“APPLICATION OF NEURAL NETWOKS IN DESIGN OF RCC COLUMNS”

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By

NIRMA MEENA
Roll No. – 2K12/STE/13

Under the guidance of

Mr. G.P.AWADHIYA
(Associate Professor)

Department of Civil Engineering

Delhi Technological University

(FORMERLY DELHI COLLEGE OF ENGINEERING)

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CERTIFICATE

*This is to certify that the thesis entitled "**Application of Neural Networks in Design of RCC Columns**" submitted by **Nirma Meena(2K12/STE/13)** to the **Delhi Technological University, Delhi** for the award of the degree of Master of Technology in **Structural Engineering** is a bona-fide record of research work carried out by her under my supervision. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.*

____

G.P Awadhiya
Associate Professor
(Supervisor)
Department of Civil Engineering
Delhi Technological University, Delhi (India)

____

Nirma Meena
2K12/STE/13
(Candidate)
Department of Civil Engineering
Delhi Technological University, Delhi

Place: DTU, Delhi
Date: _________

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Nirma Meena
Roll No.: 2K12/STE/13
Department of Civil Engineering
Delhi Technological University, Delhi

ABSTRACT

In this project work application of artificial neural network in rcc column design have been implemented. As a structural engineer we are looking forward for an optimal solution for problems encountered so here we design rcc column by using an application of artificial neural networks which provide solution with decreased computational time and increased efficiency.

Recent advancement in the field of artificial neural networking has paved way for optimization of complex and tedious design processin the field of structural engineering. The design of column cross-section for given axial load and biaxial moments is done, firstly by preassuming the dimensions of column section,steel reinforcement, grade of steel and grade of steel and then check its adequacy which is a complex trial and error process we tryed to map this complicated design procedure using artificial neural networking.

Artificial neural networks are algorithms for cognitive tasks such as optimization and learning.These algorithms are developed with capability to learn and generalize from training example data set presented to them with no knowledge of rules. Artificial neural networks are group of numerical learning technique. This whole computational model is made up of many interconnected non-linear calculation units called neurons. A multilayer perceptron and levenberg-marquardt algorithm for training the neural network have been used. The example data set for training of neural network is generated using programming in Microsoft excel. rcc column design is done based on design procedure explained in sp 16 as per IS 456:2000. 5271 column design are done to generate data for training the network. Matlab software is used to develop the neural network architecture used for column design. The effect of performance of various parameters of network on network output was studied and necessary modification was made to get desired target output. Network performance is checked by performance function vs epoch curve and by compairing network output with the result obtained through conventional design. Thus best topology of network architecture is achieved for the best performance of network in function fitting application of column design.

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CHAPTER 1

INTRODUCTION

1.1. GENERAL

Structural engineering deals basically with conceptual, modelling of material behaviour and natural behaviour and damage assessement. Structural design process is a complicated and iterative so mere use of modern computer application can not solve problem it only can bring efficiency, accuracy and speed in structural analysis. Our area of conceptual column design needs human expertise which is achieved only through artificial intelligence systems like artificial neural network.

1.2. OBJECTIVE OF PRESENT STUDY

A. Generate data set of column design for training, validation and testing of neural network.
B. Study and design the best topology of neural network for the design of rcc columns.
C. Compare the designs using neural networking with the design result of programming for column design in excel based on SP 16 as per 456:2000.

1.3. BRIEF SUMMARY OF THE WORK DONE

In this project we have study about the neural networking and their use in civil engineering i.e design of rcc column. We have designed a neural network model for column design. To achieve this objective study has been done in two phases. In phase one we have designed column data set. For this purpose we have study the design and analysis of column for biaxial and uniaxial bending. After that study a program for column design using excel programming was written. Using this program we generated a date set for different inputs for column i.e moments and axial loading. This date set generate has been used further used in neural networking for design of column. In phase two we designe neural network i.e fixed the network parameters by training of network using programming in neural networking toolbox of Matlab software. The complete training of network has been assured by achieving minimum error goal during learning of network. Network performance has been analysed by comparing network results with SP 16 results.

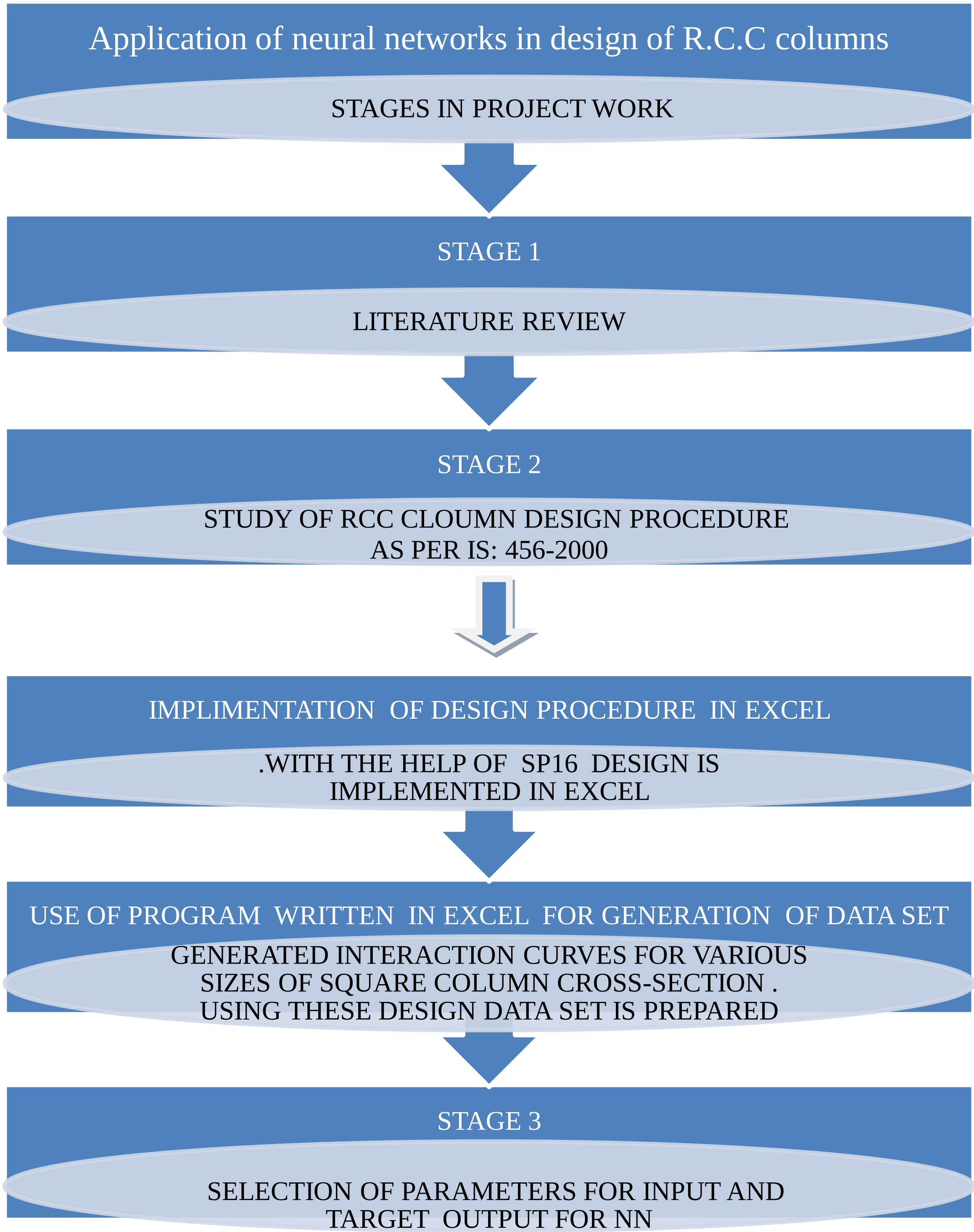
1.4. SCOPE OF PRESENT STUDY

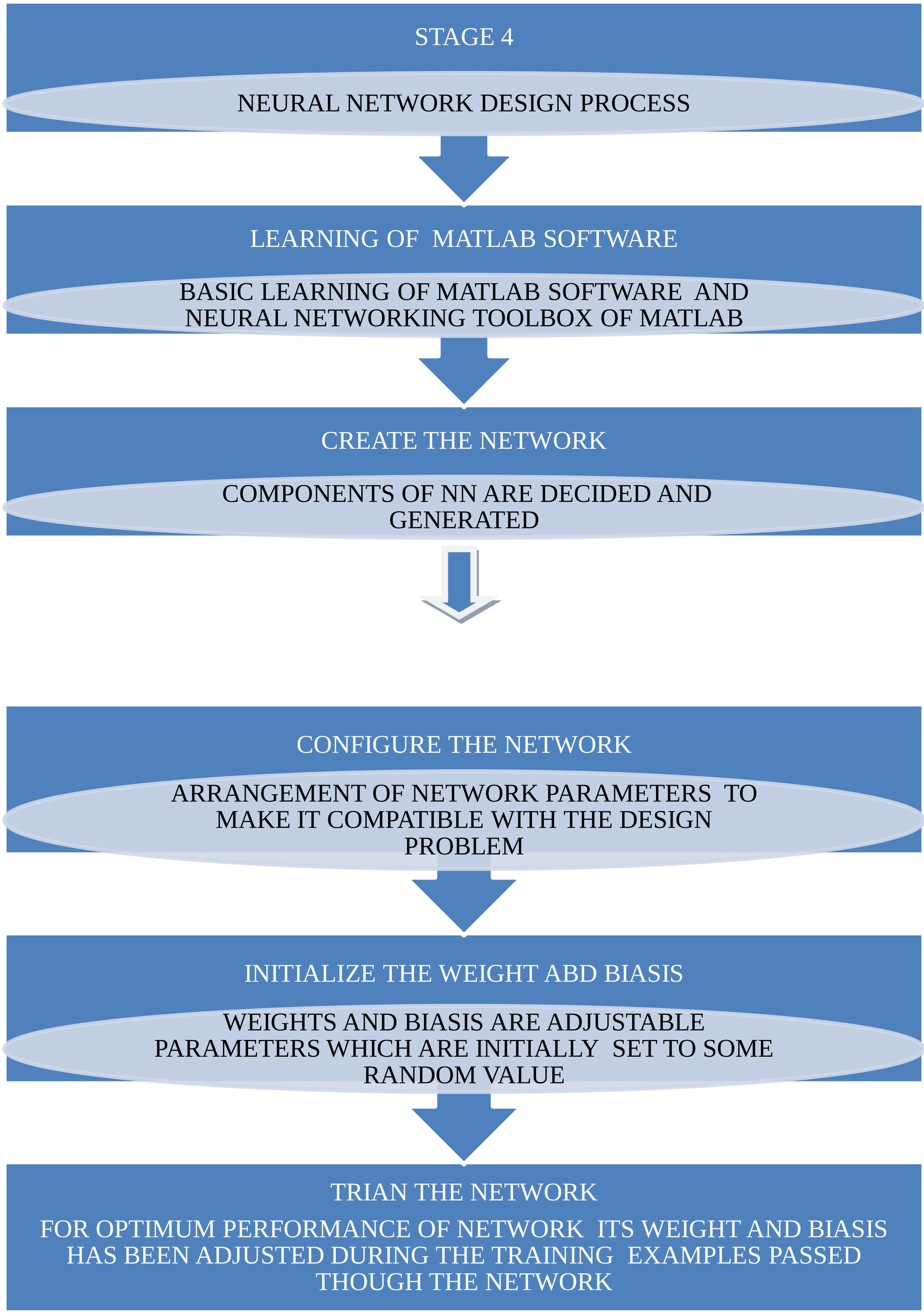
Initial design is the first peculiar stage in the process of structure design. Despite of the fact that many a aspects of structure design are governed by IS code and its regulation,the structural engineer require to be carefull and apply his conscience in addition to results obtained from interpretation of different provisions and checks of the related codes for obtaining an economical and efficient design. After this step come the stage when engineer with his knowledge, experience, requirements and restriction makes a decision from available optimum solution. Based on proposed optimum solution further analysis of structure is done. Redesigning of structure can be required if some provisions are not fulfilled or satisfied. Thus design process is dependent on initial assumptions. A correct initial guess considerably decreases the step of repetative design-analysis process. The presented column design problem for axial load and biaxial moments is highly complex non-linear design procedure using conventional design method. The column design is iterative process also the reinforcement required is highly sensitive to ratio of column depth and cover, arrangement of steel reinforcement, grade of steel and grade of concrete. Thus we can say that this iterative and conceptual design phase requires human intuition which is very dificult to computerise. Now with the advanced development in field of artificial intelligence systems good progress have been achieved to computerise to computerise this primary design procedure with the application of artificial neural networks.

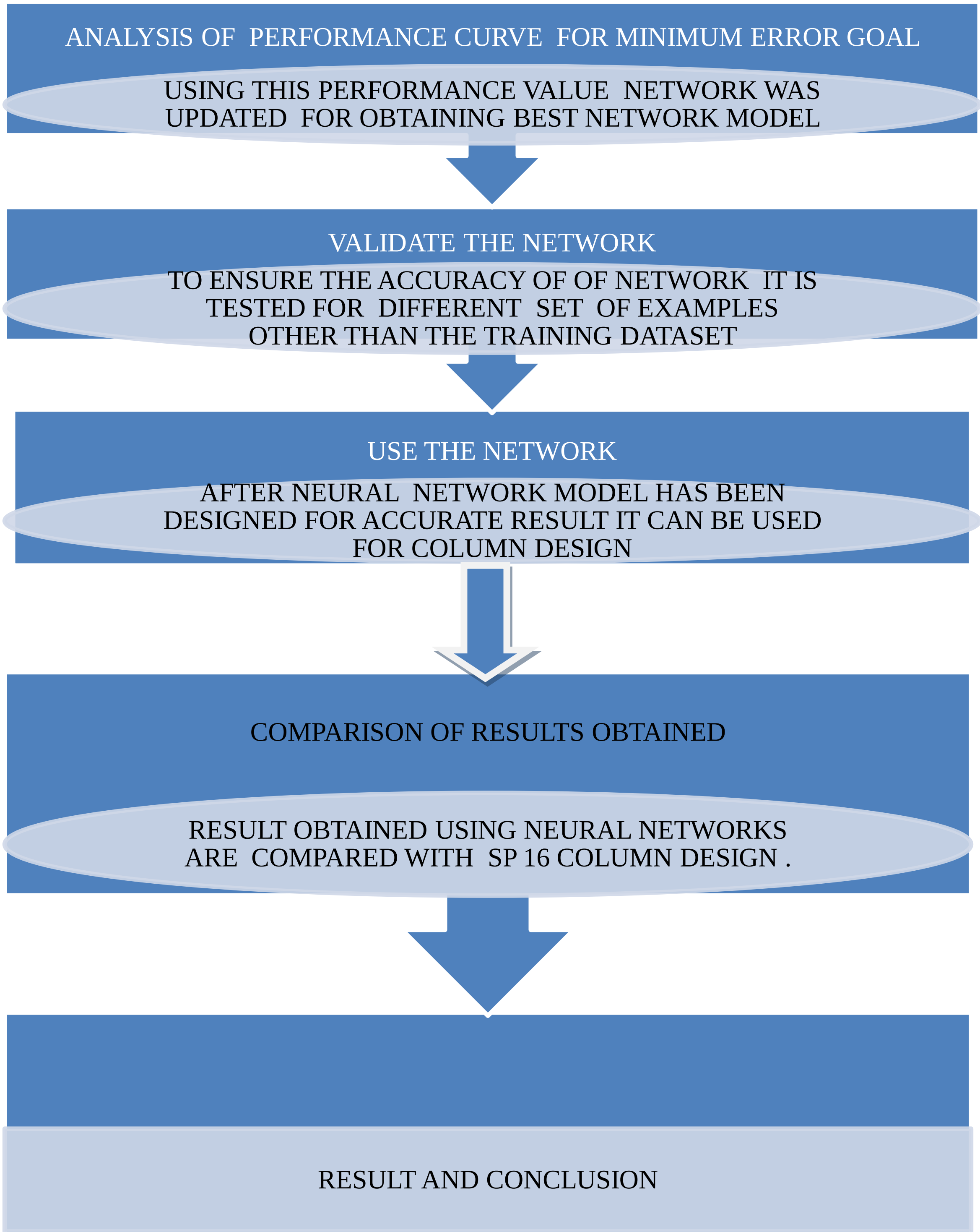
Artificial neural networks are trained to learn non-linear relationship between input and output data passed through them by performing computation on data while passing through network with the defined algorithm rules. These artificial neural networks tremendously increase the calculation efficiency relative to conventional computer programming mthod adopted for design. After proper designing and training the network architecture it is able to return desired solution to the input parameters (problem) passed to through it. Artificial neural networking is a recent technology which is developed from the efforts to simulate working process of human brain. Its application in many fields of engineering has been successfully implemented on large scale.

1.5. METHODOLOGY

1.5.1. FLOW CHART DEPICTING THE METHODOLOGY ADOPTED TO ACHIEVE THE OBJECTIVE OF PROJECT WORK




STAGE 4
NEURAL NETWORK DESIGN PROCESS
LEARNING OF MATLAB SOFTWARE
BASIC LEARNING OF MATLAB SOFTWARE AND NEURAL NETWORKING TOOLBOX OF MATLAB
CREATE THE NETWORK
COMPONENTS OF NN ARE DECIDED AND GENERATED
CONFIGURE THE NETWORK
ARRANGEMENT OF NETWORK PARAMETERS TO MAKE IT COMPATIBLE WITH THE DESIGN PROBLEM
INITIALIZE THE WEIGHT ABD BIASIS
WEIGHTS AND BIASIS ARE ADJUSTABLE PARAMETERS WHICH ARE INITIALLY SET TO SOME RANDOM VALUE
TRIAN THE NETWORK
FOR OPTIMUM PERFORMANCE OF NETWORK ITS WEIGHT AND BIASIS HAS BEEN ADJUSTED DURING THE TRAINING EXAMPLES PASSED THOUGH THE NETWORK


ANALYSIS OF PERFORMANCE CURVE FOR MINIMUM ERROR GOAL
USING THIS PERFORMANCE VALUE NETWORK WAS UPDATED FOR OBTAINING BEST NETWORK MODEL
VALIDATE THE NETWORK
TO ENSURE THE ACCURACY OF OF NETWORK IT IS TESTED FOR DIFFERENT SET OF EXAMPLES OTHER THAN THE TRAINING DATASET
USE THE NETWORK
AFTER NEURAL NETWORK MODEL HAS BEEN DESIGNED FOR ACCURATE RESULT IT CAN BE USED FOR COLUMN DESIGN
COMPARISON OF RESULTS OBTAINED
RESULT OBTAINED USING NEURAL NETWORKS ARE COMPARED WITH SP 16 COLUMN DESIGN .
RESULT AND CONCLUSION

CHAPTER 2

LITERATURE REVIEW

2.1. DESIGN OF COLUMN USING APPLICATION OF ANN

The paper by Dr T M Pillai and P I Karthekeyan demonstrates the application of neural networking in column design problem. Using ANN circular, rectangular, '+' shaped cross-section subjected to biaxial moments has been designed. The network architecture proposed for column design problem used two hidden layers and it was observed that the network performance was quite satisfactory with negligible error in result obtained. Network also converges rapidly during training and during is application in real design environment. For all three column cross-sections same configuration of network was used as the design method of all the cross-section was similar. Similar convergence pattern and training was noticed. From this presented work the author concluded that this new approach for column design is very fast as compared to conventional trial and error method. The error obtained was also very less. The developed methodology works well for all values of variables within the rnage specified. The author also suggests that this methodology can be extended to different types of cross-section such as T and L column sections. [1]

2.2. NORMALIZATION OF DATA PRESENTED TO NEURAL NETWORK

Normalization of data using some technique before the training process is essential for obtaining better results and to speed up the calculation process. Normalization influences the performance error of network which is trained to predict the desired output.

Normalization of input data can enhance network performance, J. Sola and J. Sevilla explains that the neural network simulator used, initializes weights to random values in the (-1, 1) interval. The slope of the sigmids used as activation functions is also unity. On the other hand, all normalizations considered are linear scale transformations and thus, the minimum to which the network converges should be the same one in all cases, only shifted by the same linear transformation. Therefore, the initial state for backpropagation algorithm to begin is always a point in the vicinity of coordinate space origin, while distance to the desired minimum is drastically changed by the scales considered in each case. So, scales that compress all the searching space to a unitary hypercube reduce the distance to be covered, iteration by iteration, by the backpropagation algorithm. Furthermore, if scales are very dissimilar for the different values, the bigger ones will have a higher contribution to the output error, and so, the error reduction algorithm will be focused on the variables of higher values, neglecting the information from the small valued variables. This idea was tested by tracking weights shift as backpropagation proceeds in different cases. Results obtained support this explanation. [2]

2.2.1 Methods of Normalization

Different techniques use different rules such as max rule, min rule, sum rule, product rule and so on. Some of the techniques are explained below based on.

(A). Statistical or Z-Score Normalization

This technique uses the mean and standard deviation for each feature across a set of training data to normalize each input feature vector. The mean and standard deviation are computed for each feature. The transformation is given in the equation [3]

$$x' = \frac{(x_i - \mu_i)}{\sigma_i}$$

(B). Min-Max Normalization

This method rescales the features or outputs from one range of values to a new range of values. More often, the features are rescaled to lie within a range of 0 to 1 or from -1 to 1. The rescaling is often accomplished by using a linear interpretation formula such as. [3]

$$x' = (x_{max} - x_{min}) \times \frac{(x_i - x_{min})}{(x_{max} - x_{min})} + x_{min}$$

Min-max normalization has the advantage of preserving exactly all relationships in the data.

(C). Median Normalization

The median method normalizes each sample by the median of raw inputs for all the inputs in the sample. It is a useful normalization to use when there is a need to compute the ratio between two hybridized samples. Median is not influenced by the magnitude of extreme deviations. It can be more useful when performing the distribution. [3]

$$x_i = \frac{x_i}{median\ a_i}$$

(D). Sigmoid Normalization

The sigmoid normalization function is used to scale the samples in the range of 0 and 1 or -1 to +1. There are several types of non-linear sigmoid functions available. Out of that, tan sigmoid function is a good choice to speed up the normalization process. If the parameters to be estimated from noisy data the sigmoid normalization, method is used [3]

$$x' = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

(E). Mean and Standard Deviation normalization

Another approach for scaling network inputs and targets is to normalize the mean and standard deviation of the training set. This function normalizes the inputs and targets so that they will have zero mean and unity standard deviation. The normalized inputs and targets are returned will have zero means and unity standard deviation. [3]

$$y' = (x_i - x_{mean}) \times \frac{y_{std}}{x_{std}} + y_{mean}$$

(F). Statistical Column Normalization

The statistical column normalization method normalizes each sample with a column normalization value. Calculate the normalization of each column by normalizing the columns to a length of one. Calculate each sample by dividing the normalized column attribute and multiplied by a small bias value. [3]

$$x' = \frac{x_i - n(c_a)}{n(c_a)} \times 0.1$$

The comparison of various statistical normalization methods shows the accuracy of statistical column normalization gives better results compared to other methods. [3]

2.3. OPTIMIZING NUMBER OF HIDDEN NEURONS IN NEURAL NETWORKS

Use of too much hidden neurons in neural network causes overfitting, which indicates that the neural networks over-estimate the functionality of the target problem. This normally degrades generalization ability.predictions made by network for unseen input deviates from its original path. Therefore determination of suitable number of hidden neurons to avoid overfitting is significant in function fitting application of artifical neural network. There are various approaches to build the network in a constructive or destructive way, but the commonly adopted methods to conclude whether a given number of hidden neurons are most favorable are early-stopping andcross-validation. According to these methods the data set is seperated into two independent parts one is for a training purpose and other is for testing or validation. The training set is used for learning of neural network and the testing error is computed using training set.when performance of testing data set stops improving on increasing the number of hidden neurons .the most probable cause may be the training process begin to fit the noise in training data which leads to overfitting problem. [4]

A method is proposed by Yinyin Liu, Janusz A. Starzyk and Zhen Zhu [5] for optimization of the number of hidden neurons in neural network to avoid overfitting in function approximation. The method utilizes a quantitative criterion based on the on the estimation of the signal-to-noise-ratio figure to detect overfitting automatically using the training error only, and it does not require a separate validation or testing set. The criterion has been validated using benchmark datasets and compared with the common cross-validation method. The criterion is very easy to apply, consumes small amount of computations and is suitable for practical application. The same principle applies to the optimization of other parameters of neural networks, including the number of iterations in back propagation training to avoid overtraining or the number of hidden layers. It can be applied to parametric optimization or model selection for other function approximation problems as well. [5]

Saurabh karsoliya in his paper made a survey in order to resolve the problem of number neurons in each hidden layer and number of hidden layer required. In his study he found that usually some rule-of-thumb methods are used for determining the number of neurons in the hidden nodes.

