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Prediction of Core Shear Strength in Sandwich Composites using Deep Learning and Support Vector Regression

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Abstract*: In the present study, machine learning approaches have been developed to predict the 180 days aged core shear strength of sandwich composites. The characteristics of the sandwich composites depends on the number of factors namely fibre type i.e., Chopped strand Mat, Stitched, Chopped strand Mat and Woven Roving, core density, bond between the core and the face sheets and the ability to bear the load in flexural mode. In the current approach deep learning and SVR models were worked out by taking on six different parameters namely foam density, aging temperature and variety of fiber types as input variables. For each set of these input variables, the 180 days aged shear strength of sandwich composites with a test frequency of 30 days was determined. The paper aims at predicting the core shear strength value of stitch bond sandwich composites using other three aforementioned fibers. To create the model and confirm the accuracy of the algorithm training and test data are considered. The results obtained revealed that the deep learning model develo ped provides better predictive ability than the model of SVR.

Index Terms*: Sandwich composites; Core shear strength; Stitch Bond Mat; Support Vector Regression, Deep learning.

I. INTRODUCTION

Recent developments in the field of materials synthesis and characterizations has largely benefited by the machine learning techniques for the non-linear problems of physical and mechanical properties of composite materials [1]. Presently, there has been a rapid growth in studying and using sandwich composites (SWC's) in bringing down the weight of the dynamic structural (e.g. aviation, automotive, offshore, medical and sporting) applications. SWC's are synthesized by bonding stiff composite face sheets on to the either sides of the light weight foam core. The desired properties were derived by the fibre properties and the staking sequence. It is very essential to observe the structural behavior of the SWC's subjecting to the variety of loading conditions. The structural sandwich composites have been used under some hostile conditions and wherein the sandwich undergoes aging via moisture absorption and cyclical heating. Therefore the investigation on the behavior of foam cored lightweight composite structures under the aging has received much consideration in recent years due to the quest for better materials for advanced and dynamic structural applications [2]. These structurally reliable materials are fabricated using advanced manufacturing technology. Advanced manufacturing technology offers clear prospects for use as large load carrying structures for polymer matrix composites. Advanced composites offer high specific strength and rigidit y, high fatigue life and improved corrosion resistance as wel l as significant weight reduction compared to conventional b uilding materials such as steel and aluminum. Temperature and humidity cause hydrothermal deterioration, which affects the structures long - term durability and thus associates the increased concern with the use of polymer matrix composites as building materials [3]. The optimization techniques used to tailor the structural composites include variation in the types of fibers and the use of various matrix systems [4]. Now a day's everyone expect the work to be automated. Artificial Intelligence is a way to learn intelligently about a computer, a computer - controlled robot, or software, in the same way that intelligent people think. Machine learning is belonging to AI, i.e using the rules one can know the unknown data. A. Yadollahi et al used neural network and taguchi method for predicting the optimal mixture of radiation shielding concrete. Authors found that machine learning is the best way to make the work without consuming much time and cost [5]. Temel Varol et.al used , an ANN model for the prediction of the effects of the manufacturing parameters on the density and porosity of powder metallurgy AlCuMg/B4Cp composites This model can be used to predict the densification behavior of AlCu Mg / B4Cp composites produced with different siz es and quantities reinforced with different millng times and compact pressures[6].The ANN model was developed to pre dict natural rubber (NR) composite fatigue properties.The m echanical properties of natural rubber composites and Viscoelasticity propertieswere used as input vectors whi le fatigue properties (tensile fatigue life) were used as output vector. They obtained good average accuracy [7]. Khan et al presents the work on properties of cementitious composite systems with high performance.Compressive strength, tensile strength, gas permeability and rapid chloride ion penetration of concrete incorporating composite cement materials as partial cement replacement prepared with various water – enforceable

