655	-0.076	0.73	-0.62
5160	195	42	430	1531	1670	1930	-0.071	0.4	-0.57
52100	205	11	518	1924	2015	2585	-0.09	0.18	-0.56
9262	205	14	260	455	925	1040	-0.071	0.16	-0.47
9262	195	33	280	786	1000	1220	-0.073	0.41	-0.6
9262	200	32	410	1379	1565	1855	-0.057	0.38	-0.65
950C	205	69	150	324	565	970	-0.11	0.85	-0.59
950X	205	65	150	345	440	625	0.075	0.35	-0.54
950X	205	72	156	331	530	1005	0.1	0.85	-0.61
980X	195	68	225	565	695	1055	-0.08	0.21	-0.53
1144	195	33	265	717	930	1000	-0.08	0.32	-0.58
1144	200	25	305	1020	1035	1585	-0.09	0.27	-0.53
950C	205	64	159	315	565	1170	-0.12	0.95	-0.61
SNCM630	196	49	327	951	1100	1270	-0.073	1.54	-0.823
SNCM439	208	37	323	950	1050	1380	-0.072	1.89	-0.801
525C	209	52	153	280	508	821	-0.096	0.216	-0.458
545C	206	39	234	590	798	1400	-0.107	0.449	-0.564
SFNCM85S	201	66	241	565	825	1040	-0.092	0.316	-0.522
SF60	208	53	167	580	820	978	-0.082	0.187	-0.439
SCM435	210	66	300	795	951	1100	-0.067	0.996	-0.708
SCM440	204	36	319	846	1000	1400	-0.088	0.675	-0.65

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