A. The number of hidden layer neurons is 2/3 (or 70% to 90%) of the size of the input layer. If this is insufficient then number of output layer neurons can be added later on. [6]
B. The number of hidden layer neurons should be less than twice of the number of neurons in input layer. [7]
C. The size of the hidden layer neurons is between the input layer size and the output layer size. [5]

But the above approximate rule is not always correct because not only the input layer and the output layer decides the size of the hidden layer neurons but also the complexity of the activation function applied on the neurons, the neural network architecture, the training algorithm and most important the training samples database on which the neural network is designed to execute. Multiple hidden layers are used in the applications where accuracy is the criteria and no limit for the training time is mentioned. Even the drawback of using multiple hidden layers in the neural network is that they are more prone to fall in bad local minima. The number of neurons in first and second hidden layer should be kept nearly equal so that the network can be trained easily. [4]

According to him more than three hidden layers should not be used.one or two hidden layer are sufficient to solve any non linear complex problem. Also, if accuracy is the major and most needed criteria for designing the network then one can adopt the solution of third hidden layer, but this will increase overall complexity of the neural network and the total training time will be increased. There is no need to use four hidden layer in neural network architecture. Unnecessary increasing the hidden layer may cause increase in the complexity of network. [4]

2.4. CRITERIA FOR CONVERGENCE OF NEURAL NETWORK DURING TRAINING

Backpropagation technique carries out a gradient descent within the solution's vector space towards a 'global minimum' along the steepest vector of the error surface. The global minimum is defined as a theoretical solution with the lowest possible error. The error surface itself is a hyperparaboloid but is seldom 'smooth' as is depicted in the graphic below. Indeed, in most problems, the solution space is quite irregular with numerous 'pits' and 'hills' which may cause the network to settle down in a 'local minum' which is not the best overall solution. Since the nature of the error space can not be known a prior, neural network analysis often requires a large number of individual runs to determine the best solution. Most learning rules have built-in mathematical terms to assist in this process which control the 'speed' (Beta-coefficient) and the 'momentum' of the learning. The speed of learning is actually the rate of convergence between the current solution and the global minimum. Momentum helps the network to overcome obstacles (local minima) in the error surface and settle down at or near the global miniumum. [8]

2.5. PROBLEMS ASSOCIATED WITH BACKPROPAGATION LEARNING ALGORITHMS AND SUGGESTED IMPROVEMENTS

The back propagation neural network are widely implemented in the most practical artificial neural network applications and shown quit satisfactory performance, but it is suffering from problem of slow convergence and convergence to local minima thus arise a need of improvement in existing algorithm which later on evolve many improved versions of backpropagation algorithm for feed-forward neural network. [9]

2.5.1. Problems with BP Learning

Back propagation has some problems associated with it which include network paralysis, local minima and slow convergence.

A. most widely observed problem is called “Local Minima”. This occurs because the algorithm always changes the weights in such a way as to cause the error to fall. But the error might briefly have to rise as part of a more general fall, If this is the case, the algorithm will “get stuck” (because it can’t go uphill) and the error will not decrease further. [9]

B. Network paralysis occurs when the weights are adjusted to very large values during training, large weights can force most of the units to operate at extreme values, in a region where the derivative of the activation function is very small. [9]

C. A multilayer neural network requires many repeated presentations of the input patterns, for which the weights need to be adjusted before the network is able to settle down into an optimal solution. [9]

The problem associated with BP learning is addressed in different ways using better energy function, choosing dynamic learning rate and momentum term or modifying the optimization strategy and employing adaptation rules other than the gradient descent. Most of the variations that are proposed to improve the BP algorithm involve the use of learning rate, momentum and gain tuning of the activation function to speed-up the network convergence and avoid getting stuck at local minima or by substituting BP with more efficient algorithms examples of which are Levenberg-Marquardt algorithm, Resilient back propagation algorithm and many others. [9]

<u>The problems associated with conventional BP algorithm are addressed in following modifications of BP which shows improved performance</u>

A. The Back Propagation with Adaptive Gain (BP-AG).
B. Back Propagation with Adaptive Gain, Adaptive Momentum and Adaptive Learning Rate (BP-AGAMAL).
C. Back propagation with Adaptive momentum (BP-AM).
D. Back propagation with momentum and adaptive learning rate (BP-AL).
E. Levenberg-Marquardt (L-M**).** [9]

The slow convergence rate of steepest descent algorithm encourages many ides to be developed for faster convergence rate in training a multilayer neural network.

The proposed algorithm is a developed method based on the Gauss-Newton numerical optimization technique. It resulting a quick convergence with stability in case of multilayer neural network learning. The proposed method converges according to the following criteria: [9]

MSE (Mean Square Error): The algorithm stops when it reaches the pre-specified threshold value. [10]

2.5.2. <u>Levenberg-Marquardt Algorithm</u>

The Levenberg–Marquardt (L-M) algorithm outperforms BP algorithm and many other conjugate gradient methods in a wide variety of problems. L-M is a blend of local search properties of Guass-Newton with consistent error decrease provided by gradient descent algorithm. The training of feed forward networks based on L-M is considered as an unconstrained optimization problem. The main disadvantage of L-M algorithm is its increased memory requirements to calculate jacobian matrix of the error function, determining the inverse of matrix with dimensions equal to the number of weights of neural network is cumbersome. Another disadvantage of L-M is that it does not always guarantee global optimum for an unconstrained optimization problem. The whole training process should be restarted, when the solution is acceptable-M method does not guarantee global optimum and it is just a heuristic that works extremely well in practical problems. The main drawback of this algorithm is its computational complexity to calculate matrix inversion. Generally inverse of Hessian is implemented by pseudo inverse method or singular value decomposition approach. [9]

2.5.3. Relative Merits of Different Algorithm [11]

Algorithm	Update rule	convergence	Computational complexity
Error backpropagation algorithm	$w_{k+1} = w_k - \propto g_k$	Stable and fast	gradient
Newton algorithm	$w_{k+1} = w_k - g_k H_K^{-1}$	Unstable and fast	Gradient and hessian
Gauss-newton algorithm	$w_{k+1} = w_k - (J_K^T J_K)^{-1} J_k e_k$	Unstable and fast	Jacobian
Levenberg-marquardt algorithm	$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k$	Stable and fast	Jacobian [11]
NBN algorithm	$w_{k+1} = w_k - Q_K^{-1} g_k$	Stable and fast	Quasi hessian

[11] **TABLE.2.1. RELATIVE MERITS OF DIFFERENT ALGORITHMS**

CHAPTER 3

DESIGN OF R.C.C COLUMN BY L.S.M

3.1. STEPS INVOLVED IN DESIGN PROCESS

Analysis – first step in the design process is to analysis the structure for determining the loads and moments acting on individual structural component.

Design - design of a column section consists of determination of cross-sectional dimensions B and D and area of longitudinal and transverse steel reinforcement, so as to develop a given axial load and moment of resistance.

3.1.1. Limit State Method of Design of Column Section

Basic Assumptions Made in Limit State of Collapse due to Compression

1. Plane section normal to the axis of column before deformation remains plain after deformation, i.e., the strain at any point is proportional to its distance from the neutral axis. [12]
2. The tensite strength of concrete is ignored.
3. The failure of concrete is governed by the maximum strain criteria. For member under concentric load, ultimate strain in concrete is taken as .002. Ultimate strain in concrete in bending is taken as 0.0035. [12]
4. The maximum compressive strain at the highly compressed extreme fibre in concrete subjected to axial compression and bending, and when there is no tension on the section, shall be equal to 0.0035-0.75 times the strain at the least compressed extreme fibre. [12]
5. Compressive strength of concrete in the structure is assumed to be 0.67 times the characteristic strength of concrete. The partial factor of safety γ_m equal to 1.5 is applied to the strength of concrete in addition to it. Thus design strength of concrete is $0.445f_{ck}$. Design strength of steel is taken as$0.87f_y$. [12]

3.1.2. Generally Adopted Procedure for Column Design

1. Design of Column Section Subjected to Concentric Axial Load

According to IS code 456:2000 all column should be designed for a minimum eccentricity of equal to

$e_{min} = \frac{l}{500} + \frac{B\ or\ D}{30}$ Or 20mm (whichever is more)

Where l is unsupported length of column

For short column: if $e_{min} \leq (0.05\ lateral\ dimension)$, then a short column can be designed using formula

$P_u = 0.40 f_{ck}\, A_c + \ 0.67 f_y A_{sc}$ For high strength deformed bars.

2. Design of column section subjected to concentric axial load and uniaxial moment

The design of cross-section of a column for given concentric axial load and uniaxial moment is done firstly by preassuming the dimensions of column section and steel reinforcement and after that checks its adequacy to develop desired moment of resistance and axial force.

3.1.3. Adequacy Check of Assumed Section

The Adequacy of Assumed Section Is Determined By Following Method

A. Firstly, assume the position of neutral axis.
B. Establish the Strain profile of column section based on failure criteria of column section.
C. Based on strain profile corresponding stress profile for steel and concrete are establish from their respective stress-strain curve.

   .
D. Using strain and stress profiles axial force and moment carrying capacity of column section is calculated and there respective position of application on column section is also determined.
E. For checking the adequacy of assumed section it is ensured that the internal force and external loads are acting at same eccentricity. If these criteria are not satisfied then the assumed location of neutarl axis is not correct and it is changed and

above procedure is repeated till the internal resistance act at same eccentricity as external moments and axial load are acting.

F. The assumed section is regarded as safe if applied force is within its ultimate strength i.e. ultimate load carrying capacity. [13]

Design method explained above is too long and complicated because the determination of accurate location of neutral axis needs numerous trials which involves long calculation steps .consequently an easy design approach has been developed with the use of load versus interaction curve. Interaction curves are prepared by plotting different combination of moment capacity and axial force of section calculated for various location of neutral axis.

Various load vs interaction curves are designed based on different combination of reinforcement destribution, dimensions of cross-section, clear-cover, grade of concrete and grade of steel. The interaction curves are designed based on above discussed method but in a different manner thus with the help of these interaton curve we can quickly calculate the area of steel for assumed dimension of cross-section and on the otherway capacity of cross-section can be determined for assumed area of cross-section and steel reinforcement.

The determination of axial load capacity and moment carrying capacity of a column section for assumed location of neutral axis is done with the help of strain profile made on the basis of failure criterias of column section.

3.2. CASES FOR VARIOUS NEUTRAL AXIS POSITION

Following cases corresponding to different position of neutral axis have been considered here for obtaining various combination of moment and axial load capacity of column section which are obtained for ptotting of interaction curve

Case (a). Concentric axial load (neutral axis position at infinite distance from the section)

Case (b). Axial load at eccentricity e=0.05D (neutral axis at large distance outside the section)

Case (c). Axial load at small eccentricity with neutral axis outside the section

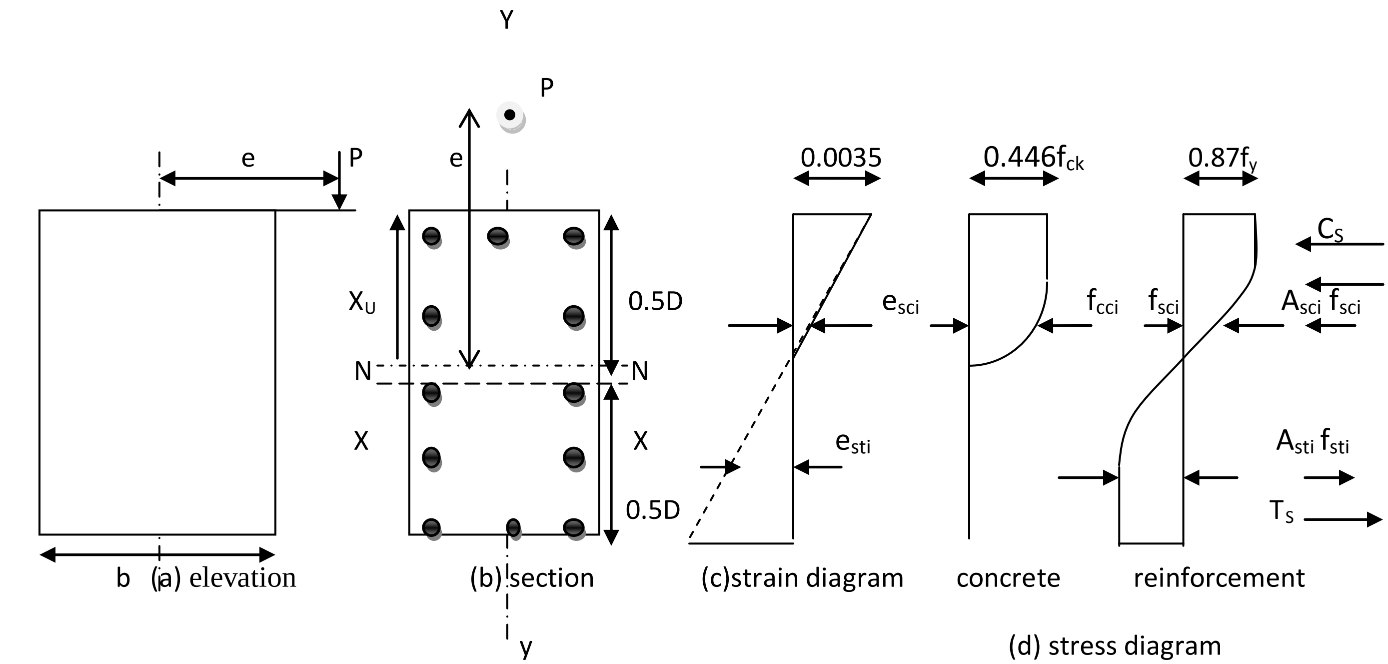
Case (d). Axial load at limiting eccentricity with neutral axis at the bottom edge of the section.

Case (e). Axial load at large eccentricity with neutral axis within the section

Case (f). Section subjected to moments only

3.2.1. Strain and Stress Diagram for Various Neutral Axis Position

For above cases for different positions of neutral axis the strain profile and corresponding stress diagram for concrete and steel are shown below. The stress diagram for steel and concrete are draw from their standard design stress-strain curves.

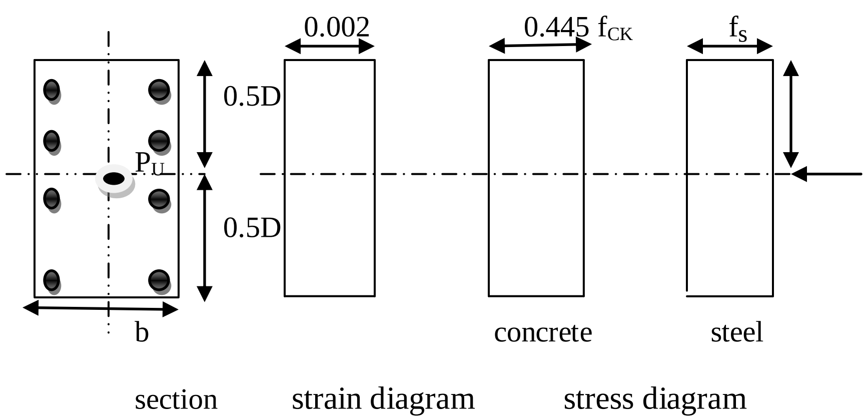


$C_S = \sum(F_{SCI} - F_{CCI})A_{SCI}$

$C_C = \sum(0.36F_{CK}\, bX_{u)}$

$T_s = \sum F_{STI}\, A_{sti}$

Section under combined axial load and uniaxial moment



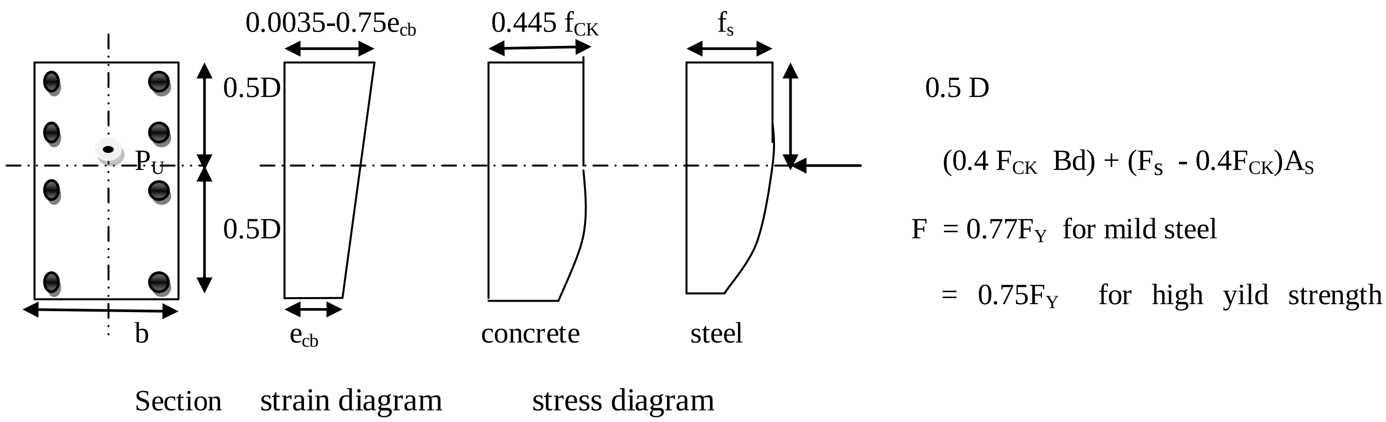
0.5 D

$(0.446\, F_{CK}\;\, Bd) + (F_Y\; - 0.446F_{CK})A_S$

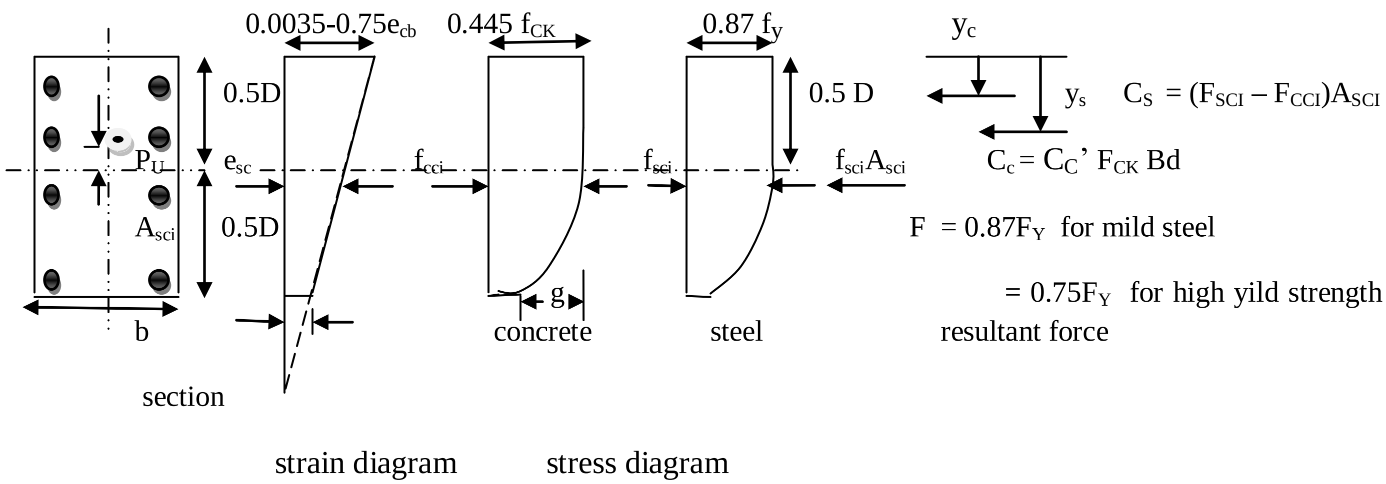
$F\;\; = 0.87F_Y$ for mild steel

$= \; 0.75F_Y$ for high yild strength

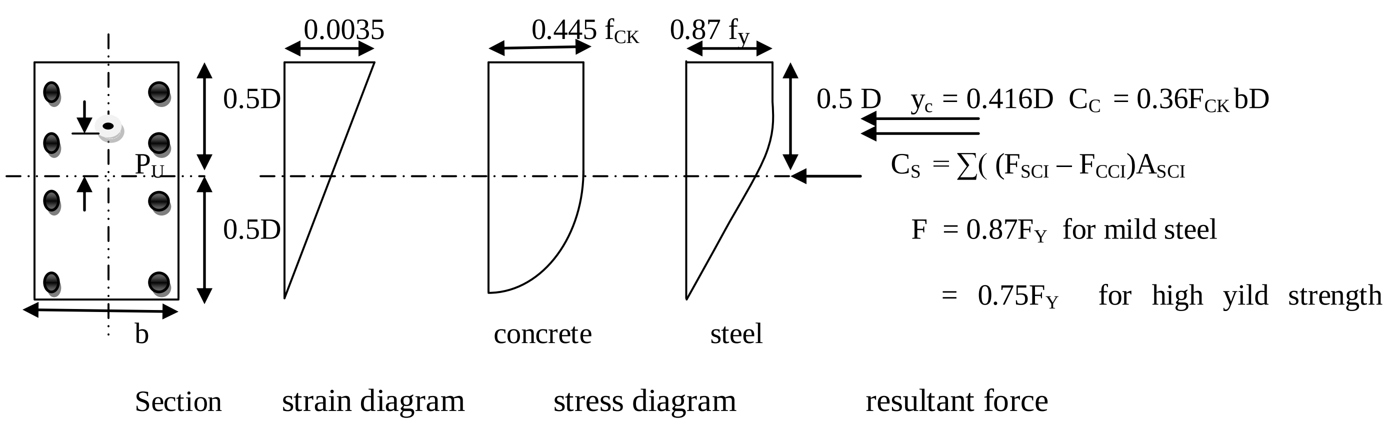
(a) CASE (I) Concentric axial load



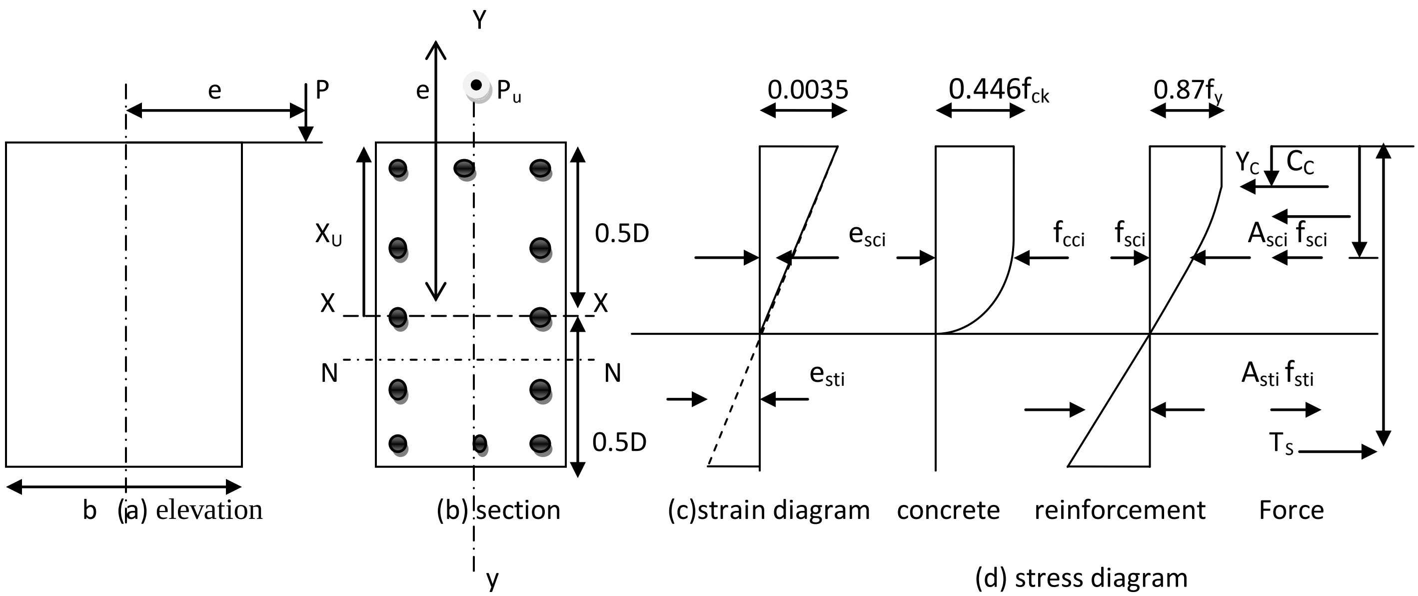
(**b**). CASE (II) Axial load at eccentricity e=0.05D