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ratios were the properties reported The toughness and conductance of high - performance reinforced concrete can therefore be predicted using artificial intelligence networks [8]. Nazemi, M. and Heidaripanah, A., have used SVM for predicting the indirect tensile strength of foamed bitumin stabilized base course materials and they also found that SVR is a reliable regression tool for predicting the materials property [9]. Guoqing Gui et al used optimization algorithms along with support vector machine to find damages in civil structures for structural health monitoring system[10].Tang, J.L.et al, applied the Support Vector Mach ine to establish a non linear mapping to verify mechanical pr operties and their performance influencing factors [11]. The model result demonstrates the established model has ideal learning and generality capacities, which performs viably in anticipating mechanical properties. In this manner it is feasible to streamline process parameters and the novelty is qualified to be applied and spread in the research of material performance.One of the primary goals of research in materia ls science has always been to determine the properties of ma terials.Computational models for property determination of materials are hampered by their high computational cost .Th e production and analysis of a computational model for a sin gle property of a single material may take weeks .A large training set of materials with known values for the target property is input in the programming of the machine learningapproach..The program uses this training set to gain experience. The program identifies data patterns and uses th ese patterns to develop a data fitting computational model.T his computational model can then be used to estimate the pr operties of non training materials. The program normally est imates the error in its prediction as well. [11].Therefore modern manufacturing technologies use machine learning. Very large production factories and plants use machine learning every day to monitor and optimize the working conditions. The numbers of variables involved is so high it makes the job unhealthy for a human being. All modern complex production systems are better optimized by machines than men. Hence machine learning is an approach which builds a computerized model built using known and established experimental data, and undiscovered data to be anticipated. Hence human works can be reducing i.e., one can predict properties of the materials using machine leaning model. It consumes time and experimental cost[12].In the present paper we are presenting the machine-learning algorithms for predicting the core shear strength (CSS) of sandwich composites. The approach is entirely based on deep learning and supporting vector regression. The objective of this work is to establish machine-learning as a tool for predicting the CSS properties of stitched bond mat (SBM) sandwich composites against the other three fibre architectures viz., CSM, CSM-S & WR with varying aging conditions.

II. MATERIALS AND METHODS

The sandwich composite instances used in the present study comprises of four different varieties of E-glass fabrics namely, chopped strand mat-Stitched (CSM-S), Chopped strand mat (CSM-S), Woven Roving (WR) and Stitch bond mat (SBM). Vinylester resin used as matrix material and three varied densities of rigid PU foam (100 kg/m^3, 200 kg/m^3 and 300 kg/m^3) used as the core material. The sandwich composites with 3 mm thick face sheet prepared by using compression molding technique and specimens are cured at room temperature for 24 hours.

A. Aging Studies

The aging studies conducted as per ASTM B117 using Salt Fog Machine. The artificial sea water prepared referring ASTM D1141. The specimens were aged for about 180 days and with 3 different operating temperatures like 30°C, 40°C & 50°C with 95% RH for about 180 days.

B. Flexural testing

Using the three-point bending test, the flexural strength of the PU foam cored, E-glass enhanced vinyl ester sandwich composites was determined for various immersion times. The purpose of the flexural test is to determine bending strength (FBS) and core shear strength (CSS) under ambient conditions using standard specimens (127 mm long, 65 mm wide and 30 mm thick) with a strain rate of 2 mm per unit. The sandwich composite's core shear strength was calculated using the equation (1).

Where: τ- is the core shear strength, P is the maximum load, d- sandwich thickness, C-core thickness (24 mm) and b- breadth of the sandwich specimen.

$$\tau = \frac{P}{(d+c)b} \quad \text{---------- (1)}$$

The average values of CSS of three sandwich composite specimens tested for each immersion time was considered for the analysis.