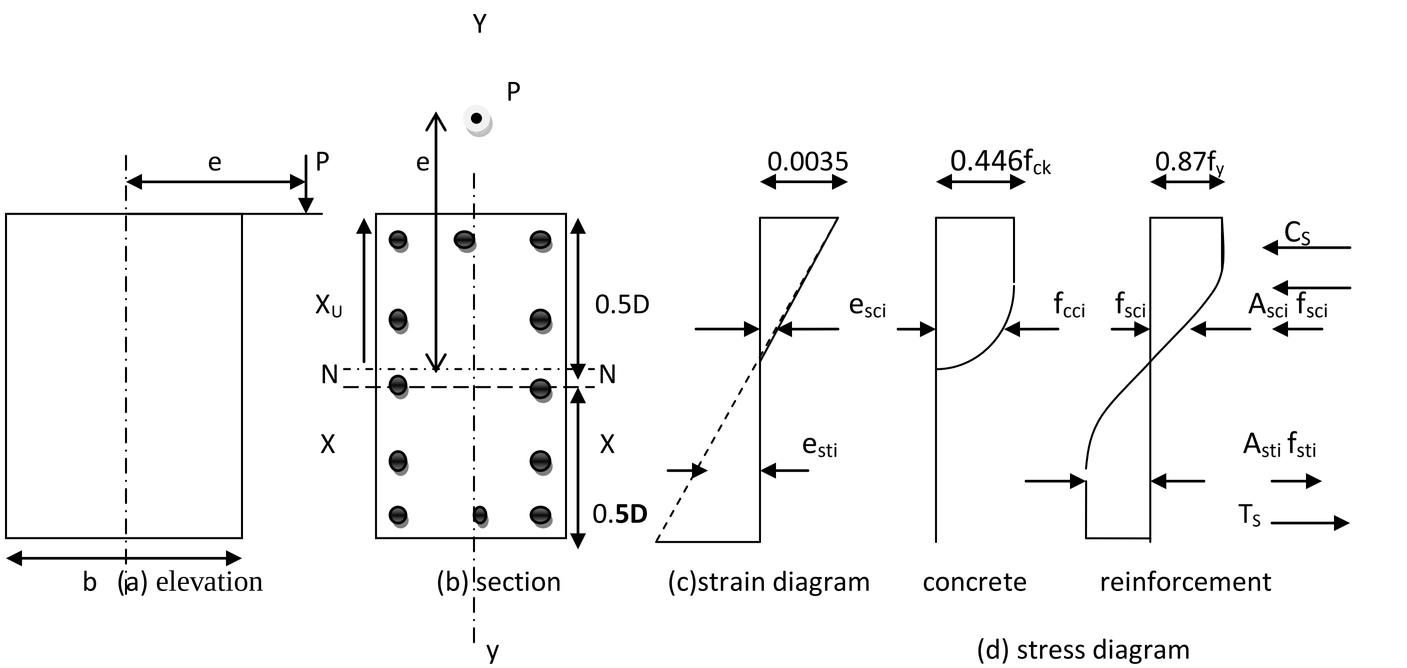
(C). CASE (III) axial load at small eccentricity with neutral axis outside the section



(d) CASE (IV) axial load at limiting eccentricity with neutral axis at the bottom edge of the section



(e) CASE (V) axial load at large eccentricity with neutral axis within the section



$C_S = \sum(F_{SCI} - F_{CCI})A_{SCI}$, $C_C = \sum(0.36F_{CK}\, bX_{u})$

$T_s = \sum F_{STI}\, A_{sti}$

(f) CASE (vi). Section Subjected To Moments Only

FIGURE.3.1. VARIOUS POSITIONS OF NEUTRAL AXIS AND THE ASSOCIATED STRAIN AND STRESS DIAGRAMS AND THE RESULTANT FORCES

3.2.2. Computation for Axial Load and Moment Capacity of Column Section

Formulae for calculation of axial force and moment carrying capacity of a column section for above mentioned cases for differnet position of neutral axis. These formulae are written using strain profile and correspondig stress diagram for concrete and steel for their respective cases drawn above.

CASE 1. $e_x = e_z$ and X_u= infinity

$P_{uz} = 0.446f_{ck}\,bD + (0.75-0.446f_{ck})A_s$

$M_{uxl}, M_{uzl} = 0$

CASE 2 . $e_x = e_z = 0.05$ and $X_u = 1.2\,D$

$P_{uz} = 0.4f_{ck}\,bD + (0.67f_{ck} - 0.4f_{ck})A_{s2}$

$M_{uxl}, M_{uzl} = P_{uz}*e_z$

CASE 3. $e_x = e_z = 0.1D$ and $X_u = 1.1D$

$P_{uz} = 0.384f_{ck}\,bD = (f_{sc1} - f_{cc1})A_{s1}+(f_{sc2}-f_{cc2})A_{s2}$

$M_{uxl}, M_{uzl} = 0.384f_{ck}\,bD(0.5D-0.443D) = (f_{sc1}- f_{cc2})A_{s1}\,(0.5-d) - (f_{sc2} - f_{cc1})A_{s2}(0.5D-d)$

CASE 4 $e_x = e_z = 0.15D$ and $X_u=D$

$P_{uz} = 0.384f_{ck}\,bD + (0.5D-0.416D) + (f_{sc1} - f_{cc2})A_{s1}*(0.5D-d)-(f_{sc2} - f_{cc2})A_{s2}(0.5D-d)$

$M_{uxl}/M_{uzl} = 0.384f_{ck}\,bD\,(0.5D-0.416D) + (f_{sc1} - f_{cc1})A_{s1}*(0.5D-d)-(f_{sc2}-f_{cc2})A_{s2}(0.5D-d)$

CASE 5 . $e_x = e_z= 0.20D$ and $X_u = (D-d)$

$P_{uz} = 0.38f_{ck}\,b(D-d) + (f_{sc1} - f_{cc1})\,A_{s1}$

$M_{uxl}, M_{uzl} = 0.36f_{ck}\,b(D-d)*(0.5D-0.416(D-d)) + (f_{sc1} - f_{cc1})A_{s1}(0.5D-d)$

CASE 6. $e_x = e_z=0.60D$ and $X_u = (D-d)/2$

$P_{uz} = 0.36bX_u + (f_{sc1} - f_{cc1})A_{s1} - 0.87f_{ck}\,A_{s2}$

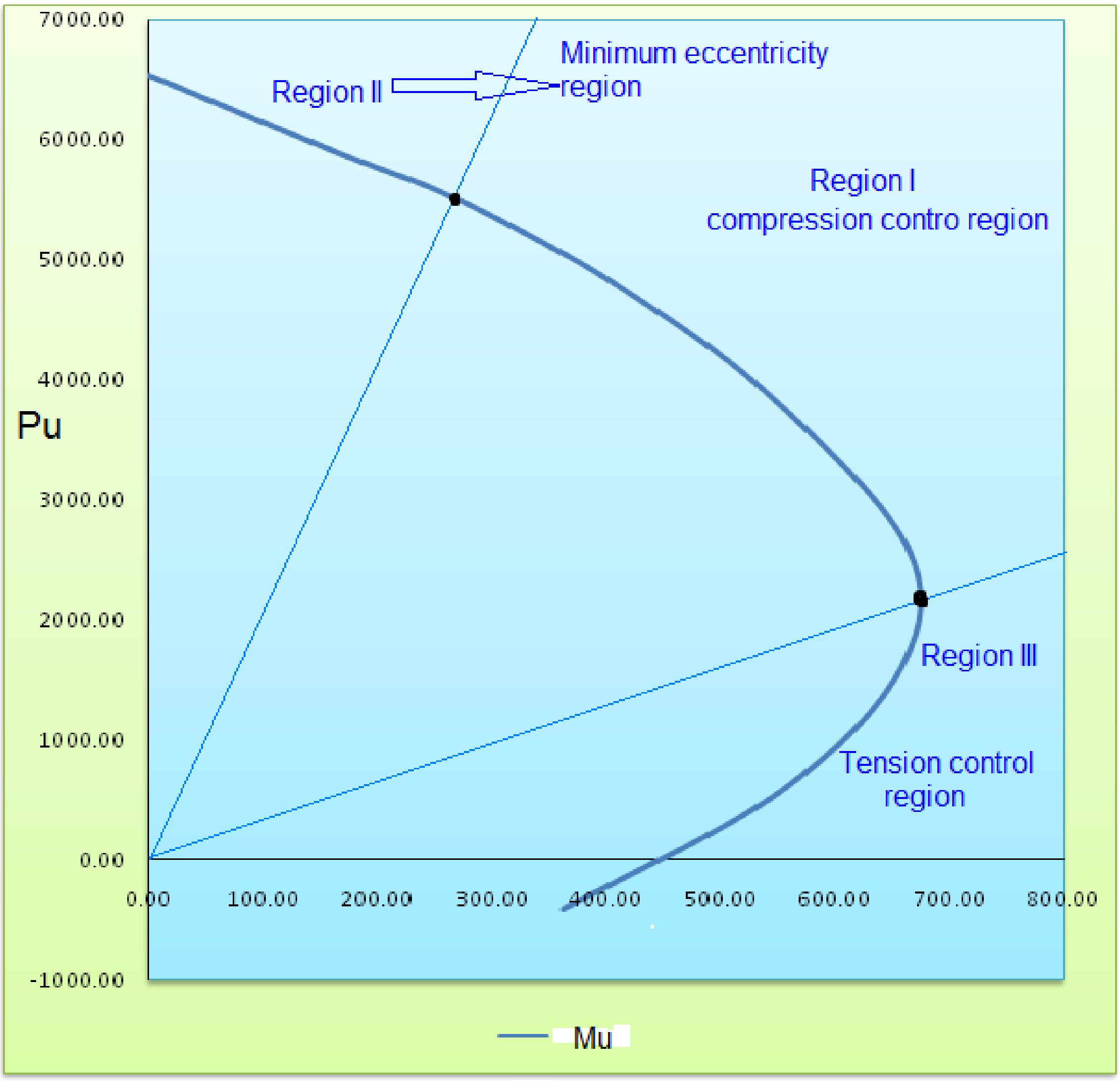
$M_{uxl}, M_{uzl} = 0.36f\,bX_u(0.5D -0.416X_u) +(f_{sc1} - f_{cc1})\,A_{s1}*(0.5D-d)+ 0.87f\,A_{s2}(0.5D-d)$

CASE 7 $e_x = e_z=0.9D$ and $X_u = (D-d)/4$

$P_{uz} = 0.36\ f_{ck}\ bX+(f_{sc1}-f_{cc1})A_{s1}$

M_{uxl} , $M_{uzl} = 0.36 f_{ck}\ bX_u(D-d-0.416X_u) + (f_{sc1}- f_{cc1})A_{s1}\ (D-2d)$

3.3. INTERACTION DIAGRAM



FIRURE.3.2. INTERACTION DIAGRAM

Interaction curves are prepared by plotting different combination of moment capacity and axial force of section calculated for various location of neutral axis. It also indicate information of balanced, compression failure and balanced failure points.every Combination of moment and axial load lying inside the interaction curve is satisfying the moment check and it is thus the safe load combination. [14]

Interaction curve can be devided into three regions depending on the eccentricity of load which in tern determine the behaviour of column during failure.

(A). Minimum Eccentricity Region

In this region load value is very high, but moment is less. Eccentricity is less than even minimum eccentricity. Total cross-section will be in compression. Neutral axis lies outside the column section.

First point on curve shows ultimate load carrying capacity of the column (with zero moment).

(B).Compression Control Region

In this region and moments are equally high if load is reduced moment carrying capacity of column increases. Net effect due to load and moment is compression throughout in column. Neutral axis is outside the column section.

(C). Tension Control Region

If load is further reduced below a particular value, the moment capacity does not increases, it get decreased in this area. Effect of load becomes less as compared to effect of moment tensile stresses are developed. Neutral axis will be within column section and eccentricity of load is large.

3.4. CHECK FOR MOMENTS

The column will be considered safe to carry external loads if following equation is satisfied

$$\left[\frac{M_{ux}}{M_{uxl}}\right]^{\alpha_n} + \left[\frac{M_{uy}}{M_{uyl}}\right]^{\alpha_n} \leq 1.0 \qquad \ldots\ldots\ldots\ldots \text{(a)}$$

Where α_n is based on the values of P_u/P_{uz}

$$\alpha_n = 0.667 + 1.667\frac{P_u}{P_{uz}} \geq 1.0\ and\ \leq 2.0\ ,\ \frac{P_u}{P_{uz}} = 0.2 \text{ to } 0.8$$

$$P_{uz} = 0.45 f_{ck} A_C + 0.75 f_y A_{sc} \text{ (For high strength deformed bars)}$$

Where P_{uz} is maximum axial load carrying capacity of column section for zero eccentricity of load?

M_{ux}, M_{uy} Are moments acting on column due to external load about x and y axes.

M_{uxl}, M_{uyl} Are limiting moment carrying capacity of column section for any axial load P_u about x and y axis respectively.

From these design check we have to generate the value of P_u, Mux and M_{uz} for rectangular column of different cross-section, diameter of bar, no. of bar is calculated.

Different interaction curves can be drawn using equation (a) for different values of P_u/P_{uz} of a given column cross-section. Every combination of moments about x and y axis lying inside the interaction curve plotted for a particular P_u/P_{uz} is satisfying the equation (a) and is a safe combination.

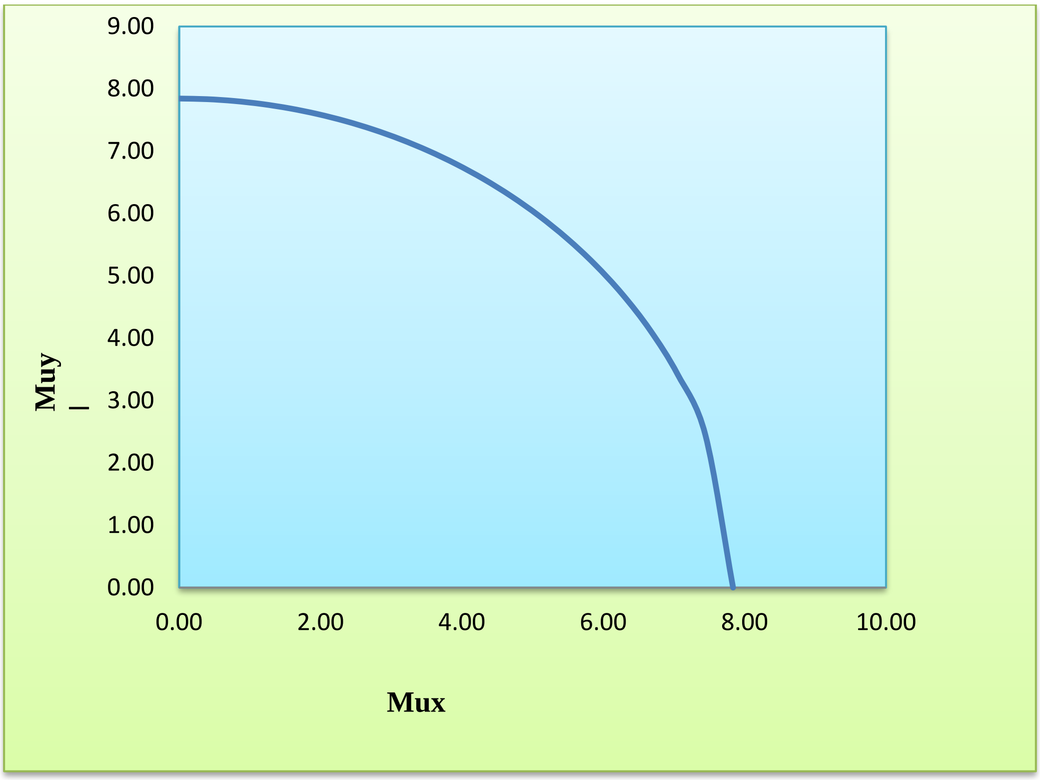


FIGURE.3.3. INTERACTION DIAGRAM FOR MOMENTS

These plots are useful in determining the safe combination of biaxial moments for a given axial load as interaction curve between axial load and uniaxial moment only is not sufficient for determining the safe biaxial moment combination.

3.5. POINTS TO KEEP IN MIND DURING PREPARATION OF EXAMPLE DATA SET

In artificial neural networks it is generally not possible to programm prior knowledge that is why we need to feed accurate data for profer training and learning of network and for accuracy in network performance. It is desired that the data cover whole range of inputs so that the network can be used for all possible cases of input. Multilayer network generalize the non-linear relationship between input and output parameter. The network can be used for inputs within the range of input which are used to train the network. Neural network are not very accurate in extrapolationg the results so training data set should be such that it cover whole range of possible inputs

3.6. SOME IS CODE RECOMMENDATIONS

(i) Minimum percentage of steel which can be used is 0.8 % of cross-section of column.

(ii) Maximum percentage of steel permitted when bars are not lapped is 6% and when bars are lapped is 4% of crossectional area of column.

(iii) Minimum diameter of bar permitted for design is 12mm.

(iv) Minimum numbers of bars which can be used for rectangular cross-section are four and for circular cross-section it is six in number.

(v) For longitudinal reinforcing bar in a column nominal cover should not be less than 40 mm, or less than diameter of longitudinal barfor columns of minimum diamension of 200mm or under, whose reinforcing bars do not exceed 12mm, a nominal cover of 25mm can be used. [12]

CHAPTER 4

ARTIFICIAL NEURAL NETWORKS

4.1. DEFINITION

An artificial neuron network is a computational tool which is developed on the basis of structure and functions of biological neural networks. Information that passes through the network affects the structure of the artificial neural network because a neural network does not understand but learns, in a sense - based on that input and output data set presented to it.

Basically artificial neural network is an appropriate effort to simulate the biological neural network, which is responsible for the understanding and learning of human brain. In the same fassion of functioning of a human biological neural network, an artificial neural network is simulated using a simple artificial neuron, which is an appropriate numerical computational model of its biological counterpart. [14]

Scientifically we can say that artificial neural networks are the self learning algorithms which do not require the traditional methods of programming. These algorithms are responsible for artificial intelligence behaviour of artificial neural network. These algorithms learn from thousands of input and output parameter presented to it during the training phase of neural network. After complete training process these algorithms produce output for unknown input parameters as per ower requirement. [14]

4.2 SPECIFICATIONS OF NEURAL NETWORK

Neural networks are a form of multiprocessor system which comprises of

(a). simple processing unit that is neuron.

(b). a high degree of interconnection between neurons.

(c). Adaptive interaction between neurons.

Basic unit of neural network – neuronal model

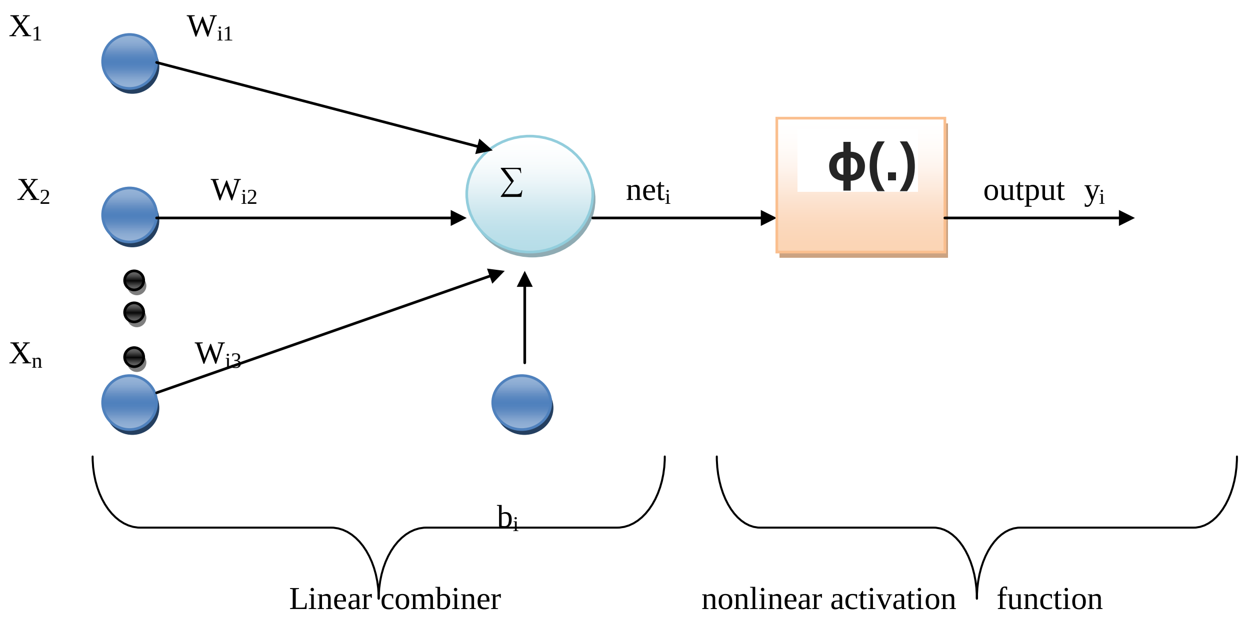


FIGURE.4.1. COMPUTATIONAL NEURON MODEL

The above fig shows the basic neuron model of neural network which is the basic functional unit of neural network. This simplest neron is presented with a set of input parameters which are developed outside the environment of neural networking system. These input parameters can be assumed to x_1, x_2, x_3, xn as shown in the figure. A neuron consists of three different mathematical operationl units. [15]

(i) Frst operation is input presented to neuron is multiplied by weight w.

(ii) Second operation is weighted input is added to bias.

(iii) Third operation is net input obtained after these two operations is passed through activation function.

4.2.1. <u>Linear Combiner</u>

First and second operation is performed by linear combiner. This consists of weight parameters which are present between interconnection of input and neuron or connection between two neurons of different layers shown with symbol w_{ij}. Bias is also a part of linear combiner. Bias is similar to weight but it is has a constant input of 1. [15]

4.2.2. Activation Function

Third operation is performed by activation function. Activation function operates on net input and produces the output at that particular neuron. Activation function is indicated by symbolφ.