C. Deep learning (Convolution neural network)

A deep neural network is a neural network with a degree of complexity, a neural network with more than two layers. Deep neural networks employ sophisticated mathematical modeling to process data in complex ways. The main reason for profound learning is the idea that artificial intelligence should inspire the brain [14].].In several conditions, deep learning algorithms tally the brain as each the brain and deep learning models involve a huge range of processing units (Neurons) that aren't very intelligent in isolation however become intelligent once interacting with one another. Artificial neurons are the fundamental building block for neural network that imitate human brain neurons. Neurons are the fundamental building block of CNN. These neurons unfold across the network's many layers. These are simple powerful computational units and activation function to weigh input signals and produce an output signal. As data travels through this artificial mesh, each layer processes a data aspect, filters outliers, spots familiar entities, and the final output is generated. Between each layer, weights are assigned. Weights refer to the energy or amplitude of a connection among two synapses.

And if you are familiar with nonparametric, you may try to examine weights on inputs inclusive of the possibilities we use in a correlation equation. Weights are regularly initialized to small random values which includes values within the range zero to 1. One of the first and most successful learning algorithms was the supervised neural networks of Feed forward.

They are also referred to as deep networks, multi-layer perceptron (MLP), or virtually neural networks, and a single hidden layer of vanilla structure is shown in figure 2.1. The network processes the neurons activating input upward as it ends up producing an output value. This is called an advance pass on the network. The network's predicted value is compared with the expected output and a function is used to calculate an error. This error is then propagated lower back over the whole network, one layer at a time, and the weights are updated based on the weight they contributed significantly to the error. This clever bit of math is called the algorithm of back - propagation. The pattern continued in your training data for all the instances. One round of network updates is called an epoch for the entire training dataset. For tens, hundreds or thousands of epochs, a network can be trained [14].

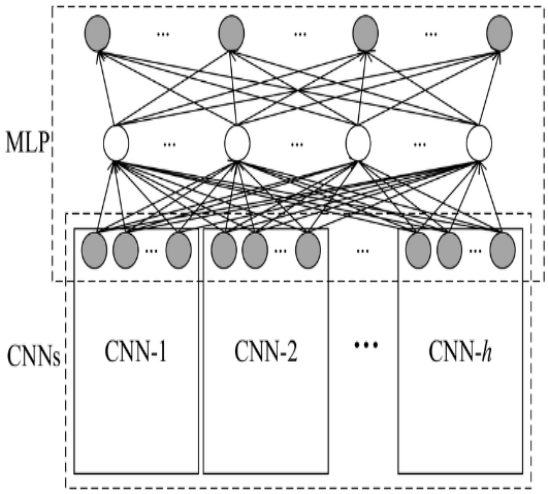

Figure 2.1: Architecture of convolution neural network

A cost function is one - valued, not a vector, as it rates how well the entire neural network has performed. The weights are updated incrementally after each epoch using the Gradient Descent optimization algorithm.[15]. The error rate can be calculated based on the actual value and the value obtained by the algorithm. Therefore convolution neural network is also known as deep learning is a preferable approach for predicting the properties of the material.

D. Support Vector Regression (SVR)

The Support Vector Regression (SVR) uses an indistinguishable organizational standard from the SVM, with only a few minor contrasts. If the output is real valued then prediction is tough to handle due to various possibilities. In the case of regression, in approximation to the SVM, a margin of acceptance (epsilon) is set which would have already been required from the issue. In addition, the procedure is complicated to minimize the error, maximize the hyper plane margin by individualizing and maintaining the tolerance for errors [16].