The whole operation can be summarised in mathematical expression as

$$\mathrm{Net_i} = \sum_{j=1}^{N} \mathrm{w_{ij}}\, \mathrm{x_j} + \mathrm{b_i} \quad \text{(output of linear combiner)}$$

$$\varphi(net_{\,\mathrm{i}}) = \frac{1}{(1+\exp(-\mathrm{net_i}))} \quad \text{(output of activation function)}$$

The choice of activation function depends on type of algorithem used for training the neural network. Generally backpropagation algorithem are used for training the network. The requirement of backpropagation algorithim derivation is that the activation function should be continously differentiable with respect to argument. All of the below listed function satisfy the condition of continuous diffrentiability. [15]

Generally used Activation Functions are

(i). Log-sigmoidal activation function

(ii).Tan-sigmoidal transfer function

(iii). Linear activation function

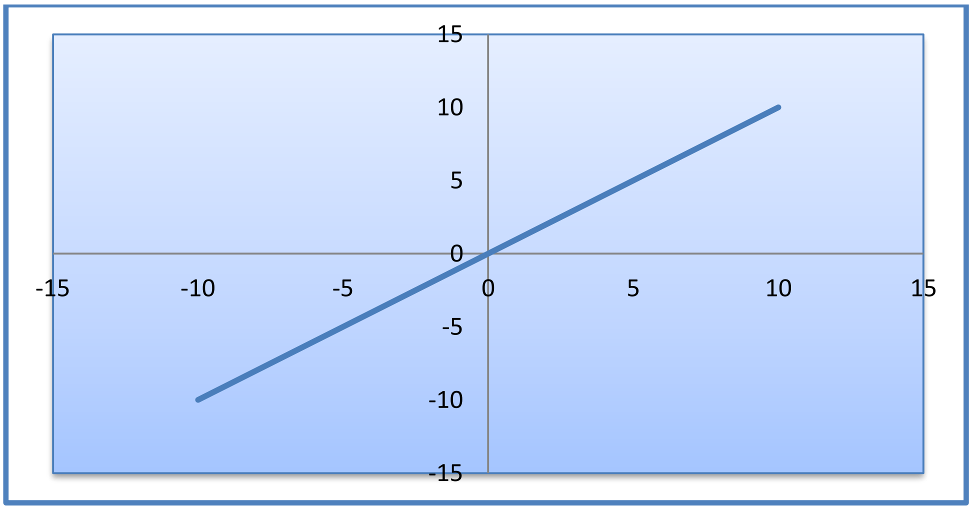


FIGURE.4.2. LINEAR TRANSFER FUNCTION

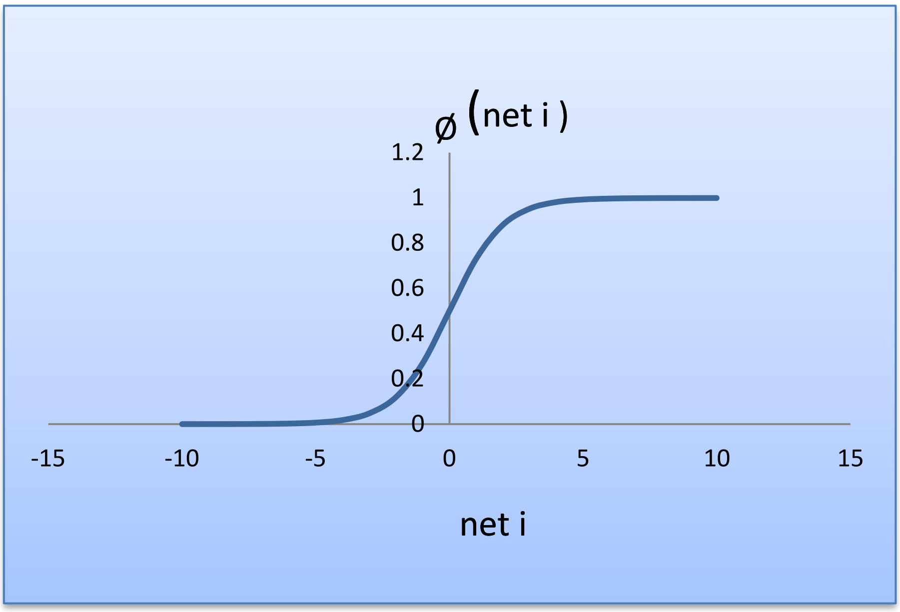


FIGURE.4.3. SIGMOIDAL FUNCTION

Sigmoidal activation function is applied in hidden layer neuron of neural network where as linear function is used in final layer neuron as function approximator

4.3. MULTILAYER PERCEPTRON

Multilayer perceptron is a neural network which is a assembly of various neuron model. Assembling of neural models is done in hidden layer and output layer which are computational layers of neuron. It also consists of an input layer for feeding input parameters to multilayer perceptron. Hidden neurons are the main functional unit of neural network on which performance and feature of neural network depends. Output layer provides the output of network which is obtained by processing on input parameters provided. [15]

4.3.1. <u>Features of Multilayer Perceptron</u>

(i). MLP is a feedforward network - it is so called, because input presentented to network travels in forward direction and generate output of network.

(ii). Mlp is fully connected – every neuron in each layer is interconnected to every other neuron in the in the adjacent layer of that layer.

4.3.2.Design Requirement of Multilayer Perceptron

(i) Number of nodes in input layer – it is decided on the basis of number of input presented to the network externally.

(ii) Number of neurons in output layer- it is decided on the basis of number of output desired by the proposed problem.

(iii) Number of hidden layer.

(iv) Number of neurons in each hidden layer of network – it is the among most important requirement which determined with utmost trials of mlp performance during training of network. It influence the response of network . very less number of neurons leads to incomplete and inefficient learning of network and output of network for unseen input data will not be exactly correct. More than desired neuron usage will generate faulty features inbetween points of training surfaces . therefore determination of number of neuron should be done with care. [15]

(v) Specification of weights which are the interconnection between neurons of different layers. Back-propagation algorithem is generally used to adjust the weight of network. Determining the specification of weight by adjusting weight between interconnection of neurons using back-propagation algorithm is basically the training process. Initially, at starting point of training process all the weight are assigned some random value which improves as training progress and become stable when further learning of network ceases.stable weights thus obtained become specification of weight for that perticular network after complte trainig of it. [15]

4.3.3. Training of Multilayer Perceptron

Before training of MLP weight and biases of network are set to some initialized random value, and then starts the network training. The multilayer perceptron is train for function estimatation (i.e nonlinear regression).The training procedure needs a whole collection of examples for appropriate network performance.The course of training a network includes tuning the magnitude of the biases and weights of the neural network to improve network's performance, which can be determined by the performance function.The predefined performance function for MLP is mean square error which is the mean of squared error. Error is the difference between network outputs and desired outputs. It is defined as follows:

$$f=mse = 1/N \left(\sum_{i=1}^{N} e_i^2 \right) = 1/N \left(\sum_{i=1}^{N} t_i - a_i \right)^2$$

Network training is implemented in two distinct methods: incremental mode and batch mode. All the input parameters in the training data set are feed to the network before its weights are modified in the batch mode training. On the other hand in the incremental mode, gradient of error is calculated and weight are modified to for optimum performance after every input feed to the neural network.when workinf on Neural Network batch training give smaller errors and considerably faster than that of incremental training.

For training multilayer perceptron, any of the standardized numerical optimization algorithms can be used to optimize the mean square error performance function, but only a few compatible ones have given away exceptional performance in training neural networks. These optimization techniques make use of either the gradient of neural network performance parameter w.r.to the weights of network or it can be Jacobian of errors w.r.to weight of network. The Jacobian and the gradient are computed by a method known as the backpropagation algorithm, which includes performing computation in backward direction i.e from output to input layers of neuron through the neural network. The backpropagation steps are derived with the use chain rule of calculus. [14]

4.4. BACKPROPAGATION ALGORITHM

A multilayer perceptron that is a feed forward network requires backpropagation (BP) algorithm for its training. A high quality response of mlp is guaranteed on condition that ample information in form of input and output is made available to the mlp.This facilitate accurate mapping of the desired correlation between the chosen input/output parameters.artificial neural networking-based modelling has the potenetial to map the desired relationship using feed-forward and backpropagation architecture. An artificial neural network comprises of a many number of processing units that are placed logically into two or more no. of layers and attach with each other through weights that forms the connections between them to form a network. The computational features of neural networks are significant in their capability to discover functional relationships between input and output examples pattern presented for training and to discover patterns.error produced are propagated rear through the hidden intermediate layers of neuron in the direction the input layer. Figure.4 shows the distinctive structural design of backpropagation neural networks consist of an input layer, hidden layer and output layer .function of input layer neurons is to pass the input data set to the hidden layer present next to it without any calculation on input pattern values. Neurons in hidden layer calculate a weighted summation of its input and pass the net input obtained through activation function used in the neuron and present the result activation function's computation to the output layer. Until error is minimized to an acceptable level the procedure of forward and backward propagation continueously goes on. Primarily learning is the process of determination of connection's significant weight matrices and the type of the connections between neuron of adjacent layers. the pick of an activation function considerably influence the processing of a training algorithm as it direct how the net input obtained by a neuron changes with its existing levels of activation to calculate a new stage of activation. Choice for the activation function to be bounded and contineous is fulfilled by the use of a sigmoid function.Its derivative is easy to calculate thus it minimizeses the calculation complexity of algorithem. Pictorial presentation of data processing inside a neural network making use of BP algorithm is shown below. [14]

4.4.1. <u>Implementatiom of BP Algorithm</u>

<u>In the Implimentation of BP Algorithm there are Two Passes of Data</u>

(i) <u>Forward Pass</u>

The network is subjected to input data set and weight are set to some fixed values. After that the network output is computed.

(ii) <u>Backward Pass</u>

To minimize cost function which is the sum of square of error weights are adjusted .this is done by starting with calculating the error which is difference between the output provided by the network and target output and then move backward in the network to compute new adjusted weights layer by layer until whole network is completed.BP algorithm get its name from its implementation in backward direction to compute error and weight update. [15]

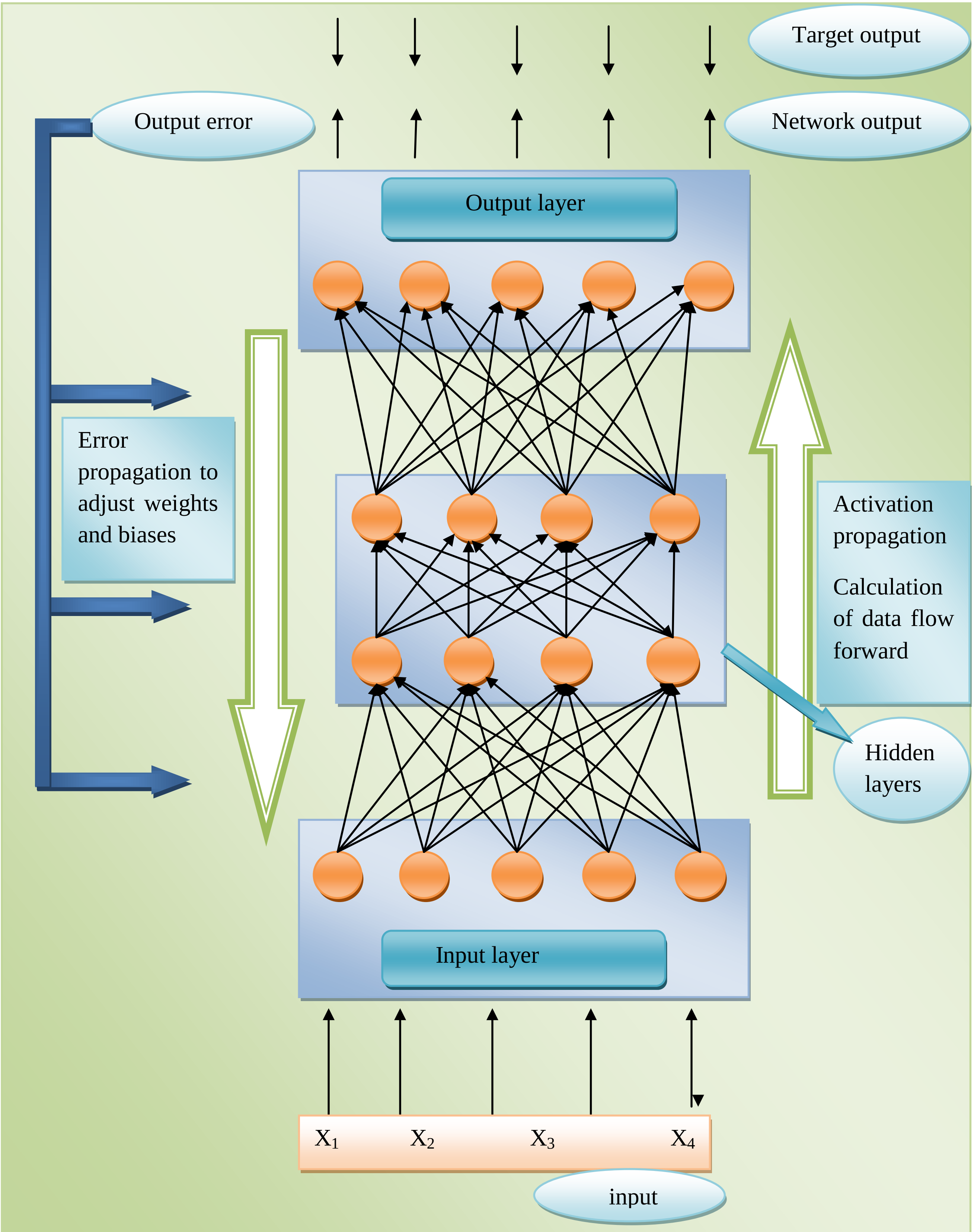


FIGURE.4.4. BACKPROPAGATION NEURAL NETWORK ARCHITECTURE

Relationship between input and out of a neuron i of some layer l am given by the following nonlinear quation [16]

$x_i^{(l+1)} = \varphi(\sum_{p=1}^{N} w_{ip}^{(l)} x_p^{(l)} + b_i^{(l)}$ $\quad l = 0,1,\ldots\ldots\ldots M-1.$

Error term is defined as the difference of actual output and desired output of the given network.

$e_i(n) = d_i - y_i(n)$ $\quad i = 1,2,\ldots\ldots\ldots N_{M.}$, where N_M total no. of output layer (i.e Mth layer) neurons and n is no. of algorithm iterations.

$y_i(n)$ = output computed by the ith neuron of output layer

$d_i =$ desired output at ith neuron of output layer

Cost function is defined as summation of squared error generated by thr given network

$$\varepsilon(n) = \frac{1}{2}\sum_{i=1}^{Nm} e_i(n) e_i(n) = \frac{1}{2}\sum_{i=1}^{Nm} |e_i(n)|^2$$

Basically BP algorithm reduces the sum of squared error $\varepsilon(n)$ (cost function) by repetitive adjustment of the weights of network, by utilizing the gradient-descent method

The equation to update weights is given by

$$w_{ip}^{(l)}(n+1) = w_{ip}^{(l)}(n) + \Delta w_{ip}^{(l)}(n)$$

Weights modify in accordance with the -ve of gradient. Update expression is given as

$$\Delta w_{ip}^{(l)}(n) = -\mu \nabla_{wip}^{(l)} \varepsilon(n) \ldots\ldots\ldots(i)$$

μ is rate of learning of neural network and $\nabla_{wip}^{(l)} \varepsilon(n)$ is gradient of $\varepsilon(n)$ w.r.to weight of lth layer's ith neuron $w_{ip}^{(l)}$

On solving equation (i), it becomes, $\Delta w_{ij}^{(l-1)}(n) = \mu\, x_j(n)\, \delta_i^{(l-1)}(n)$

Update in bias is given as $\Delta b_i^{(l-1)}(n) = \mu\, \delta_i^{(l-1)}(n)$

$$\text{Where } \delta_i^{(l-1)}(n) \begin{cases} = \varphi'(net_i^{(l-1)})[\, d_i - y_i(n)\,], & l=M \\ = \varphi'(net_i^{(l-1)}) \sum_k w_{ki}\, \delta_k^{(l-1)}(n), & 1 < \text{OR} = l < M \text{ [14]} \end{cases}$$

4.4.2. Complete Sequence of Operation In Implementation of BP Algorithm

4.4.2.1. Process

Input layer: $j = 1, 2, 3, \ldots\ldots\ldots\ldots..N$

Hidden layer of neurons: $I = 1, 2, 3, \ldots\ldots\ldots\ldots...L$

Output layer of neurons: $k= 1,2, 3, \ldots\ldots\ldots\ldots...M$

Training pattern (sets of data available for training the network) available: p

4.4.2.2. Steps of Analysis

Forward Pass

1. Apply inputs vector to the input neurons (i.e. this is p^{th} pattern applied as input)

$$X_p = \begin{bmatrix} x_{p1} \\ x_{p2} \\ x_{pi} \\ x_{pN} \end{bmatrix}$$

Here j^{th} input variable is x^I_{pj} for p^{th} pattern (these simulate as input frequency in neural network

2. The input units distribute the values to the hidden layer units. Calculate net input values to the hidden layer units. Calculate the net input value to the hidden layer units. The net input to the i^{th} hidden unit is

$$net^H_{pi} = \sum_{j=1}^{N} w_{ij}^H \sum_{j=1}^{N} w_{ij}^H\, x_{pj}^I + \theta^H_i$$

Where: $\theta^H_i = (w_0x_0)_l = (w_0)_l$ = bias parameter with constant frequency 1 i.e. $x_0 = 1$

= threshold limit

X^I_{pj} = j^{th} input variable for p^{th} pattern

W^H_{ij} =weight associated from j^{th} layer to i^{th} neuron

= magnitude of influence with which frequency transmitted

3. Now this net input Net^H_{pi} is transformed using sigmoidal function to get output from this i^{th} neuron which is equal to activation value for this neuron

$$a^H_{pi} = net^H_{pi} = \sum_{j=1}^{N} w_{ij}^H\, x_{pj}^I + \theta^H$$

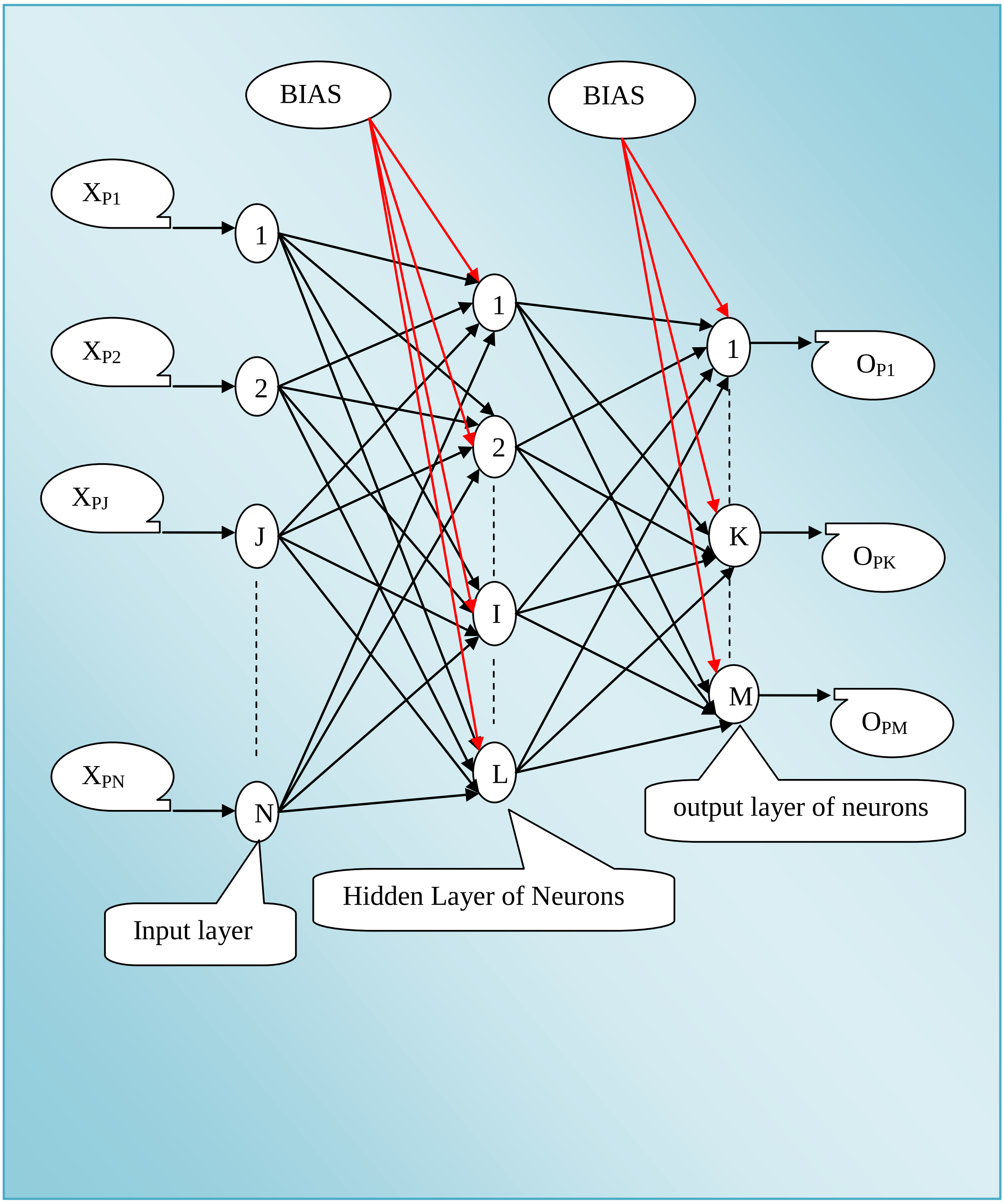


FIGURE.4.5. NEURAL NETWORK

Output from this neuron: (sigmoidal or logistic function)

$$x^H_{pi} = f^H_{pi}(a^H_{pi}) = \frac{1}{1 + e^{-(\sum_{j=1}^{N} w^H_{ij} x^I_{pj} + \theta^H_i)}}$$

This X^H_{pj} will serve as frequency fortransfer from hidden layer units to output layer units.

4. Now calculate net input in output layer units from hidden layer units

$a^o_{pk} = net^o_{pk} = \sum_{i=1}^{L} w^o_{ki}\, x^I_{pj} + \theta^o_k$

Output from this neuron: (sigmoidal or logistic function)

$$o_{pk} = f^o_{pk}(a^o_{pk}) = \frac{1}{1 + e^{-(\sum_{i=1}^{L} w^o_{ki} x^H_{pi} + \theta^o_k)}}$$

5. Calculate the error terms for this output (generalised delta rule) :

$\delta^o_{pk} = (T_{pk} - O_{pk})\, f^{o'}_k(net^o_{pi}) = (T_{pk} - O_{pk})\, f^{o'}_k(\sum_{i=1}^{L} w^o_{ki}\, x^H_{pi} + \theta^o_k)$

Where: T_{pk} = desired output value

O_{pk} =actual output value obtained from the network

$f^{o'}_k$ = 1for linear output

$f^{o'}_k = f^o_k(1- f^o_k) = O_{pk}(1- O_{pk})$ for sigmoidal output

Calculate the error term for the hidden units (generatised delta rule):

$\delta^o_{pi} = f^{H'}_j(net^H_{pi}) \sum_{k=1}^{M} \delta^o_{ki}\, w^o_{ki}$

Where: $f^{H'}_j = f^H_j(1- f^H_j) = x^H_{pi}(1- x^H_{pi})$

Backward Pass

1. Calculate the error in output y_{p1}

$\delta_{p1} = (t_{p1} - y_{p1})\, (f_1)^o(net)^o_1$

$\delta^o_{\ p1} = (t_{p1} - y_{p1})\, (y_{p1}(1- y_{p1}))(net)^o_1$

2. Weight correction between hidden layers and output layer using generalized delta rule

$\Delta_p w^2_{11} = \eta\, (\delta^o_{p1} x^H_{p1}) + \alpha\, \delta_{p-1}\, w^2_{11}$

$\Delta_p w^2_{21} = \eta\, (\delta^o_{p1} x^H_{p2}) + \alpha\, \delta_{p-1}\, w^2_{21}$

$\Delta_p w^2_{31} = \eta\ (\delta^o_{p1} x^H_{p3}) + \alpha\ \delta_{p-1}\ w^2_{31}$

3 Corrected weights between hidden layer and output layer available for next pattern

$w^2_{11} = w^2_{11}\ (t) + \Delta_p\ w^2_{11}$

$w^2_{21} = w^2_{21}\ (t) + \Delta_p\ w^2_{21}$

$w^2_{31} = w^2_{31}\ (t) + \Delta_p\ w^2_{31}$

4. Corrected error in the output of hidden layer say neuron 1

$\delta^H_{p1} = (\ f_1)^H (net)^H{}_1 (\delta^o_{p1}\ w^2_{11})$

5. Weighted correction between input layer and hidden layer using generalized delt rule:

$\delta_p\ w^1_{ij} = \ \eta\ ((\$^H_{pj} x_j) + \alpha \delta_{p-1}\ w^1_{ij}$

6. Corrected weighta between input layer and hidden layer available for next pattern application.

$w^1{}_{ij}(t+1) = w^1_{ij}(1) + \delta_p\ w^1_{ij}(t)$

Initially all the weights are assumed as random number. Then for one cycle of iteration all the pattern are applied then mean square error is obtained

MSE = $\sum_P (t-y)^2$/ no. of patterns (for all the patterns presented in one cycle)

7. Now in the next cycle of iteration again same pattern are applied on the network and MSE is obtained.

8. As the number of cycle increase error converges and from the above graph best minimum error can be obtained for one network architecture.

9. Now network architecture are modified and then best network is selected for global minimum error.

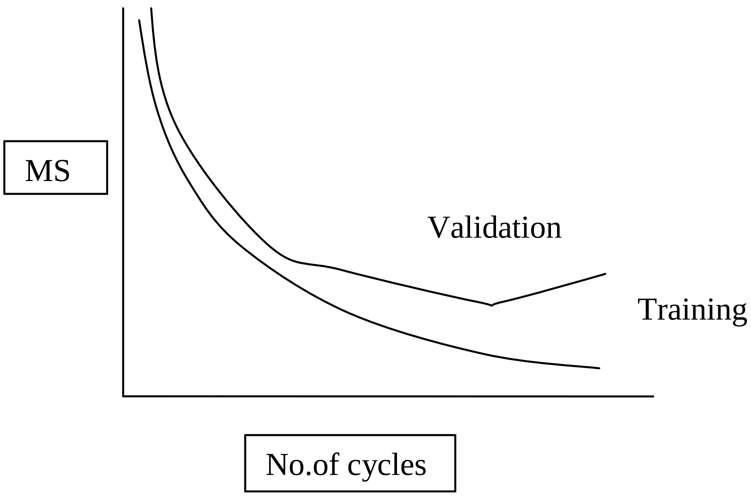


FIGURE.4.6. MSE V/S NO. OF CYCLES OF ITERATION PLOT

4.5. LEVENBERG-MARQUARDT ALGORITHM

Levenberg-marquardt algorithm make use of both the error backpropagation algorithm (steepest descent algorithm) and gauss-newton algorithm in its derivation thus incoorporates the advantages of both the algorithms.