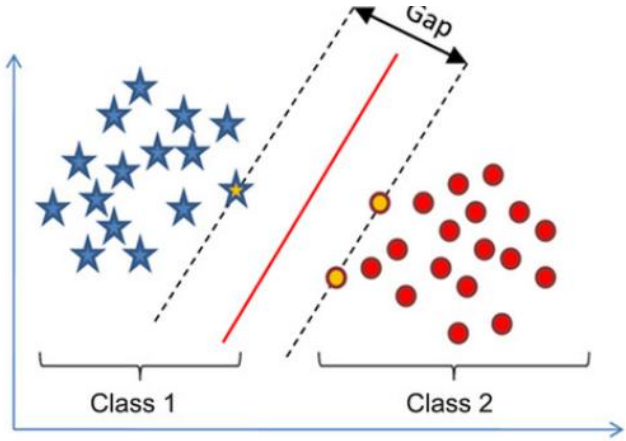

Figure .2.2: Support vector regression

Support Vector Machine can also be used for prediction by preserving all the main characteristics of the algorithm (maximum margin). Figure 2.2 shown nonlinear SVM. SVM can solve the classification problems and is also extended for regression tasks [17]. The term SVM is typically used to describe classification with support vector methods and support vector regression (SVR) being used to describe regression [18]. Practically, SVR creates a hyper plane to separate the positive and negative data. The selection boundary ought to be as far away from the records of each instruction as feasible. We should maximize the margin. The decision boundary should categorize all points properly. The decision boundary can be found by solving the following equations 2 and 3 constrained optimization problem

$$\text{Minimize } \tfrac{1}{2}||w||2 \text{------- (2)}$$

$$\text{Subject to } Yi(W^T X_i + b) \geq 1 \ \forall i \text{ ---------- (3)}$$

Where w is a weight vector, x is input vector and b is bias. SVR also uses suitable kernel function and support vectors to find the best hyper plane that maximizes the hyper plane.

III.RESULTS AND DISCUSSIONS

The prediction of core shear strength of sandwich composites consisting of CSM, CSM- Mat and WR fibers is performed using a computerized universal testing machine. The Table 3.1 shows the tabulated values of CSS values of CSM-Mat, CSM and WR fiber reinforced foam cored sandwich composites. The values were used to predict the CSS value of SBM using back-propagation neural network and support vector regression models.

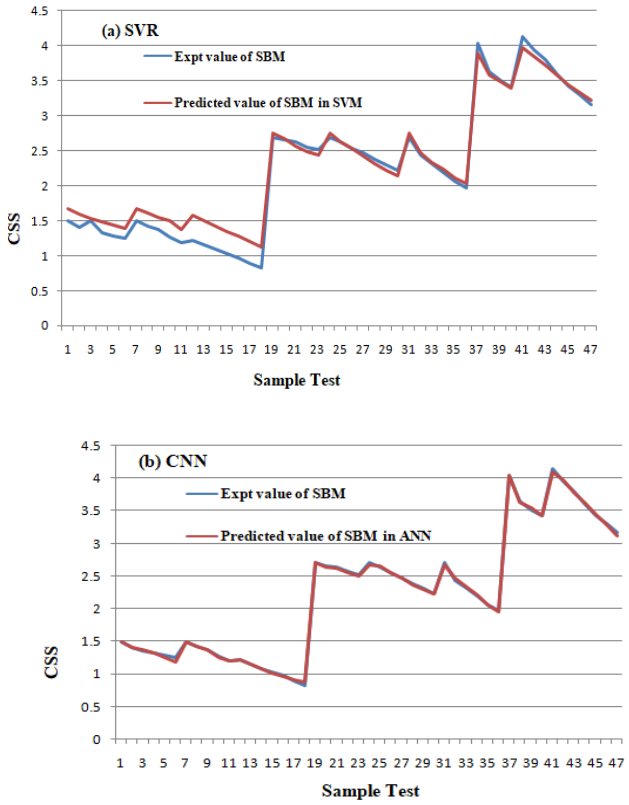

FIGURE 3.1: PRACTICAL AND PREDICTED VALUE OF SBM USING SVR AND CNN

Table 3.1 shows the experimental values we have considered to build the model on the basis of aging days, temperature, CSM-Mat, CSM, WR and the foam core density. There were more than 200 experimental values considered as the training data and built the model using both ANN and SVR. The Remaining 47 experimental values were considered as test data and both the models were tested. The predicted value using ANN and SVR models are depicted in the table 3.1. Support vector regression model is being used to predict value of core shear strength of SBM taking the entire experimental data divided into training and test set. Also, in the present work, SVR uses the Gaussian Kernel regression model for the prediction. SVR performs better than the one used in the linear kernel because it uses Gaussian kernel [19]. In the current work cvpartition(),randomly partition the observations into a training set and a stratified holdout (or test) set using the group prediction value. Both the training and test sets have roughly the same prediction proportions as in the group. The fitrsvm() function trains or cross - validates the regression model of a support vector machine (SVM) on a low - through medium - dimensional predictor set of data. Fitrsvm() supports mapping the predictor data using kernel functions and supports SMO, ISDA, or $L1$ soft-margin minimization via quadratic programming for objective-function minimization and it has shown that SVR predicts the data more accurately as experimental data. Figure. 3.1(a & b) depicts the graphical representation of experimental and predicted data using SVR and CNN method [20].