LM algorithm is the fastest training algorithm. It is most efficient algorithm for larger network which need more memory and also require more time for computation. Feedforward neural networks i.e MLP are generally trained by this algorithm. Lmalgorithm give better performance in function fitting problem as compared to problems of pattern recognition.

Levenberg –marquardt algorithm inherits stability and speed advantage of the steepest descent algorithm and gauss-newton algorithm respectively. it is more robust but little bit slowerer as compared to gauss-algorithm but its converge more rapidly than steepest descent algorithm.

4.5.1. <u>Steps of Analysis</u>

Levenberg-marquardt algorithm is derived from both the steepest descent algorithm (error backpropagation algorithm) and gauss-newton's algorithm so, here we present brief summary of both the algorithm and then proceeds to LM algorithm which incorporates the expressions of these two algorithms.

The training process is evaluated by sum square error function, which is expressed as follows

$$E(x,w) = \frac{1}{2}\sum_{p=1}^{p}\sum_{m=1}^{M} e_{p,m}^{2} \qquad \text{(i)}$$

Where p indicate no. of pattern presented p = 1, 2,…….. P

m denotes no. of outputs m= 1,2,…………..M

i, j are index of weight i , j = 1,2,………N

x= input pattern presented to network

w = weight matrix

$e_{p,m}$ indicates the network error during training process at mth output neuron when pth pattern is applied.

$$e_{p,m} = d_{p,m} - o_{p,m} \qquad \text{(ii)}$$

d is target output

o is output computed by network

A. <u>Steepest Descent Algorithm</u>

Steepest descent algorithm uses the gradient of total error function with respect to weight of network. It is the simplest algorithm for optimization of performance function (sum of squared error). This algorithm updates the biasis and weight in the path in which error function is most rapidly decreasing i.e -ve of gradient. Main advantage of this algorithm is that it is the most stable one but its major brawback is slow rate of convergence of error.

It comprises of 1^{st} order derivative of performance function i.e total error function which is given in terms of gradient g

$$g = \frac{\partial E(x,w)}{\partial w} = \left[\frac{\partial E}{\partial W_1}\frac{\partial E}{\partial W_2}\dots\dots\dots\frac{\partial E}{\partial W_N}\right]^T \quad [11] \qquad \text{(iii)}$$

Rule for updating weights in steepest descent algorithm is given as

$$w_{k+1} = w_k - \alpha\, g_k \qquad \text{(iv)}$$

Where ∝ denotes step size which indicates learning rate constant

B. Newton Method

This method assumes gradient g_1, g_2,…...,g_N as dependent function on weight and weight are independent linear parameters.

$$g_1 = f_1\,(w_1\,, w_2\; \dots \dots w_N)$$

$$g_2 = f_2(w_1\,, w_2\; \dots \dots w_N) \qquad \text{(v)}$$

$$g_1 = f_N\,(w_1\,, w_2\; \dots \dots w_N)$$

. $f_1\,, f_2\;, \dots \dots, f_N$ function representing nonlinear relation between gradient and weight

On solving above equations by taylor series, we get

$$g_1 \approx g_{1,0} + \frac{\partial g_1}{\partial w_1}\Delta w_1 + \frac{\partial g_1}{\partial w_2}\Delta w_2 + \cdots + \frac{\partial g_1}{\partial w_N}\Delta w_N$$

$$g_2 \approx g_{2,0} + \frac{\partial g_2}{\partial w_1}\Delta w_1 + \frac{\partial g_2}{\partial w_2}\Delta w_2 + \cdots + \frac{\partial g_2}{\partial w_N}\Delta w_N \qquad \text{(vi)}$$

$$g_N \approx g_{N,0} + \frac{\partial g_N}{\partial w_1}\Delta w_1 + \frac{\partial g_N}{\partial w_2}\Delta w_2 + \cdots + \frac{\partial g_N}{\partial w_N}\Delta w_N \;\; [11]$$

$$\frac{\partial g_i}{\partial w_j} = \frac{\partial\left(\frac{\partial E}{\partial w_j}\right)}{\partial w_j} = \frac{\partial^2 E}{\partial w_i\, \partial w_j} \qquad \text{(vii)}$$

By using equation (vii) in equation (vi)

$$\{ g_1 = g_{1,0} + \frac{\partial^2 \mathrm{E}}{\partial \mathrm{w}_1^2}\Delta w_1 + \frac{\partial^2 E}{\partial w_1 w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_1 w_N}\Delta w_N$$

$$\{ g_2 = g_{2,0} + \frac{\partial^2 \mathrm{E}}{\partial w_2 w_1}\Delta w_1 + \frac{\partial^2 E}{\partial \mathrm{w}_2^2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_2 w_N}\Delta w_N \qquad \text{(viii)}$$

…….

$$\{ g_N = g_{N,0} + \frac{\partial^2 \mathrm{E}}{\partial w_N w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_N w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial \mathrm{w}_N^2}\Delta w_N \; [11]$$

For obtaining minimum value of erron function gradient of error function is set to zero value thus equation (viii) becomes

$$\{0 = g_{1,0} + \frac{\partial^2 \mathrm{E}}{\partial \mathrm{w}_1^2}\Delta w_1 + \frac{\partial^2 E}{\partial w_1 w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_1 w_N}\Delta w_N$$

$$\{0 = g_{2,0} + \frac{\partial^2 \mathrm{E}}{\partial w_2 w_1}\Delta w_1 + \frac{\partial^2 E}{\partial \mathrm{w}_2^2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_2 w_N}\Delta w_N \quad [11] \qquad \text{(ix)}$$

$$\cdots\cdots$$

$$\{0 = g_{N,0} + \frac{\partial^2 \mathrm{E}}{\partial w_N w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_N w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial \mathrm{w}_\mathrm{N}^2}\Delta w_N$$

Equation (iii) and (ix) gives

$$\{-\frac{\partial E}{\partial w_1} = -g_{1,0} \approx \frac{\partial^2 \mathrm{E}}{\partial \mathrm{w}_1^2}\Delta w_1 + \frac{\partial^2 E}{\partial w_1 w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_1 w_N}\Delta w_N$$

$$\{-\frac{\partial E}{\partial w_2} = -g_{2,0} \approx \frac{\partial^2 \mathrm{E}}{\partial w_2 w_1}\Delta w_1 + \frac{\partial^2 E}{\partial \mathrm{w}_2^2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial w_2 w_N}\Delta w_N \qquad \text{(x)}$$

$$\cdots\cdots$$

$$\{-\frac{\partial E}{\partial w_N} = -g_{N,0} \approx \frac{\partial^2 \mathrm{E}}{\partial w_N w_1}\Delta w_1 + \frac{\partial^2 E}{\partial w_N w_2}\Delta w_2 + \cdots + \frac{\partial^2 E}{\partial \mathrm{w}_\mathrm{N}^2}\Delta w_N \ [11]$$

Above equation (x) is used to find Δw_i as there are N number of equation available to solve for N number of weights that are needed to be updated.

Matrix form of equation (x) is written as

$$\begin{bmatrix} -g_1 \\ -g_2 \\ \cdots \\ -g_n \end{bmatrix} == \begin{bmatrix} -\frac{\partial E}{\partial w_1} \\ -\frac{\partial E}{\partial w_2} \\ \cdots \\ -\frac{\partial E}{\partial w_N} \end{bmatrix} = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\ \frac{\partial^2 E}{\partial w_2 \partial w_1} & \frac{\partial^2 E}{\partial w_2^2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial^2 E}{\partial w_N \partial w_1} & \frac{\partial^2 E}{\partial w_N \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_N^2} \end{bmatrix} \times \begin{bmatrix} \Delta w_1 \\ \Delta w_2 \\ \cdots \\ \Delta w_N \end{bmatrix} \quad [11] \qquad \text{(xi)}$$

Square matrix in equation (xi) is hessian matrix. Hassian matrix is 2nd order derivative of sum of squared error i.e. error function.

$$H = \begin{bmatrix} \frac{\partial^2 E}{\partial w_1^2} & \frac{\partial^2 E}{\partial w_1 \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_1 \partial w_N} \\ \frac{\partial^2 E}{\partial w_2 \partial w_1} & \frac{\partial^2 E}{\partial w_2^2} & \cdots & \frac{\partial^2 E}{\partial w_2 \partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial^2 E}{\partial w_N \partial w_1} & \frac{\partial^2 E}{\partial w_N \partial w_2} & \cdots & \frac{\partial^2 E}{\partial w_N^2} \end{bmatrix} \quad [11] \qquad \text{(xii)}$$

Equation (xi) is written as

-g = $H\Delta w$ (xiii)

$\Delta w = -H^{-1}$g (xiv)

Newton method update rule is

$w_{k+1} = w_k - H_k^{-1} g_k$ [11] (xv)

C. <u>Gauss Newton Algorithm</u>

Computational complication in calculation of hassian matrix makes whole process complicated and tedious. In order to overcome this problem jacobian matrix J was

$$J=\begin{bmatrix} \frac{\partial e_{1,1}}{\partial w_1} & \frac{\partial e_{1,1}}{\partial w_2} & \cdots & \frac{\partial e_{1,1}}{\partial w_N} \\ \frac{\partial e_{1,2}}{\partial w_1} & \frac{\partial e_{1,2}}{\partial w_2} & \cdots & \frac{\partial e_{1,2}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{1,M}}{\partial w_1} & \frac{\partial e_{1,M}}{\partial w_2} & \cdots & \frac{\partial e_{1,M}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{P,1}}{\partial w_1} & \frac{\partial e_{P,1}}{\partial w_2} & \cdots & \frac{\partial e_{P,1}}{\partial w_N} \\ \frac{\partial e_{P,2}}{\partial w_1} & \frac{\partial e_{P,2}}{\partial w_2} & \cdots & \frac{\partial e_{P,2}}{\partial w_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_{P,M}}{\partial w_1} & \frac{\partial e_{P,M}}{\partial w_2} & \cdots & \frac{\partial e_{P,M}}{\partial w_N} \end{bmatrix} \quad [11] \qquad \text{(xiv)}$$

Introduced in newton method as

From equation (i) and (iii), gradient vector is given by

$$g_i = \frac{\partial E}{\partial w_i} = \frac{\partial\left(\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2\right)}{\partial w_i} = \sum_{p=1}^{P}\sum_{m=1}^{M}\left(\frac{\partial e_{p,m}}{\partial w_i} e_{p,m}\right) \quad [11] \qquad \text{(xvii)}$$

Using equating (xvi) and (xvii) relationship between gradient vector and jacobian matrix can be interpreted as

g = Je (xviii)

Error vector is given by

$$e = \begin{bmatrix} e_{1,1} \\ e_{1,2} \\ \cdots \\ e_{1,M} \\ \cdots \\ e_{P,1} \\ e_{P,2} \\ \cdots \\ e_{P,M} \end{bmatrix} \qquad \text{(xix)}$$

Elements of hassian matrix can be computed by following equation

$$h_{i,j} = \frac{\partial^2 E}{\partial w_i w_j} = \frac{\partial^2\left(\frac{1}{2}\sum_{p=1}^{P}\sum_{m=1}^{M} e_{p,m}^2\right)}{\partial w_i w_j} = \sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\partial e_{p,m}}{\partial w_i}\frac{\partial e_{p,m}}{\partial w_j} + s_{i,j} \qquad \text{(xx)}$$

$$s_{i,j} = \sum_{p=1}^{P}\sum_{m=1}^{M} \frac{\partial^2 e_{p,m}}{\partial w_i \partial w_j} e_{p,m} \qquad \text{(xxi)}$$

From equation (xx) relationship between jacobian matrix and hessian matrix can be written as

$$H \approx J^T J \qquad \text{(xxii)}$$

Using equation (xv), (xviii) and (xxii) gauss-newton algorithm weight update rule becomes

$$w_{k+1} = w_k - (J_k^T J_k)^{-1} J_k e_k \qquad \text{(xxiii)}$$

Levenberg-marquardt algorithm

To ensure invertiblity of hassian matrix J^TJ LM algorithm introduce 2nd approximation to already approximated hassian matrix J^TJ so that convergent problem like that in newton algorithm does not occur in this LM algorith

$$H \approx J^T J + \mu I \qquad \text{(xxiv)}$$

This equation ensures that hessian matrix always remain invertible

I = identity matrix,

μ=combination coefficient, which is always positive

From equation (xxiii) and (xxiv) weight update rule of LM algorithm can be written as

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \tag{xxv}$$

As Lm algorithm is a combination gauss-newton algorithm and error backpropagation algorithm so, during training process its response switches between these two algorithms. When μ is very large equation (xxv) approaches to equation (iv) and its behaviour is similar to steepest descent method. When μvery small equation (xxv) is approximates to equation equation (xxiii) and behaves like gauss-newton algorithm.

$$\alpha = \frac{1}{\mu} \tag{xxvi}$$

(When μ is very large then α is rate of learning of network in steepest descent algorithm)

.

CHAPTER 5

PROPOSED METHODOLOGY

VARIOUS STAGES IN DEVELOPMENT OF NEURAL NETWORK MODEL FOR COLUMN DESIGN

5.1. GENERATE EXAMPLE DATA SET FOR TRAINIG OF NEURAL NETWORK

Program Developed For Column Design As Per SP 16 Based on IS 456:2000 Using Microsoft Excel Programming.

The design of section of column for given concentric axial load and uniaxial moment is done firstly by preassuming the dimensions of column section and steel reinforcement and after that checks its adequacy to develop desired moment of resistance and axial force.

(i). Different column cross-sectional dimensions used in design.

200×200	400×400	500×800
200×300	400×500	600×600
200×400	400×600	600×700
200×500	400×700	600×800
300×300	400×800	700×700
300×400	500×500	700×800
300×500	500×600	700×900
300×600	500×700	

TABLE.5.1. COLUMN CROSS-SECTIONAL DIMENSIONS

(ii). Diameter of bars used in design

Diameter of bar in mm					
12 mm	14 mm	16 mm	18mm	22 mm	25 mm

TABLE.5.2. DIAMETER OF BARS USED IN DESIGN

(iii). Grade of steel and grade of concrete selected for design

Grade of steel	$\boldsymbol{fe}$ **415**		
Grade of concrete	f_{ck} 25	f_{ck} 30	f_{ck} 35

TABLE.5.3. GRADE OF STEEL AND GRADE OF CONCRETE

(iv).Various Pattrens of uniform distribution of reinforcement used in column cross-section

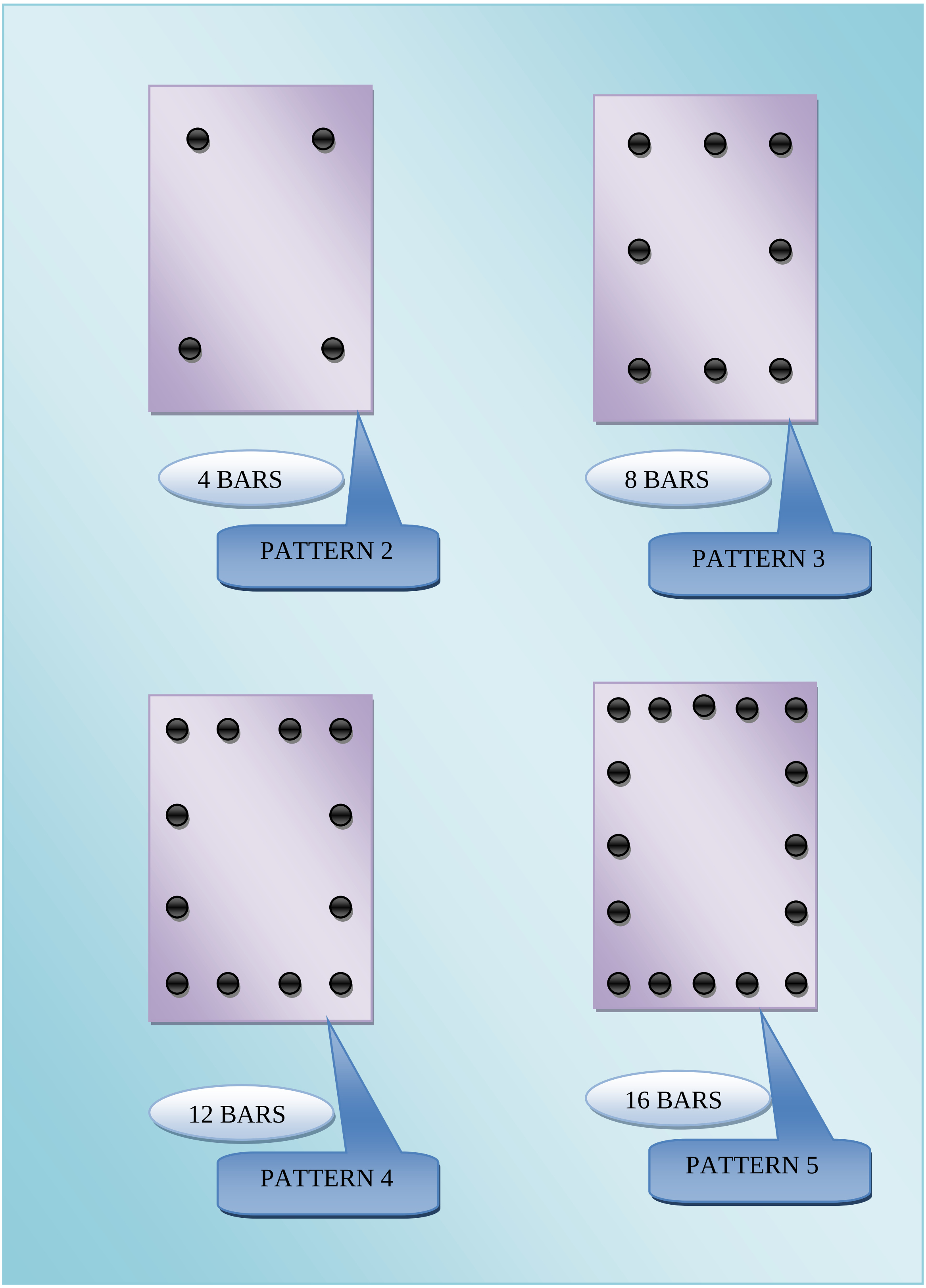


FIGURE.5.1. COLUMN CROSS-SECTION WITH DIFFERENT REINFORCEMENT DISTRIBUTION PATTERNS

(v) For assumed cross-sectional area, area of steel reinforcement, grade of steel, grade of concrete , nominal concrete cover etc. the interaction curve has been plotted. These interaction curves shows the limiting axial load and limiting moment carrying capacity of column section corresponding to different positions of neutral axis and eccentricities of load.

Following interaction curve has been obtained for rectangular cross-section of dimension 400mm×600 mm, 22 mm diameter bars, Fe 415 grade of steel, F_{ck} 25 grade of concrete, 40mm clear cover and area of steel used is 4561.59 mm^2.

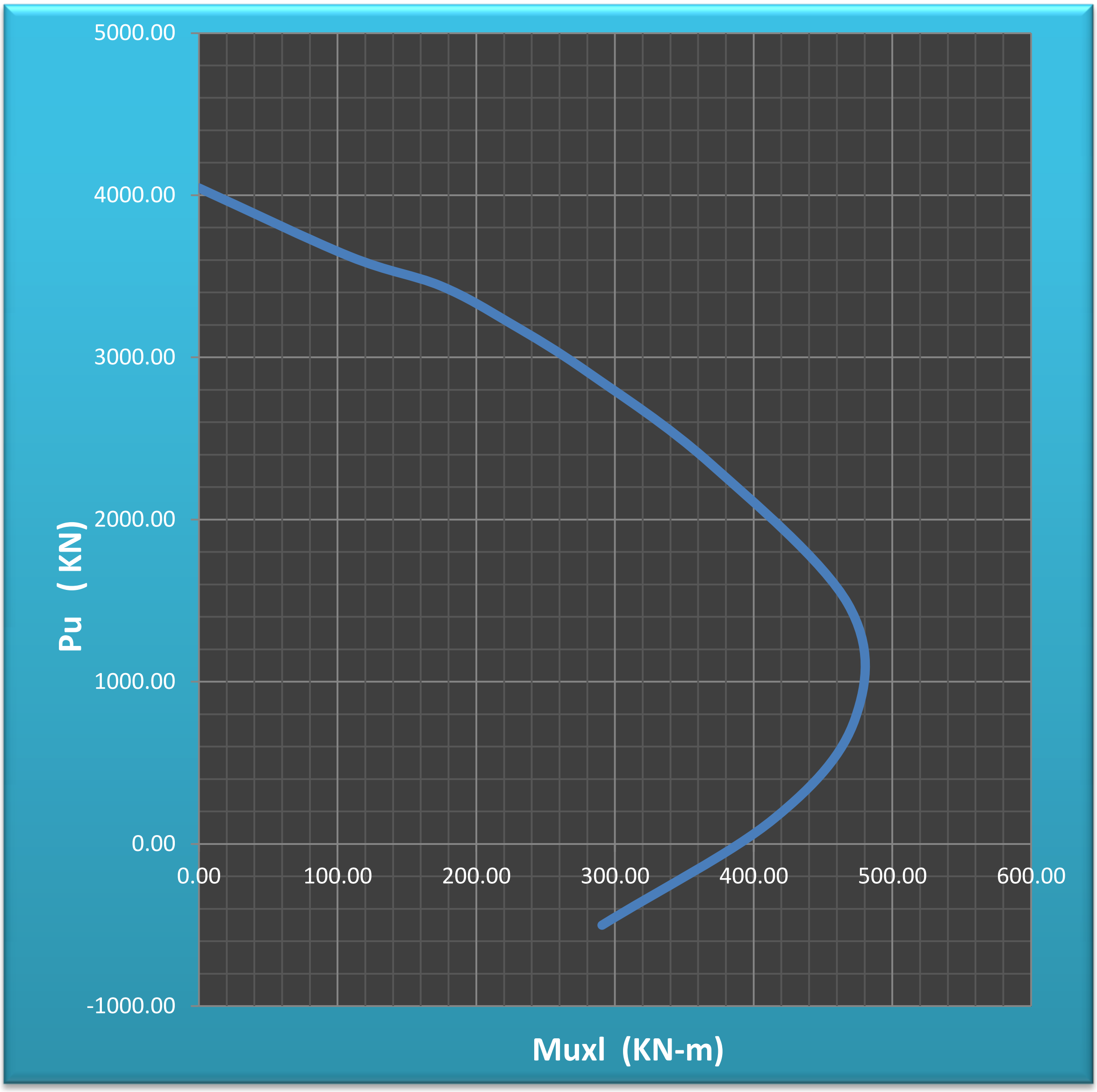


FIGURE.5.2. INTERACTION CURVE FOR COMPRESSION WITH BENDING ABOUT X-AXIS –RECTANGULAR SECTION REINFORCEMENT DISTRIBUTED EQUALLY ON ALL FACES

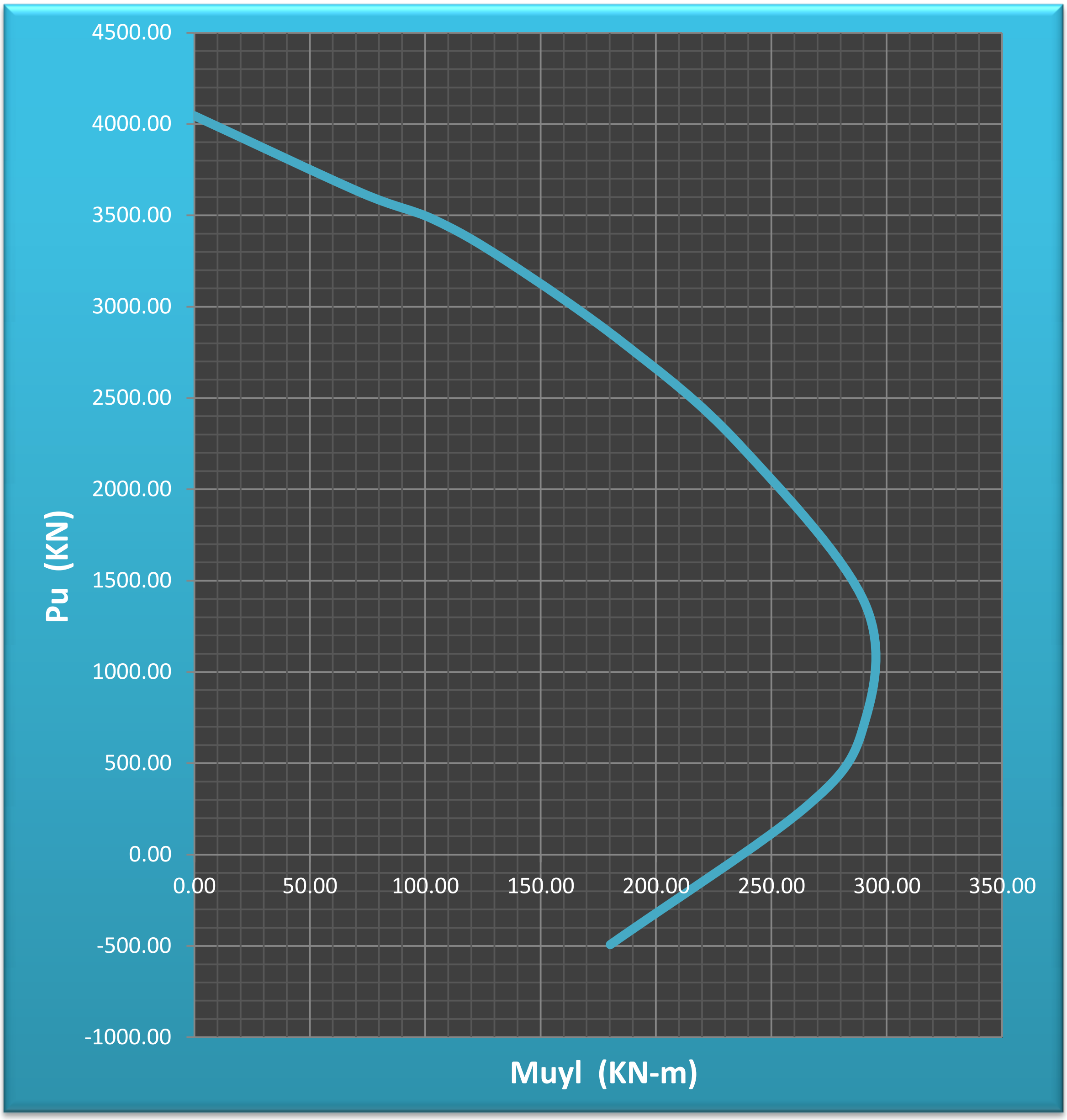


FIGURE.5.3. INTERACTION CURVE FOR COMPRESSION WITH BENDING ABOUT Y AXIS–RECTANGULAR SECTION REINFORCEMENT DISTRIBUTED EQUALLY ON ALL FACES

(vi) These interaction curves are utilized to generate external load and moments combinations which can be applied to column successfully without failure. This excersise can be explained as follows.

a) For any axial load on column within its limiting capacity the corresponding limiting moments about x-axis and about y-axis are obtained from above plotted interaction curve.