Different training algorithms were used as part of applications for neural networks. Predicting the optimized training algorithms for the best fit is not usual. To degree the accuracy and performance of the community, the proper selection of information structure and consistency of the schooling information set is vital. In the course of the learning process, abstaining from overtraining with an end intention of having the quality fit is a capability trouble with the usage of capable nonlinear regression strategies in the demonstration of neural networks. An over-skilled model tends to recollect the relationship among input and output variables and thereby dispose of simplification.Computer programs using profound learning go through much of the same process. Each algorithm in the hierarchy applies on its input a nonlinear transformation and uses what it learns to create as output a statistical model. Iterations continue until an acceptable level of accuracy has been achieved. The number of processing layers that data must pass through is what deeply inspired the label. The network weights are used regularly during the training process until the difference between the predicted output and the experimental value is minimized resulting in error function. It is known as mean square error (MSE). Training a model from scratch and transfer learning are the two commonly used approaches to deep learning. Both approaches have advantages and can be used for various deep learning tasks. Developing and training a scratch model works better for very specific tasks that cannot be used for pre - existing models. The downside is typically that this approach requires a great deal of data to produce accurate results. Back-prop is simply a method of calculating a function's partial derivatives (or gradient) that has the shape as a function composition (as in Neural Nets). Using a gradient-based method (gradient descent is just one of them) to solve an optimization problem, you want to calculate the function gradient at each iteration. After the completion of the training the model can be worked for test data set. The results obtained from this are used to find the accuracy of the model.The performance graph Figure 3.2 of the training data reveals the ideal trend and the best validation performance were observed at 0.00068659 i.e., 18th epoch and the total model completed with 247th epochs. It is being observed from the performance plot, the MSE values of learning decreased with the increase in the epochs. Ideally a well trained CNN must possess a very low MSE (close to zero), and in the present work it is observed to be very small (all most nearing to zero) i.e., 1.0276e-025, means desired outputs and the ANN's outputs for the training set have become very close to each other

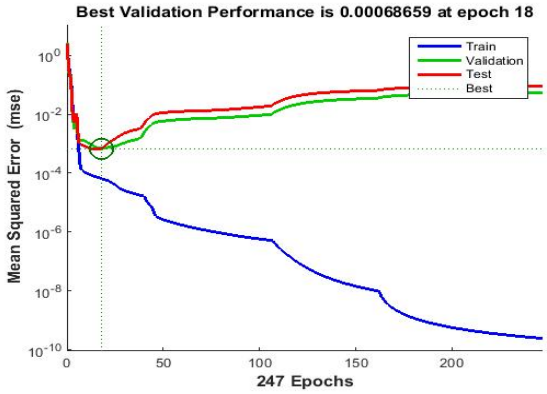

Figure 3.2: Best valid performance plot of ANN

The convergence / gradient of mean square error (MSE) for core shear strength with the number of epochs during training of selected network are shown in the Figure 3.3.

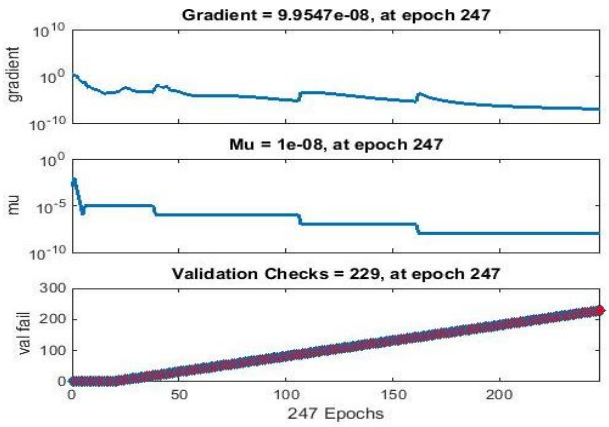

Figure 3.3: Learning Behavior of Convolution Neural network Model

However, a linear regression between the network response and the experimental target value was performed to analyze the network's capability. For the current scenario, the entire shear strength data was worked out to perform the regression analysis for training, validation and testing. The result of the analysis of regression is shown separately and is shown in Figure 3.4. R= 0.99997 for training, 0.99979 for validation, 0.99968 for testing and R=0.99988 for testing. If the fit is perfect, the outputs will be equal to the target sets and the data will fall along the 45 ° line. The higher' R' value in the plots confirms the logical fit accepted. It can therefore be attributed that from a statistical point of view, CNN can be considered if the value of correlation coefficient(R) approaches to unity.The comparison of experimental and

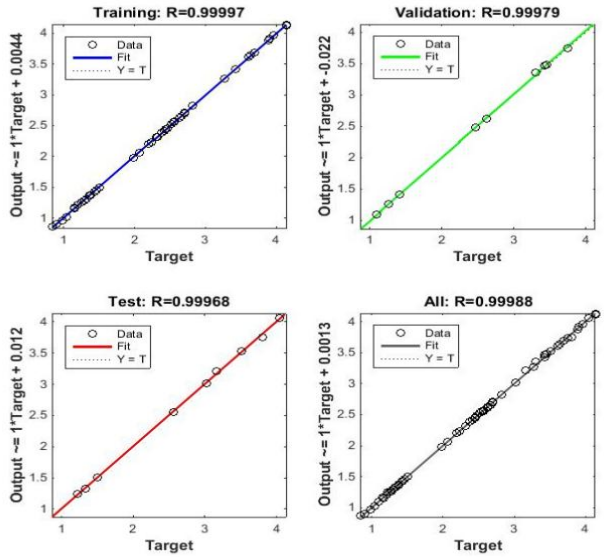

Fig 3.4: Regression correlation between the experimental and predicted values using CNN.

predicted results by convolution neural network for the sandwich composites considered is given in Fig 3.4. Thus the results show good consent between experimental and predicted value.

IV.CONCLUSION

In any engineering design, determining the mechanical properties of materials is very important. Poorly designed often leads to loss of life and property, and the economy is also adversely affected. Therefore the prediction of material properties through analytical methods helps us in understanding the material systems better. The objective of this study was to apply data-driven models, i.e., CNN and SVR prediction models for core shear strength of SBM composites and to compare their results with each other. Results demonstrate that deep learning has better predictions of the experimental core shear strength values than those of support vector regression model. Hence, using CNN model; 180 days aged sandwich composite the core shear strength can be predicted both accurately and easily. Finally to conclude with the CNN predictions were in very good agreement with experimental results and hence could be used as substitute to costly time consuming experiments.

Table 3.1: Predicted and Experimental Core Shear Strength value of SBM using CNN and SVR models

Sl. No	Days	Temp	CSM-MAT	CSM	WR	Kg	Experimental SBM Value	CNN Predicted Value	SVR Predicted Value
1.	0	30	1.2591	1.19315	1.747	100	1.50305	1.5038	1.676203
2.	60	30	1.213	1.131622	1.622884	100	1.417942	1.4193	1.583455
3.	90	30	1.181	1.087657	1.55598	100	1.36849	1.3774	1.530262