For example for axial load of 2905 KN corresponding limiting moment about x-axis is 280 KN-m and limiting moment about y-axis is 174 KN-m as read from respective interaction curve plotted above.

b) For the considered axial load and its corresponding limiting moments about x and y axis another interaction curve is poltted using following equation

$$\left[\frac{M_{ux}}{M_{uxl}}\right]^{\alpha_n} + \left[\frac{M_{uy}}{M_{uyl}}\right]^{\alpha_n} \leq 1.0$$

For example this interaction curve is for plotted for axial load of 2905 KN the corresponding limiting moments about x-axis and y-axis are 280 KN-m and 174 KN-m respectively.

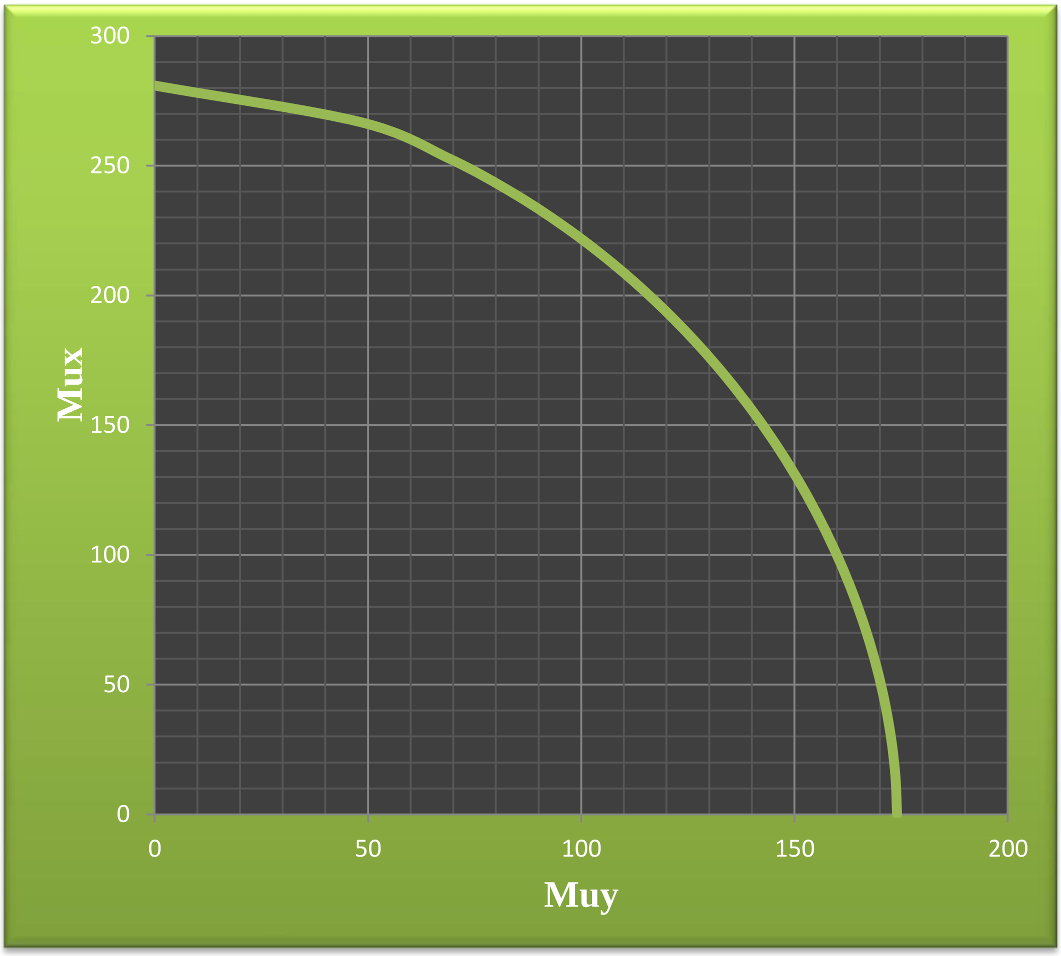


FIGURE.5.4. INTERACTION CURVE FOR A PARTICULAR AXIAL LOAD AND CORRESPONDING LIMITING MOMENTS ABOUT X AND Y AXIS

c) Using the above curve any number of Mux and Muy combination for the considered axial load can be calculated. Any moments combination lying within this curve is a safe combination mean they are satisfying the check provided by IS 456:2000 for safe design of column.

For examlpe: moment about x-axis 154.52 KN-m and moment about y-axis 140.60 KN-m are safe moment combination determined from above interaction curve for axial load of 2905 KN thus from this plot we can design any number of safe moment combination wihich can be applied on column.

d) Thus we generate external load and moments combinations which can be applied to column successfully without failure.

It is required that the that the prepared data samples should cover whole range of possible inputs so that network can be used for all possible cases of input problem and it can be trined with accuracy for satisfactory performance.

For each assumed column cross-section ten axial load values are determined and for each axial load consideration ten moment combination are calculated and thus we get hundred design load and moments for each column-cross section. In this way we have done total 5271 column design.

<u>In our design maximum and minimun limit of axial load and moments are as follows</u>

Maximum axial load =7000 KN and minumum axial load =3.24 KN

Maximum moment about x-axis = 823.0469 KN-m and Minimum moment about x-axis is 143.724 KN-m

Maximum moment about y-axis = 637.02 KN-m and Minimum moment about y-axis is 116.55 KN-m.

5.2. SELECTION OF FORM OF INPUT AND OUTPUT PARAMETERS

we are developing neural model for column design, so it is obvious that it should calculate the area of steel for the purpose of column design for given dimension of column i.e breadth and depth , loads, moments, clear cover, grade of steel and grade of concrete. Therefore the input and output of MLP has been selected in the form of

Input has been selected in the form of	
Axial load	Pu
Moment along x-axis	Mux
Moment along y-axis	Muy
Breadth of column	B
Depth of column	D
Grade of concete	f_{ck}
Grade of steel	f_y
Clear cover	$c.c$

TABLE.5.4. FORM OF INPUT PARAMETERS

Output has been selected in the form of	
Area of steel reinforcement	A_{st}
Number of bars	$1/k_1$
Diameter of dar	d
Design check	k_2

TABLE.5.5. FORM OF OUTPUT PARAMETERS

Finally this priliminary form of input and output is transformed into the form of non-dimensional parameters or in the form of ratio of each other so that there final values lies between 0 and 1 according to SP 16. Thus the network can be used for any type of input and it can be trained in efficient way.

Finally selected input and output parameters used in nueral network modelling

Input paremetes					
$\boldsymbol{\frac{Pu}{F_{CK}BD}}$	$\frac{Mux}{F_{CK}BD^2}$	$\frac{Muy}{F_{CK}DB^2}$	$\frac{B}{D}$	$\frac{Clear\ Cover}{D}$	$\frac{F_{CK}}{BD}$

TABLE.5.6. INPUT PARAMETERS

Output parameters		
$\boldsymbol{\frac{p}{f_{ck}}}$, **where** $(\boldsymbol{p = \frac{A_{st}}{BD} \times 100})$	$k_1 = \frac{\frac{\pi}{4}d^2}{A_{st}}$, $(\frac{1}{k_1})$=no. of bar	Check(k_2)= $\left[\frac{M_{ux}}{M_{uxl}}\right]^{\alpha_n} + \left[\frac{M_{uy}}{M_{uyl}}\right]^{\alpha_n} \leq 1.0$

TABLE.5.7. OUTPUT PARAMETERS

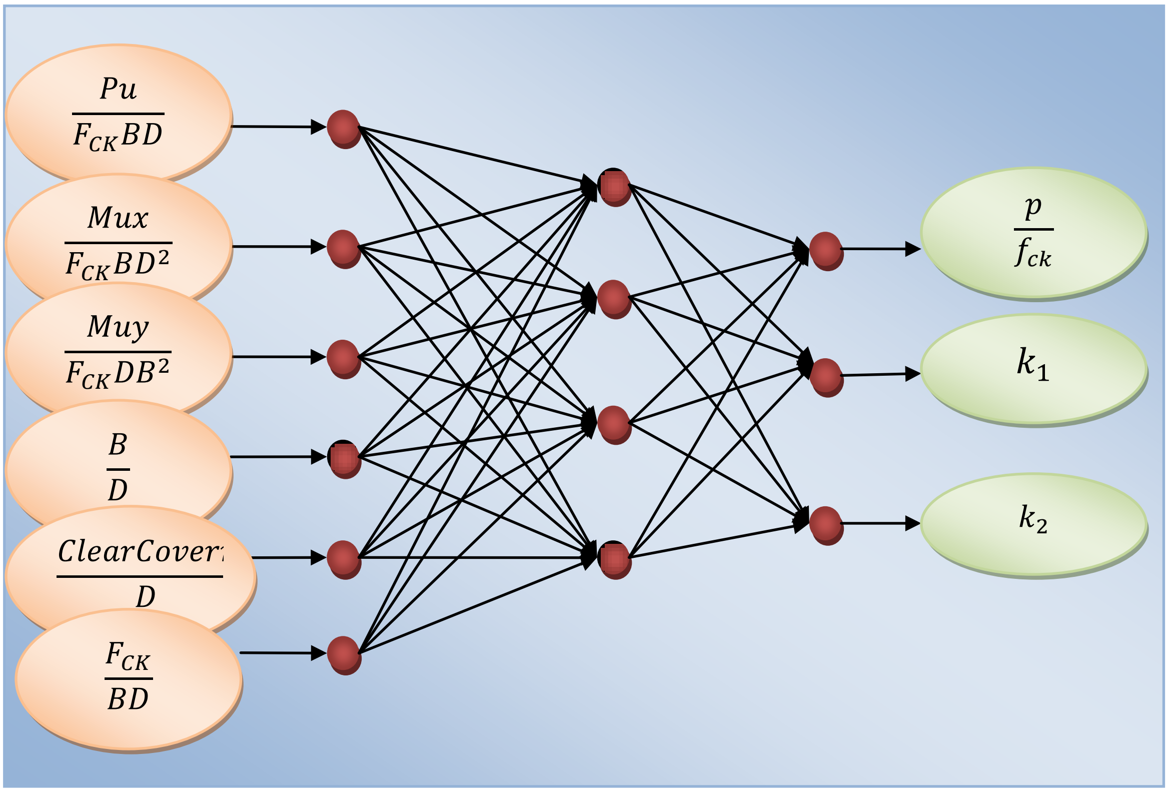


FIGURE.5.5. CONFIGURATION OF NETWORK WITH INPUT AND OUTPUT PARAMETER

5.3. NORMALIZATION OF PREPARED DATA SET

Normalization of data using statistical normalization technique before the training process has been done for obtaining better results and to speed up the calculation process. Normalization influences the performance error of network which is trained to predict the desired output.

5.3.1 Statistical or Z-Score Normalization of Data Set

Using this technique data was normalized. This calculates the standard deviation and mean for data range of each input and output parameter.thus we obtain the normalization of training data using the transformation given in the following equation.

$$x' = \frac{(x_i - \mu_i)}{\sigma_i}$$

A Sample of Design Data Set before Normalization

Pu/(fck*BD)	Mux/(Fck*BD^2)	Muy/(Fck*DB^2)	B/D	c.c/D	Fck/BD
0.37968996	0.07875	0.07384998	1	0.2	0.000625
0.3588	0.08532	0.05454	1	0.2	0.000625

TABLE.5.8. A SAMPLE OF INPUT DESIGN DATA SET BEFORE NORMALIZATION

P/Fck	k1	check (k2)
0.19635	0.25	0.761764
0.19635	0.25	0.690707

TABLE.5.9. A SAMPLE OF OUTPUT DESIGN DATA SET BEFORE NORMALIZATION

A Sample of Design Data Set after Normalization

Pu/(fck*BD)	Mux/(Fck*BD^2)	Muy/(Fck*DB^2)	B/D	c.c/D	Fck/BD
0.698917	0.800181	0.77876	1	0.811658	0.773873
.68512	0.810204	0.729481	1	0.811658	0.773873

TABLE.5.10. A SAMPLE OF INPUT DESIGN DATA SET AFTER NORMALIZATION

P/Fck	k1	check (k2)
0.883601	0.884551	0.761764
0.883601	0.884551	0.690707

TABLE 5.11.A SAMPLE OF INPUT DESIGN DATA SET AFTER NORMALIZATION

5.4. DESIGN OF NEURAL NETWORK

Neural networking tool of Matlab software has been used for neural network design.

A MLP network i.e a feedforward network is proposed for design of neural network model. In feedforward neural network there are two passes of data during trainig of network one is forward pass and another is back-ward pass. In forward pass input travel from input layer to hidden layer and then to output layer during this process some computations takes place on input and it get refined to ouput of network . In backward error is determined at each layer level and it propogates in backward direction starting from output layer to hidden layer and then input layer and correspondingly weights are updated at each layer level.

Feedforward generally consists of two layers of hidden neurons. Components of feedforward network are as follows.

5.5. DATA DEVISION FOR OPTIMAL ARTIFICIAL NEURAL NETWORK TRAINING

During the training of feedforward network the available date set is seperated in three subsets, the training set, the validation set, the test set.

5.5.1. <u>Training Set</u>

Calculation of gradient, and network weights and biases are adjusted using the training data set.

5.5.2. <u>Validation Set</u>

Validation set is used for error monitering during training process. Generally in the initial stage of trainig validation set error decreases as does the error of trainig set. When network starts to overfit the training data the validation set error begin to rise. Finally the network biases and weights are fixed at the least of the validation data set error.

5.5.3. <u>Trainig Set</u>

Error of test set is used for compairing different model and it is not utilized in the training process. Test set error is plotted during training of network. If test set error and validation set error attain there minimum values at considerably different iteration number then it is an indication of poor data set devision.

From 5271 available design data set 1581 data set has been used for calculation of percentage error in the result obtained and remainig 3690 data set are used in network trainig.

5.6. DESIGNED PARAMETER OF FEED-FORWARD NETWORK

Output layer = 1

Number of hidden layer = 2

Input neuron = 6

No.of epochs =5000

In input layer and hidden layer tansig activation function and in output layer purlin activation function is used.

Incremental training has been implemented – in incremental training the weights and biases are adjusted after each pass of input to the network.

5.7. TRAINING OF NETWORK

Training is the process of learning of network the ralationship between input and output presented to network. Learning of network is accomplished by a specified algorithm which encoorporates the step which direct the processing of data and make network learn. Trining can be defined as the process in which network weights are updated and finally attains a value at which network error is minimum during validation.

Levenberg –marquardt algortihm is used for training of MLP network

5.7.1. Training Algorithm Perform Five Major Operation

I. Initialization of weights and biases arbitrarily to some small value that can be between -1 to 1.

II. Pass the input and output pattern and compute the network output by propagating the input pattern in forward direction through the network.

III. Compute the network error by compairing target output and network output.

IV. Propagate the error backward through network.

V. Update the weights of network during backward error propagation using the given update rule.

$$w_{k+1} = w_k - (J_k^T J_k)^{-1} J_k e_k$$

VI. Repeat from step II for next pattern of data untill error cease to changes below a prespecified value or a specified number of iteration has reached.

Design Step of Iterative Training Process for Weight Update Using Levenberg-Marquardt Algorithm are as Follows

I. Evaluate the total error i.e sum squared error with the initialized weights randomly selected at the starting of trainig process.

II. Adjust the weights using equation ($w_{k+1} = w_k - (J_k^T J_k)^{-1} J_k e_k$) .thus we get updated network.

III. Evaluate the new total error with the new weights obtained in step (ii).

IV. If the new total error is increased as a result of last update, then reset the weights to the previous value and increase μ (combination coefficient) by multiplying it with some factor or by a factor of 10. μ is increased because error increases so we need to maximize the influence of gradient descent in update rule as gradient descent look for proper curvature for quadratic approximation. This will slow down the training process.

V. If the new total error decreases as a result of last update then change the weights to new adjusted weights and decreases the combination coefficient deviding it with some factor or by a factor of 10. μ Is reduced to minimize the effect of gradient descent part in weight update rule thus the training process speed up.

VI. Repeat step (ii) to step (v) untill the total new error reduces to desired error goal.

Performance plot have been used for analysing the network performance which is based on mean square error calculation.

CHAPTER 6

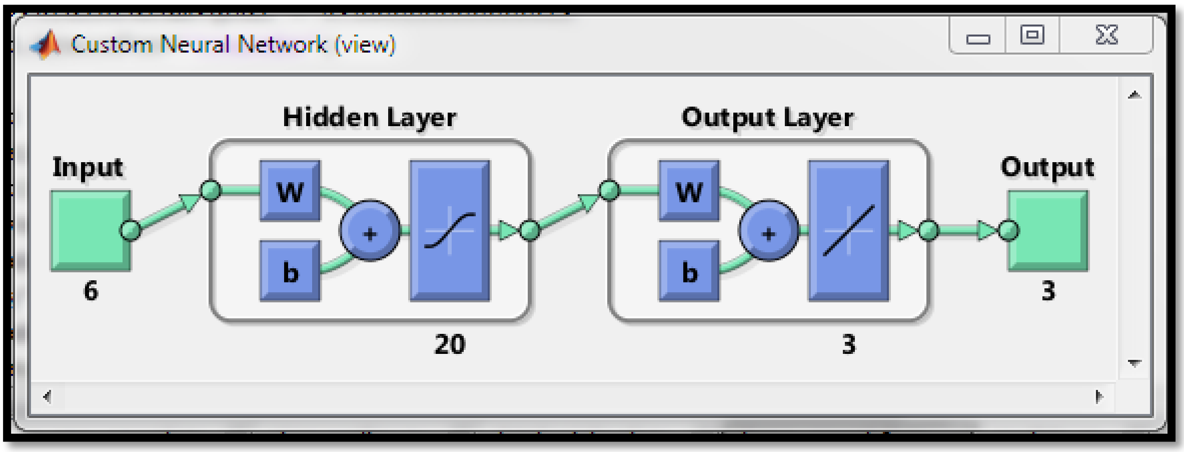
RESULTS AND CONCLUSION

6.1. PROGRAMMING OF NEURAL NETEORKING

```
data=xlsread('input  - 2.xlsx');
data1=xlsread('output  - 2.xlsx');
count=0;
count1=0;count2=0;count3=0;count4=0;
for i =1:5272

   if (data(i,32)>=0.33 && data(i,32)<0.45)
      count=count+1;
      data_1(count,:)=data(i,32:37);
      t_1(count,:)=data1(i,17:19);

   elseif (data(i,32)>=0.45 && data(i,32)<0.55)
      count1=count1+1;
      data_2(count1,:)=data(i,32:37);
      t_2(count1,:)=data1(i,17:19);

   elseif (data(i,32)>=0.55 && data(i,32)<0.65)
      count2=count2+1;
      data_3(count2,:)=data(i,32:37);
      t_3(count2,:)=data1(i,17:19);

   elseif (data(i,32)>=0.65 && data(i,32)<0.75)
      count3=count3+1;
      data_4(count3,:)=data(i,32:37);
      t_4(count3,:)=data1(i,17:19);

   elseif (data(i,32)>=0.75)
      count4=count4+1;
      data_5(count4,:)=data(i,32:37);
      t_5(count4,:)=data1(i,17:19);


   end
end

d1=length(data_1);
d2=length(data_2);
d3=length(data_3);
d4=length(data_4);
d5=length(data_5);
```

```
d1_tr=round(0.70*d1);
d2_tr=round(0.70*d2);
d3_tr=round(0.70*d3);
d4_tr=round(0.70*d4);
d5_tr=round(0.70*d5);

train1=[data_1(1:d1_tr,:);data_2(1:d2_tr,:);data_3(1:d3_tr,:);data_4(1:d4_tr,:);data_5(1:d5_tr,:)];
target=[t_1(1:d1_tr,:);t_2(1:d2_tr,:);t_3(1:d3_tr,:);t_4(1:d4_tr,:);t_5(1:d5_tr,:)];

k=train1;
t=target;

k_test=[data_1(d1_tr+1:d1,:);data_2(d2_tr+1:d2,:);data_3(d3_tr+1:d3,:);data_4(d4_tr+1:d4,:);data_5(d5_tr+1:d5,:)];
% k_test=[0.05232593 0.0168899 0.11708444 0.666 0.0888 0.000185185];
% k_test=input('Enter the 6 column 1 row array');
target_test=[t_1(d1_tr+1:d1,:);t_2(d2_tr+1:d2,:);t_3(d3_tr+1:d3,:);t_4(d4_tr+1:d4,:);t_5(d5_tr+1:d5,:)];
count1=0;
net = newff(k',t',20);
net=init(net);
net.divideParam.trainRatio = 100/100;  % Adjust as desired
net.divideParam.valRatio = 10/100;  % Adjust as desired
net.divideParam.testRatio = 10/100;  % Adjust as desired

view(net);
net.trainParam.epochs = 5000;
net.trainParam.goal = 0.00000001;
net = train(net,k',t');
y=sim(net,k_test');
net1=net;
save('net1.mat','net1');
y=y'
r=target_test-y;
result=r;
disp(y);
```