4.	120	30	1.145	1.05325	1.512015	100	1.328508	1.3277	1.483127
5.	150	30	1.127	1.020754	1.456581	100	1.291791	1.2584	1.438821
6.	180	30	1.106	0.965319	1.399235	100	1.252618	1.1878	1.387071
7.	0	40	1.2591	1.19315	1.7470	100	1.50305	1.5046	1.676203
8.	30	40	1.2217	1.131622	1.634353	100	1.428026	1.4364	1.607984
9.	60	40	1.204	1.064719	1.544511	100	1.374256	1.3795	1.547628
10.	120	40	1.15	0.930912	1.389678	100	1.269839	1.264	1.490389
11.	150	40	1.1	0.886947	1.299836	100	1.199918	1.2012	1.364909
12.	0	50	1.2591	1.19315	1.19315	100	1.226125	1.2229	1.569298
13.	30	50	1.2217	1.087657	1.087657	100	1.154679	1.1615	1.490342
14.	60	50	1.204	0.986346	0.986346	100	1.095173	1.0922	1.418288
15.	90	50	1.1773	0.886947	0.886947	100	1.032124	1.0231	1.344872
16.	120	50	1.15	0.808575	0.808575	100	0.979287	0.96448	1.28116
17.	150	50	1.1	0.697706	0.697706	100	0.898853	0.91734	1.196523
18.	180	50	1.07	0.596395	0.596395	100	0.833198	0.88483	1.121383
19.	0	30	2.569	2.05279	2.8328	200	2.702795	2.7152	2.746662
20.	30	30	2.429	1.991808	2.815674	200	2.663741	2.6472	2.671289
21.	60	30	2.1533	1.945931	2.794648	200	2.630289	2.6201	2.56528
22.	90	30	2.019	1.867559	2.739214	200	2.563386	2.5617	2.47915
23.	120	30	2.01	1.823594	2.693337	200	2.518465	2.5022	2.435786
24.	0	40	2.569	2.05279	2.8328	200	2.702795	2.6806	2.746662
25.	30	40	2.326	1.945931	2.794648	200	2.630289	2.6537	2.628743
26.	60	40	2.1435	1.867559	2.704806	200	2.546182	2.5593	2.523878
27.	90	40	1.9714	1.791098	2.637903	200	2.4745	2.4764	2.426577
28.	120	40	1.7896	1.701256	2.538504	200	2.37988	2.3728	2.316881
29.	150	40	1.6274	1.622884	2.481158	200	2.312021	2.3067	2.223382
30.	180	40	1.512	1.567449	2.381759	200	2.234604	2.226	2.13983
31.	0	43	2.569	2.05279	2.8328	200	2.702795	2.6806	2.746662
32.	60	43	2.1336	1.768159	2.593938	200	2.441049	2.4722	2.472596
33.	90	43	1.856	1.645822	2.4716	200	2.318711	2.341	2.32548
34.	120	43	1.7889	1.544511	2.326324	200	2.195418	2.212	2.23256
35.	150	43	1.6274	1.422174	2.192518	200	2.067346	2.0607	2.112345
36.	180	43	1.5307	1.332332	2.102676	200	1.977504	1.9544	2.025845
37.	30	30	3.7688	3.062261	4.310759	300	4.03978	4.0378	3.886358
38.	120	30	3.0923	2.861551	4.180502	300	3.636401	3.6326	3.575764
39.	150	30	2.8763	2.794648	4.138722	300	3.507511	3.5435	3.474932
40.	180	30	2.7556	2.704806	4.094484	300	3.425042	3.418	3.391214
41.	0	40	3.885	3.1212	4.3905	300	4.13775	4.091	3.967283
42.	30	40	3.69	3.016384	4.224741	300	3.95737	3.9764	3.837339
43.	60	40	3.43	2.894047	4.180502	300	3.805251	3.7919	3.709714
44.	90	40	3.1	2.806117	4.123976	300	3.611988	3.6247	3.571638
45.	120	40	2.864	2.693337	3.993719	300	3.42886	3.4409	3.436065
46.	150	40	2.664	2.605407	3.937193	300	3.300596	3.2969	3.330606
47.	180	40	2.491	2.492627	3.836428	300	3.163714	3.1179	3.216532

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