6.2. NEURAL NETWORK CONFIGURATION



SCREEN SHOT.6.1.CONFIGURED NEURAL NETWORK

<u>Neural Network Configuration</u>

Number of input neurons – 6

Number of output neurons -3

Number of hidden neurons – 20

Total number of input layers -2

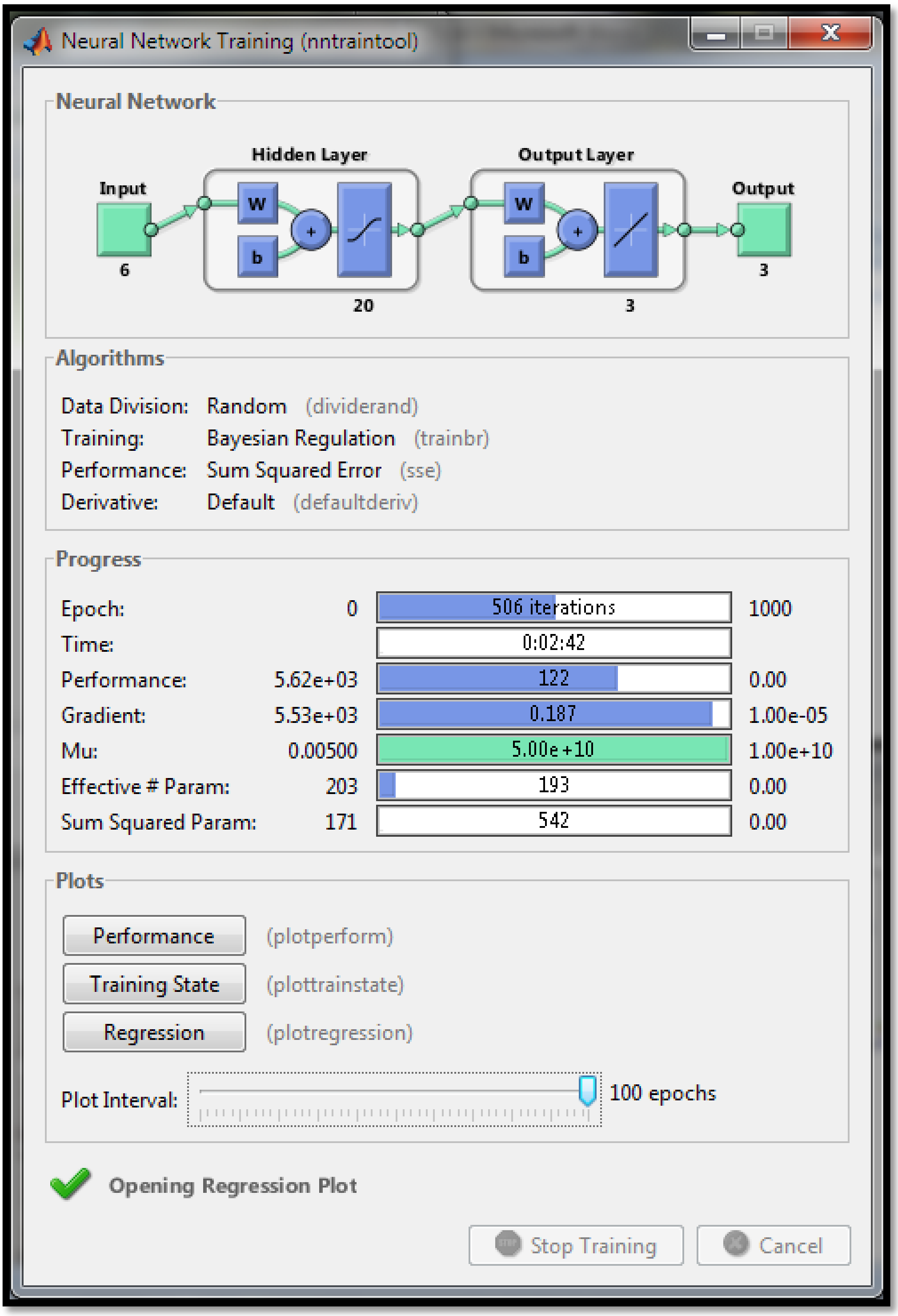
Activation function in hidden layers– tansig, Activation function in output layer – Purelin

Learning algorithm – levenberg-marquardt

Weight and Bias learning function -learngdm

Performance function – MSE

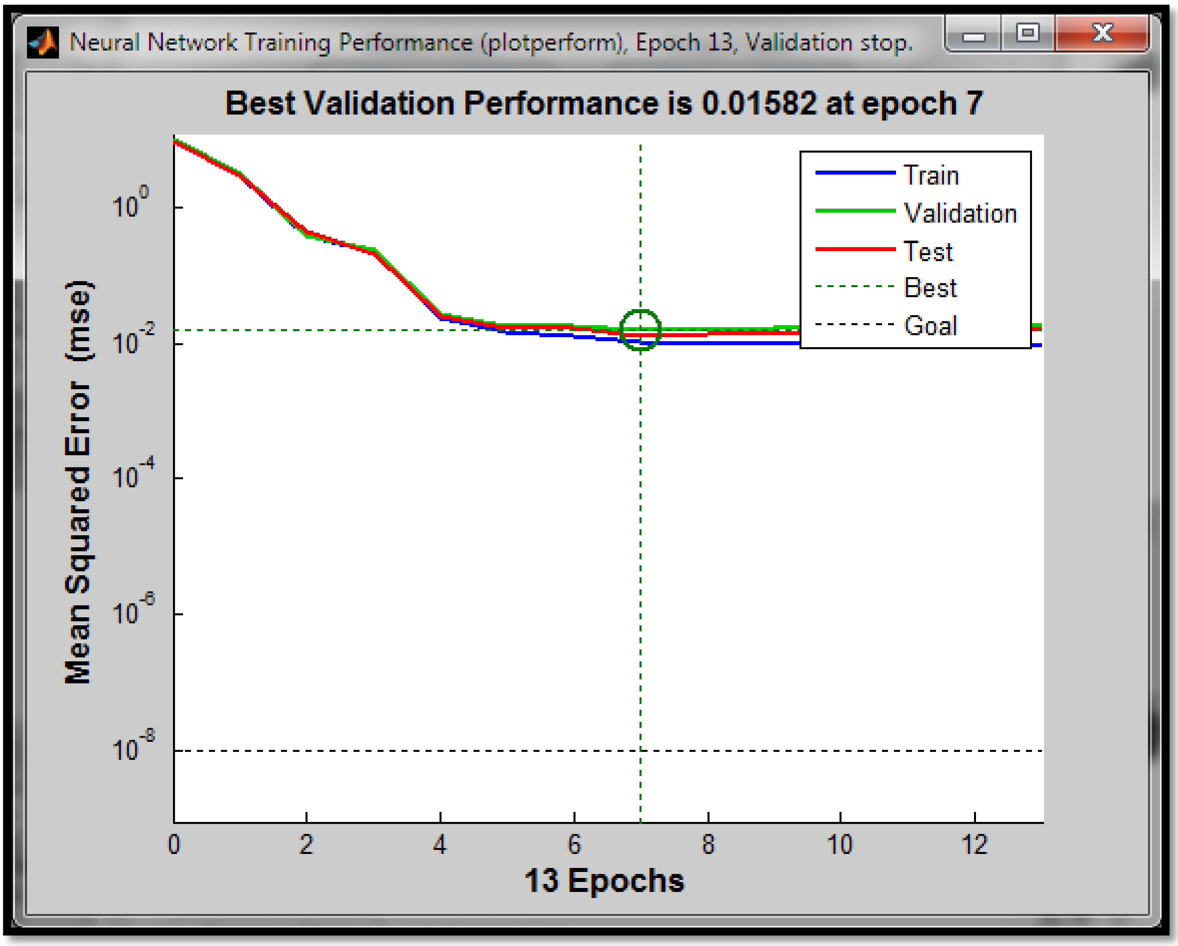
6.3. NEURAL NETWORK TRAINING



SCREEN SHOT.6.2.NEURAL NETWORK TRAINING

6.4. PERFORMANCE PLOT

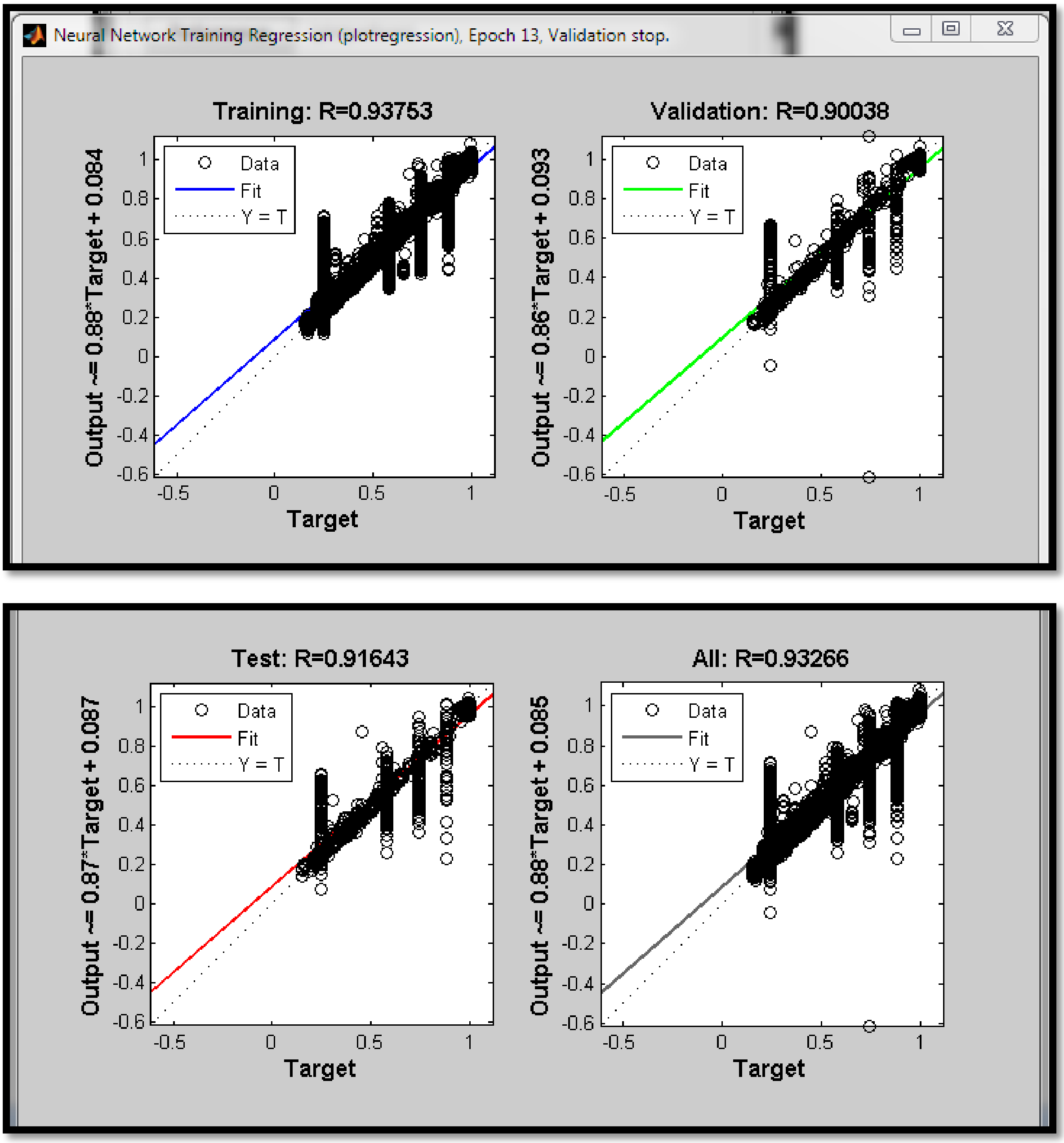
6.4.1. MSE versus Epoch Curve



SCREEN SHOT.6.3.MSE VERSUS EPOCH CURVE

Best validation performance obtained was 0.00854 for 20 hidden neurons and two hidden layers.

6.4.2. <u>Regression Plot</u>



SCREEN SHOT.6.4.REGRESSION PLOT

Regression plot shows the linear regression of outputs as compared to actual targets. For our neural network model we have obtained a regression value of 0.93266. Regression value of one show exact fitting of network output with target values.

6.5. ERROR OBTAINED IN ANN RESULTS FOR UNKNOWN INPUT PARAMETERS

% error in Ast	% error in dia of bar	% error in no of bar	% error in check
-5.558693317	-0.397262673	-4.724974108	0.209331337
0.103613856	-43.61575094	51.56652492	1.796077825
7.09358616	-30.28161476	45.26319659	-0.750890731
7.975370088	1.93943838	4.299253141	2.175480629
15.8524904	22.97031002	-41.81591367	4.441485147
8.119582152	22.05628989	-51.23796079	2.700616284
-10.75102207	-51.17360795	51.53861896	0.746248043
-4.556711962	-66.10390796	62.10410078	-1.22735307
-0.430395335	-35.00834953	44.90097472	-0.517209901
9.628015961	-19.00455491	36.18736941	2.032815577
2.841300653	-4.546086532	11.1072931	5.357884039
-9.949744501	4.575917414	-20.74752507	3.216155087
-12.4588451	-5.387148991	-1.255426554	-2.839121631
0.028984184	10.81697808	-25.69260781	-3.875667048
-3.650002637	10.38320484	-29.05965501	-4.356666229
7.790392686	-18.70481749	34.56057369	-3.653657048
-19.36415098	10.92097705	-50.42604028	-2.664593405
-12.33432558	7.814637461	-32.18693913	-2.804345344
-3.434656624	8.873237149	-24.55873568	-0.626169823
-10.85149291	18.56258938	-67.14509391	-0.572705295
1.582356754	2.593367476	-3.727975592	1.985761286
-9.62792143	-82.32370417	67.02119546	-2.308865672
-1.819214188	-97.51448065	73.90051976	-2.418395184
2.012371622	-17.24611839	28.71891542	-2.685776979
7.569084131	8.015168334	-9.240787063	-2.535701162
-2.421129684	17.47285304	-50.3820147	-3.334528705
0.840612925	5.046237445	-9.978926658	-0.820060995
-0.836157745	-3.008774993	4.968443164	1.744042142
-4.593565658	-205.8203364	88.81664155	-2.378934797
11.36125286	-1.34360129	13.69599643	-2.731178649
9.408847688	12.23572511	-17.61162373	-4.307879331
3.900642223	3.389520408	-2.960823924	-2.602280329
-7.383040335	-6.348590743	5.054974088	-1.680981414
-22.88388355	-291.8341109	91.99630654	-0.933236919
-15.13421142	-397.8145534	95.3541069	-1.43395661
-5.991673353	-19.51644114	25.7978578	-1.543472412
-21.90957148	-7.06032706	-6.360574168	-2.41817366

-14.57457599	-6.480983147	-1.051823297	-0.335666246
-24.43576374	-11.42935951	-0.218050245	-1.066518807
-6.489755486	-11.58640737	14.47654461	-0.727223223
5.20089642	-179.5554979	87.86979459	-1.796177942
13.98192381	-31.00981502	49.8833471	-2.340108769
6.533711666	12.02586311	-20.76607935	-1.603256217
4.970425602	2.901251496	-0.79326638	-1.299036072
1.682113353	10.41694118	-22.51260094	0.439524298
-1.94673421	-2.173302626	2.344107219	0.629050613
8.959961902	-387.6561187	96.17170783	0.779333266
17.69904122	-139.085437	85.60211675	0.966002971
8.652626694	-11.17372166	26.09194472	-0.872042639
14.89145821	-5.395759904	23.38269518	-0.735876932
7.242790355	3.441848891	0.512207875	-1.746929828
12.49879545	0.901170247	10.90014861	-0.977924227
9.086019908	-204.3680211	90.18630335	2.430143589
2.380785941	-0.442887023	3.239760966	-1.304100542
5.163080781	-29.00359202	43.01325764	1.343427428
6.467776259	-3.94137034	13.42661801	-0.51574622

TABLE 6.1.ERROR OBTAINED IN ANN RESULTS

The error obtained in the calculation of area of steel, diameter of bar and no.of bars using the neural network application has been found to vary over a large range after complete training of network for a large data set. Percentage of error in predicting the area of steel lies in the range of 0.0223 to 67.1 for unknown input parameters feeded to neural model for testing the performance of metwork.

6.6. CONCLUSION

In the present work an attempt has been made to design rcc column using an application of neural networking. 5271 design of column subjected to axial load and biaxial moments have been done using programming in Microsoft excel. The training examples are so designed to cover a wide range of design loads on column. The neural network has been trained to approximate the non-linear relationship between the input and target output data that has been designed. Using neural network toolbox of matlab software a feedforward type of neural network has been trianed using levenberg-marquardt training algorithm. The performance of network have been analysed using mean square error method and result of network have been compared with test data set obtained from the available design data which were not used in training of network. It takes several hit and trial attempts to arrive at the best performance of network .The best performance of network have been obtained using two number of hidden layers. Thus the developed neural network architecture is able to predict the area of reinforcement for a new column problem with a minimum 0.022 percentage and maximum of 67.1 percentage of error when compared with SP 16 design result.

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APPENDIX

INPUT						TARGET OUTPUT				ERROR
P_u	M_{ux}	M_{uy}	B	D	F_{ck}	A_{st}	$d(dia\ of\ bar)$	$No.of\ bars$	$check$	% Error in A_{st}
171.6667	39.37989	16.3424	200	300	35	1963.495	25	4	1	17.87947
221.8063	63.62061	18.0218	200	400	35	1963.495	25	4	1	13.46232
177.5611	57.8	17.48701	200	400	35	1963.495	25	4	0.965727	0.352361
80.83333	52.5	16.31786	200	400	35	1963.495	25	4	0.97882	0.423988
92.44865	86.45301	22.97357	200	400	35	3926.991	25	8	1	0.753375
200	86.05201	23.68371	200	400	35	3926.991	25	8	1	2.251796
299.0995	90.17685	20.02745	200	500	35	1963.495	25	4	1	10.54223
215.2268	83.5	19.00131	200	500	35	1963.495	25	4	0.986967	0.432286
102.5	74.77771	17.12925	200	500	35	1963.495	25	4	1	3.709056
192.6453	121.0447	25.07848	200	500	35	3926.991	25	8	1	2.248726
99.01485	163.7857	31.48615	200	500	35	5890.486	25	12	1	1.470368
296.6667	158	32.03078	200	500	35	5890.486	25	12	0.988429	0.406081
225.6149	44.24531	36.20071	300	300	35	1963.495	25	4	1	20.25895
133.3333	39.82653	32.781	300	300	35	1963.495	25	4	1	11.17799
53.13877	58.98249	48.2584	300	300	35	3926.991	25	8	1	6.970366
175	59.07592	48.33484	300	300	35	3926.991	25	8	1	2.879501
346.6457	72.59852	40.43849	300	400	35	1963.495	25	4	1	15.44711
282.9361	69.84496	39.34699	300	400	35	1963.495	25	4	1	13.42623
217.288	95.43092	52.42563	300	400	35	3926.991	25	8	1	3.021064
26.2848	92.46171	50.58214	300	400	35	3926.991	25	8	1	19.68946
111.1562	126.5758	68.21041	300	400	35	5890.486	25	12	1	12.84851
459.8639	104.3974	44.70223	300	500	35	1963.495	25	4	1	10.11381
337.1018	97.75319	42.12269	300	500	35	1963.495	25	4	1	7.216619
170	82.22805	35.58424	300	500	35	1963.495	25	4	1	1.278887
353.4097	135.2653	56.66722	300	500	35	3926.991	25	8	1	1.873829
58.44477	128.29	52.78984	300	500	35	3926.991	25	8	1	15.93174
259.7792	178.0063	72.33376	300	500	35	5890.486	25	12	1	8.165773
214.7716	220.5646	88.2385	300	500	35	7853.982	25	16	1	10.79427
389.748	127.9354	44.85203	300	600	35	1963.495	25	4	1	2.921908
478.4791	178.6131	60.93949	300	600	35	3926.991	25	8	1	5.3722

102.126	166.4172	55.36702	300	600	35	3926.991	25	8	1	11.70447
393.0227	232.9557	76.52789	300	600	35	5890.486	25	12	1	6.333479
362.4979	287.0981	92.44226	300	600	35	7853.982	25	16	1	11.90656
471.4851	81.57642	66.74435	400	400	35	1963.495	25	4	1	12.49681
388.3111	78.04879	63.65798	400	400	35	1963.495	25	4	1	9.480891
342.1274	104.4088	85.4254	400	400	35	3926.991	25	8	1	7.204744
131.6598	100.6655	81.75795	400	400	35	3926.991	25	8	1	1.618125
235.9956	135.5537	110.9075	400	400	35	5890.486	25	12	1	3.155884
26.00681	129.9042	105.881	400	400	35	5890.486	25	12	1	1.958288
167.3244	166.5638	136.2795	400	400	35	7853.982	25	16	1	1.263062
458.9768	109.9797	69.05329	400	500	35	1963.495	25	4	1	5.641497
514.1741	149.4859	92.89881	400	500	35	3926.991	25	8	1	8.505546
180.3198	140.5165	87.31525	400	500	35	3926.991	25	8	1	5.808781
420.5436	192.2269	118.1478	400	500	35	5890.486	25	12	1	2.302693
58.89288	178.9774	110.7571	400	500	35	5890.486	25	12	1	7.784314
375.536	234.7852	143.3876	400	500	35	7853.982	25	16	1	3.25497
528.123	144.9259	74.13492	400	600	35	1963.495	25	4	1	3.962604
675.1685	199.2648	100.4452	400	600	35	3926.991	25	8	1	10.04485
240.501	183.4078	92.41931	400	600	35	3926.991	25	8	1	6.142926
589.7121	253.6074	125.5418	400	600	35	5890.486	25	12	1	2.230166
104.7111	230.6548	115.7309	400	600	35	5890.486	25	12	1	10.20441
559.1872	307.7498	150.7202	400	600	35	7853.982	25	16	1	5.133613
830.4769	253.7611	108.0285	400	700	35	3926.991	25	8	1	10.06784
303.7167	229.3115	96.94703	400	700	35	3926.991	25	8	1	5.547671
750.7923	319.7038	133.0172	400	700	35	5890.486	25	12	1	1.549055
154.9728	285.1588	119.788	400	700	35	5890.486	25	12	1	11.04597
730.0041	385.4485	158.1677	400	700	35	7853.982	25	16	1	7.397909
982.4765	312.9831	115.6328	400	800	35	3926.991	25	8	1	8.370715
368.036	278.2091	101.5456	400	800	35	3926.991	25	8	1	5.2594
907.0835	390.5218	140.5407	400	800	35	5890.486	25	12	1	0.322039
207.8509	342.5516	123.9594	400	800	35	5890.486	25	12	1	11.64026
893.2696	467.8783	165.6809	400	800	35	7853.982	25	16	1	10.62662
56.48079	415.7589	149.3931	400	800	35	7853.982	25	16	1	24.37163
674.9385	163.7065	133.9417	500	500	35	3926.991	25	8	1	13.36935
302.1948	152.743	123.6518	500	500	35	3926.991	25	8	1	3.336007
581.308	206.4475	168.9116	500	500	35	5890.486	25	12	1	8.723512
180.7679	191.2039	155.2718	500	500	35	5890.486	25	12	1	3.538961
536.3004	249.0058	203.732	500	500	35	7853.982	25	16	1	2.396729
15.02865	231.8552	187.7404	500	500	35	7853.982	25	16	1	3.02262
871.8578	219.9165	145.7423	500	600	35	3926.991	25	8	1	12.99377

378.876	200.3984	132.1803	500	600	35	3926.991	25	8	1	0.890327
786.4014	274.2592	180.4894	500	600	35	5890.486	25	12	1	7.991494
243.0861	247.6454	163.0918	500	600	35	5890.486	25	12	1	0.282305
755.8766	328.4015	215.1407	500	600	35	7853.982	25	16	1	1.501584
81.80313	299.0788	195.8741	500	600	35	7853.982	25	16	1	7.574364
1063.091	282.0324	157.5985	500	700	35	3926.991	25	8	1	10.55981
458.5917	251.8075	140.6823	500	700	35	3926.991	25	8	1	2.122933
983.4067	347.9751	192.1888	500	700	35	5890.486	25	12	1	5.815057
309.8478	307.6548	170.9763	500	700	35	5890.486	25	12	1	3.924642
962.6185	413.7197	226.7436	500	700	35	7853.982	25	16	1	1.309108
153.56	369.9588	204.076	500	700	35	7853.982	25	16	1	12.2353
539.411	306.952	148.4025	500	800	35	3926.991	25	8	1	6.446223
1175.623	427.601	203.9604	500	800	35	5890.486	25	12	1	2.054013
379.2259	371.2945	178.7254	500	800	35	5890.486	25	12	1	7.711767
1161.809	504.9575	238.4582	500	800	35	7853.982	25	16	1	5.618018
227.8558	444.5018	212.2937	500	800	35	7853.982	25	16	1	16.87919
1068.547	240.5682	196.8285	600	600	35	3926.991	25	8	1	12.48547
517.251	217.3889	175.6284	600	600	35	3926.991	25	8	1	5.97139
983.0908	294.9109	241.2907	600	600	35	5890.486	25	12	1	7.717617
381.4611	264.6359	214.6618	600	600	35	5890.486	25	12	1	5.4222
952.566	349.0533	285.589	600	600	35	7853.982	25	16	1	0.371463
220.1781	316.0693	255.5951	600	600	35	7853.982	25	16	1	2.15661
1295.706	310.3037	214.7371	600	700	35	3926.991	25	8	1	8.993303
613.4667	274.3036	187.6056	600	700	35	3926.991	25	8	1	1.130566
1216.021	376.2463	258.1889	600	700	35	5890.486	25	12	1	6.052428
464.7228	330.1508	225.8917	600	700	35	5890.486	25	12	1	1.784324
1195.233	441.991	302.3144	600	700	35	7853.982	25	16	1	0.679315
308.435	392.4548	267.1865	600	700	35	7853.982	25	16	1	5.402592
710.786	335.6949	199.5235	600	800	35	3926.991	25	8	1	5.820222
1444.162	464.6803	275.1825	600	800	35	5890.486	25	12	1	2.419907
550.6009	400.0374	237.1557	600	800	35	5890.486	25	12	1	2.590721
1430.348	542.0368	319.1983	600	800	35	7853.982	25	16	1	3.890545
399.2308	473.2447	278.7994	600	800	35	7853.982	25	16	1	9.291472
768.3417	296.7996	239.3555	700	700	35	3926.991	25	8	1	5.633463
1448.635	404.5176	330.969	700	700	35	5890.486	25	12	1	2.554134
619.5978	352.6469	285.7152	700	700	35	5890.486	25	12	1	7.329319
1427.847	470.2623	384.7601	700	700	35	7853.982	25	16	1	5.587776
463.31	414.9508	335.1253	700	700	35	7853.982	25	16	1	0.609899
1712.702	501.7596	354.1584	700	800	35	5890.486	25	12	1	2.242658
721.9759	428.7803	300.9232	700	800	35	5890.486	25	12	1	4.911158

1698.888	579.1161	407.7851	700	800	35	7853.982	25	16	1	4.476033
570.6058	501.9875	350.7253	700	800	35	7853.982	25	16	1	1.188269
826.4959	510.0333	316.1734	700	900	35	5890.486	25	12	1	0.991142
679.4362	594.1594	366.3264	700	900	35	7853.982	25	16	1	2.896309
932.6689	596.418	331.4587	700	1000	35	5890.486	25	12	1	3.568456
789.1447	691.4374	381.9124	700	1000	35	7853.982	25	16	1	4.965699
45.75815	11.00238	9.001947	200	200	35	1017.876	18	4	1	8.34728
109.5068	11.83987	9.68717	200	200	35	1017.876	18	4	1	10.23275
83.33333	11.49602	9.405836	200	200	35	1017.876	18	4	1	7.696944
60.81709	15.47732	12.66326	200	200	35	2035.752	18	8	1	0.175156
90	15.67058	12.82138	200	200	35	2035.752	18	8	1	2.426866
161.2702	25.87023	11.39204	200	300	35	1017.876	18	4	1	2.414676
141.7118	20.1	11.17384	200	300	35	1017.876	18	4	0.88846	35.88231
83.33333	22.30796	10.13352	200	300	35	1017.876	18	4	1	12.57596
78.22023	33.84666	14.2447	200	300	35	2035.752	18	8	1	4.421457
19.14698	26.4	13.88891	200	300	35	2035.752	18	8	0.888482	9.999454
175	33.96637	14.8276	200	300	35	2035.752	18	8	1	12.75005
14.87523	44.50989	17.89166	200	300	35	3053.628	18	12	1	7.510702
238.7575	42.35841	13.38213	200	400	35	1017.876	18	4	1	8.273044
175.9717	36.2	12.66369	200	400	35	1017.876	18	4	0.953382	25.77614
102.5	34.20517	11.14442	200	400	35	1017.876	18	4	1	21.52744
175.762	54.51766	16.298	200	400	35	2035.752	18	8	1	14.54992
29.26265	46.4	15.34002	200	400	35	2035.752	18	8	0.945133	5.826832
85.83333	46.3	15.70995	200	400	35	2035.752	18	8	0.93329	19.47465
122.9238	71.18925	19.96953	200	400	35	3053.628	18	12	1	4.614599
214.1667	70.73283	20.47921	200	400	35	3053.628	18	12	1	8.837512
83.33333	62.4	19.74838	200	400	35	3053.628	18	12	0.93992	11.74696
91.55331	87.78713	23.92585	200	400	35	4071.504	18	16	1	0.07462
208.4547	55.30493	13.79955	200	500	35	1017.876	18	4	1	19.10989
145.8333	49.35533	12.61823	200	500	35	1017.876	18	4	1	27.40172
166.6667	51.33469	13.01124	200	500	35	1017.876	18	4	1	24.87908
260.8927	77.50353	18.29456	200	500	35	2035.752	18	8	1	19.52701
55.93017	71.40146	16.10578	200	500	35	2035.752	18	8	1	6.113534
214.0565	100.188	21.98077	200	500	35	3053.628	18	12	1	8.558236
157.5	92.5	21.64292	200	500	35	3053.628	18	12	0.969381	14.03543
193.7902	122.7798	25.99046	200	500	35	4071.504	18	16	1	2.104051
251.4419	30.82892	25.22367	300	300	35	1017.876	18	4	1	13.35349
223.4618	29.91883	24.46193	300	300	35	1017.876	18	4	1	10.21342
165	27.07962	22.21236	300	300	35	1017.876	18	4	1	1.031614
168.392	38.80535	31.74983	300	300	35	2035.752	18	8	1	2.028801

100.897	37.81985	30.93317	300	300	35	2035.752	18	8	1	4.107789
105.047	49.46858	40.47429	300	300	35	3053.628	18	12	1	1.909589
36.3835	48.0418	39.27386	300	300	35	3053.628	18	12	1	6.971301
52.56854	60.10038	49.17304	300	300	35	4071.504	18	16	1	5.899167
364.8542	51.37838	29.59652	300	400	35	1017.876	18	4	1	1.851047
272.7217	47.33934	27.1493	300	400	35	1017.876	18	4	1	3.642355
301.8587	63.53762	35.99682	300	400	35	2035.752	18	8	1	11.05722
126.0126	59.32865	33.22885	300	400	35	2035.752	18	8	1	3.076193
249.0206	80.20921	44.60416	300	400	35	3053.628	18	12	1	3.348372
54.63705	74.23666	41.36086	300	400	35	3053.628	18	12	1	10.1054
217.6501	96.8071	53.28492	300	400	35	4071.504	18	16	1	1.82938
422.9144	91.7732	40.27265	300	500	35	2035.752	18	8	1	17.01451
167.6802	82.9574	35.65098	300	500	35	2035.752	18	8	1	3.099107
376.0783	114.4577	48.81344	300	500	35	3053.628	18	12	1	9.067935
84.2882	102.2003	43.49912	300	500	35	3053.628	18	12	1	5.715996
355.8119	137.0494	57.49811	300	500	35	4071.504	18	16	1	3.055411
538.8407	123.5495	44.56129	300	600	35	2035.752	18	8	1	19.45417
211.3494	108.686	38.14455	300	600	35	2035.752	18	8	1	8.93087
495.94	152.2482	53.05845	300	600	35	3053.628	18	12	1	12.77707
117.2244	132.122	45.72439	300	600	35	3053.628	18	12	1	0.647989
482.5039	180.8495	61.7538	300	600	35	4071.504	18	16	1	6.510784
35.18644	159.0206	54.54001	300	600	35	4071.504	18	16	1	11.28119
427.9555	72.55758	59.3653	400	400	35	2035.752	18	8	1	11.69337
222.7626	67.11555	54.70331	400	400	35	2035.752	18	8	1	3.516597
375.1173	89.22918	73.00569	400	400	35	3053.628	18	12	1	9.56097
151.387	82.02357	66.94498	400	400	35	3053.628	18	12	1	2.260393
343.7468	105.8271	86.58578	400	400	35	4071.504	18	16	1	8.621745
61.68028	97.85027	79.76198	400	400	35	4071.504	18	16	1	0.985694
584.9362	106.0429	66.94427	400	500	35	2035.752	18	8	1	16.02387
279.4302	94.51333	59.39785	400	500	35	2035.752	18	8	1	7.709219
538.1	128.7274	80.46372	400	500	35	3053.628	18	12	1	12.33741
196.0382	113.7562	71.2584	400	500	35	3053.628	18	12	1	2.37118
517.8337	151.3191	93.98987	400	500	35	4071.504	18	16	1	9.948465
110.2619	135.1154	84.36743	400	500	35	4071.504	18	16	1	3.894583
736.7875	144.2573	75.1831	400	600	35	2035.752	18	8	1	16.06219
338.0994	124.6986	63.6736	400	600	35	2035.752	18	8	1	10.48989
693.8868	172.956	87.9924	400	600	35	3053.628	18	12	1	14.1835
243.9744	148.1347	75.11186	400	600	35	3053.628	18	12	1	4.500975
680.4506	201.5574	101.4962	400	600	35	4071.504	18	16	1	11.47146
161.9364	175.0333	88.42563	400	600	35	4071.504	18	16	1	3.191414

845.8544	221.9186	95.55923	400	700	35	3053.628	18	12	1	13.55042
294.2513	185.1931	79.07042	400	700	35	3053.628	18	12	1	5.981662
837.0242	256.5373	109.0548	400	700	35	4071.504	18	16	1	11.5134
215.7618	217.6549	92.58115	400	700	35	4071.504	18	16	1	1.867179
346.2628	224.9487	83.10747	400	800	35	3053.628	18	12	1	6.46442
271.1527	262.99	96.80731	400	800	35	4071.504	18	16	1	0.660989
746.9579	120.3125	98.43754	500	500	35	2035.752	18	8	1	16.38784
391.1802	106.0693	86.37581	500	500	35	2035.752	18	8	1	13.44438
700.1218	142.9971	116.9976	500	500	35	3053.628	18	12	1	15.76723
307.7882	125.3121	102.1954	500	500	35	3053.628	18	12	1	10.29519
679.8554	165.5888	135.4817	500	500	35	4071.504	18	16	1	14.7563
222.0119	146.6713	119.4831	500	500	35	4071.504	18	16	1	5.719969
891.8335	193.6638	128.7863	500	600	35	3053.628	18	12	1	15.08974
370.7244	164.1474	109.3198	500	600	35	3053.628	18	12	1	9.866201
878.3974	222.2652	147.2032	500	600	35	4071.504	18	16	1	14.449
288.6864	191.0459	126.9809	500	600	35	4071.504	18	16	1	4.168539
1079.726	250.253	141.8886	500	700	35	3053.628	18	12	1	10.78007
436.0013	206.3503	115.5323	500	700	35	3053.628	18	12	1	7.110236
1070.896	284.8716	159.0103	500	700	35	4071.504	18	16	1	12.14023
357.5118	238.8121	133.4748	500	700	35	4071.504	18	16	1	2.39
427.9027	289.9793	140.0633	500	800	35	4071.504	18	16	1	0.914564
1089.78	214.3716	175.6184	600	600	35	3053.628	18	12	1	13.54791
497.4744	180.1601	146.8296	600	600	35	3053.628	18	12	1	12.58676
1076.344	242.973	198.7961	600	600	35	4071.504	18	16	1	13.86594
415.4364	207.0586	168.5778	600	600	35	4071.504	18	16	1	9.54025
499.2618	259.9692	179.5971	600	700	35	4071.504	18	16	1	5.359007
584.6527	316.9686	189.2479	600	800	35	4071.504	18	16	1	0.639553
641.0118	281.1264	228.7283	700	700	35	4071.504	18	16	1	9.842776
932.5216	108.7118	89.63212	400	500	30	2035.752	18	8	1	6.812101
586.3549	106.1997	69.46214	400	500	30	2035.752	18	8	1	7.995003
695.8333	106.9942	76.6619	400	500	30	2035.752	18	8	1	10.0596
977.7317	129.1194	103.3581	400	500	30	3053.628	18	12	1	9.242825
540.43	128.9527	80.60074	400	500	30	3053.628	18	12	1	7.735375
711.6667	129.018	88.56593	400	500	30	3053.628	18	12	1	11.4078
1009.637	150.1388	116.9223	400	500	30	4071.504	18	16	1	7.022697
732.5	150.9797	100.3889	400	500	30	4071.504	18	16	1	10.45606
1133.032	147.818	101.6268	400	600	30	2035.752	18	8	1	1.644767
738.2061	144.4531	80.56297	400	600	30	2035.752	18	8	1	7.328956
933.3333	146.1161	92.66501	400	600	30	2035.752	18	8	1	7.002868
1183.243	173.4908	115.6597	400	600	30	3053.628	18	12	1	6.611592

696.2811	173.2403	88.74897	400	600	30	3053.628	18	12	1	8.738388
1003.333	173.3982	108.3461	400	600	30	3053.628	18	12	1	9.756267
1215.308	199.6521	129.5567	400	600	30	4071.504	18	16	1	5.929685
683.6041	201.9382	101.6808	400	600	30	4071.504	18	16	1	7.600884
933.3333	200.8645	115.2848	400	600	30	4071.504	18	16	1	9.400022
1385.39	222.7745	127.7058	400	700	30	3053.628	18	12	1	1.347819
848.2908	222.2618	100.1638	400	700	30	3053.628	18	12	1	6.357927
1417.378	254.0566	141.8305	400	700	30	4071.504	18	16	1	2.602592
840.2052	256.9963	110.1582	400	700	30	4071.504	18	16	1	6.209852
1584.73	276.9206	139.6038	400	800	30	3053.628	18	12	1	5.559309
998.0197	276.021	111.1407	400	800	30	3053.628	18	12	1	1.901495
1365.833	276.585	133.0066	400	800	30	3053.628	18	12	1	0.85897
1617.4	313.364	153.901	400	800	30	4071.504	18	16	1	2.319983
993.23	316.7958	121.7895	400	800	30	4071.504	18	16	1	2.164018
1152.384	124.1961	135.129	500	500	30	2035.752	18	8	1	0.647171
748.3766	120.4694	105.2445	500	500	30	2035.752	18	8	1	3.987777
835	121.2684	112.0957	500	500	30	2035.752	18	8	1	5.20593
1197.594	144.6037	154.6077	500	500	30	3053.628	18	12	1	5.770468
702.4517	143.2223	117.1819	500	500	30	3053.628	18	12	1	6.64831
835.8333	143.5944	127.8351	500	500	30	3053.628	18	12	1	9.053844
1229.499	165.6231	173.3713	500	500	30	4071.504	18	16	1	5.636704
682.9646	165.8913	135.7293	500	500	30	4071.504	18	16	1	7.659734
861.6667	165.8036	144.7148	500	500	30	4071.504	18	16	1	9.639435
1451.855	195.8004	173.5993	500	600	30	3053.628	18	12	1	3.704116
894.2278	193.9481	134.7723	500	600	30	3053.628	18	12	1	6.807434
1483.92	221.9618	192.8091	500	600	30	4071.504	18	16	1	5.875528
881.5509	222.6461	148.3484	500	600	30	4071.504	18	16	1	7.842876
1300	222.1707	181.7438	500	600	30	4071.504	18	16	1	8.753465
1702.752	253.1408	192.2862	500	700	30	3053.628	18	12	1	2.988713
1082.163	250.5962	152.0278	500	700	30	3053.628	18	12	1	3.191369
1528.333	252.4257	184.2633	500	700	30	3053.628	18	12	1	0.76232
1734.74	284.4229	211.8004	500	700	30	4071.504	18	16	1	1.838068
1074.077	285.3307	166.6835	500	700	30	4071.504	18	16	1	5.188804
1983.512	353.0181	230.5415	500	800	30	4071.504	18	16	1	4.286481
1263.027	353.9452	184.1945	500	800	30	4071.504	18	16	1	0.075358
1750	353.3186	220.0031	500	800	30	4071.504	18	16	1	1.009562
1720.468	218.1101	240.7847	600	600	30	3053.628	18	12	1	4.357665
1092.175	214.6559	188.2055	600	600	30	3053.628	18	12	1	1.688212
1516.667	216.9897	225.0634	600	600	30	3053.628	18	12	1	0.560982
1752.533	244.2715	265.3339	600	600	30	4071.504	18	16	1	0.138995

1079.498	243.3539	206.5353	600	600	30	4071.504	18	16	1	3.039947
1485.833	243.9079	243.9304	600	600	30	4071.504	18	16	1	4.03921
2052.103	314.7892	292.499	600	700	30	4071.504	18	16	1	0.022381
1307.949	313.6651	232.056	600	700	30	4071.504	18	16	1	2.618724
2349.625	392.6723	319.3751	600	800	30	4071.504	18	16	1	4.087603
1532.823	391.0946	256.6262	600	800	30	4071.504	18	16	1	0.847003
2369.465	345.1555	383.8249	700	700	30	4071.504	18	16	1	3.853719
1541.82	341.9994	306.0626	700	700	30	4071.504	18	16	1	0.75121
1919.167	343.4384	343.8986	700	700	30	4071.504	18	16	1	1.215252
220.8333	16.20131	13.91676	200	200	35	1963.495	25	4	1	5.709388
155	17.20953	14.08053	200	200	35	1963.495	25	4	1	13.25803
166.6667	17.03086	13.93434	200	200	35	1963.495	25	4	1	11.37446
243.4964	39.49952	15.89797	200	300	35	1963.495	25	4	1	19.00362
377.5	34.76047	17.69978	200	300	35	1963.495	25	4	1	13.89763
348.2431	63.42268	18.8257	200	400	35	1963.495	25	4	1	14.49997
413.9551	85.25429	22.51652	200	400	35	3926.991	25	8	1	3.25256
299.1667	85.4	23.14428	200	400	35	3926.991	25	8	0.998188	2.448527
449.0551	89.77946	21.78826	200	500	35	1963.495	25	4	1	14.14947
613.3333	79.0125	23.59044	200	500	35	1963.495	25	4	1	8.125531
528.3333	84.58349	22.81734	200	500	35	1963.495	25	4	1	10.02779
375	88.5	20.53465	200	500	35	1963.495	25	4	0.99092	6.920586
530.3938	119.1915	25.85434	200	500	35	3926.991	25	8	1	1.829786
650	112.305	27.55817	200	500	35	3926.991	25	8	1	1.079686
405	117	24.85994	200	500	35	3926.991	25	8	0.986789	7.548146
611.6162	157.5867	31.16021	200	500	35	5890.486	25	12	1	4.033135
452.5	156	30.78913	200	500	35	5890.486	25	12	0.987894	1.535855
364.1527	45.01252	38.67996	300	300	35	1963.495	25	4	1	21.88163
508.3333	40.54126	41.33882	300	300	35	1963.495	25	4	1	7.16569
305.8333	44.68955	36.56418	300	300	35	1963.495	25	4	1	19.57844
401.1148	59.24928	48.47668	300	300	35	3926.991	25	8	1	0.872379
495	56.74398	50.04537	300	300	35	3926.991	25	8	1	0.861945
299.1667	59.17111	48.41273	300	300	35	3926.991	25	8	1	4.012238
517.6494	73.30242	45.82448	300	400	35	1963.495	25	4	1	15.25557
711.6667	64.64731	48.0124	300	400	35	1963.495	25	4	1	1.355924
452.5	73.03425	43.31713	300	400	35	1963.495	25	4	1	13.52469
583.3613	95.13403	55.66401	300	400	35	3926.991	25	8	1	1.164033
502.5	95.19961	52.95177	300	400	35	3926.991	25	8	1	4.133515
647.7545	123.4227	68.46141	300	400	35	5890.486	25	12	1	8.804693
389.1667	124.9422	68.00665	300	400	35	5890.486	25	12	1	1.572829
667.2113	105.2572	52.41771	300	500	35	1963.495	25	4	1	12.0395

840.8333	95.44847	54.20216	300	500	35	1963.495	25	4	1	1.266443
640	95.3	51.95019	300	500	35	1963.495	25	4	0.946834	7.008108
748.55	134.6692	63.02398	300	500	35	3926.991	25	8	1	4.447496
574.1667	134.9323	57.30175	300	500	35	3926.991	25	8	1	8.5777
829.7724	173.0644	76.78643	300	500	35	5890.486	25	12	1	7.022491
569.1667	175.3239	72.37974	300	500	35	5890.486	25	12	1	1.778021
889.08	212.8111	90.3561	300	500	35	7853.982	25	16	1	18.39257
815.269	140.883	58.77969	300	600	35	1963.495	25	4	1	12.24073
570.6288	139.7271	49.22671	300	600	35	1963.495	25	4	1	7.634606
1037.5	125.9404	60.61794	300	600	35	1963.495	25	4	1	0.795362
655	140.1257	53.64551	300	600	35	1963.495	25	4	1	8.856752
906.4063	177.8641	69.83714	300	600	35	3926.991	25	8	1	5.715475
998.1843	226.3731	84.15842	300	600	35	5890.486	25	12	1	5.503115
620.8333	230.4777	76.74149	300	600	35	5890.486	25	12	1	1.069843
1058.065	276.0269	98.13988	300	600	35	7853.982	25	16	1	16.89347
745	281.0099	92.63098	300	600	35	7853.982	25	16	1	10.9415
687.0556	83.18216	79.08664	400	400	35	1963.495	25	4	1	11.0354
836.6667	77.24251	81.16329	400	400	35	1963.495	25	4	1	1.982541
565	82.273	70.72603	400	400	35	1963.495	25	4	1	10.13177
752.7676	105.0138	95.74482	400	400	35	3926.991	25	8	1	9.902979
574.1667	104.7507	85.70508	400	400	35	3926.991	25	8	1	12.19208
817.1608	133.3024	117.5198	400	400	35	5890.486	25	12	1	2.602279
1028.333	124.8393	123.8576	400	400	35	5890.486	25	12	1	4.884379
873.7235	163.0479	139.2712	400	400	35	7853.982	25	16	1	7.437636
619.1667	164.3149	134.4395	400	400	35	7853.982	25	16	1	1.586153
885.3676	120.7349	90.63239	400	500	35	1963.495	25	4	1	9.822943
620.6282	118.618	74.49899	400	500	35	1963.495	25	4	1	9.395895
1102.5	109.8249	92.55762	400	500	35	1963.495	25	4	1	5.075674
704.1667	119.286	80.19039	400	500	35	1963.495	25	4	1	8.192407
966.7063	150.1469	108.372	400	500	35	3926.991	25	8	1	12.06719
1047.929	188.5421	131.5034	400	500	35	5890.486	25	12	1	5.11745
1107.236	228.2889	154.3196	400	500	35	7853.982	25	16	1	5.45241
833.3333	230.7207	142.0838	400	500	35	7853.982	25	16	1	0.819608
1082.175	163.1899	101.8518	400	600	35	1963.495	25	4	1	13.72438
767.3181	160.3788	84.4978	400	600	35	1963.495	25	4	1	10.09089
1313.333	149.3528	103.6571	400	600	35	1963.495	25	4	1	1.514503
880.8333	161.3923	91.86957	400	600	35	1963.495	25	4	1	10.21426
1173.313	200.1711	120.2209	400	600	35	3926.991	25	8	1	11.28903
852.5	199.5874	103.3087	400	600	35	3926.991	25	8	1	14.31606
1265.091	248.68	144.1238	400	600	35	5890.486	25	12	1	5.188348

1324.971	298.3338	167.6412	400	600	35	7853.982	25	16	1	4.800093
1016.667	302.1247	150.3128	400	600	35	7853.982	25	16	1	0.738186
1376.114	255.0941	131.6883	400	700	35	3926.991	25	8	1	8.026752
1475.119	313.7183	156.087	400	700	35	5890.486	25	12	1	3.12442
1534.95	373.2307	180.1136	400	700	35	7853.982	25	16	1	6.038711
1576.701	314.9231	142.9436	400	800	35	3926.991	25	8	1	2.914606
1239.167	313.8211	129.0601	400	800	35	3926.991	25	8	1	8.086106
1680.707	383.646	167.682	400	800	35	5890.486	25	12	1	0.652139
1740.548	453.0049	192.0997	400	800	35	7853.982	25	16	1	9.011493
1184.863	165.6246	161.3284	500	500	35	3926.991	25	8	1	14.69316
840	164.3274	134.4497	500	500	35	3926.991	25	8	1	16.65274
1266.085	204.0198	194.4726	500	500	35	5890.486	25	12	1	9.292345
1325.393	243.7666	226.2135	500	500	35	7853.982	25	16	1	1.098126
1440.219	222.478	179.5289	500	600	35	3926.991	25	8	1	12.79357
1531.997	270.9869	213.6001	500	600	35	5890.486	25	12	1	9.91835
1591.878	320.6407	246.331	500	600	35	7853.982	25	16	1	1.812516
1691.77	285.4615	197.2565	500	700	35	3926.991	25	8	1	6.747748
2116.667	258.0256	200.5751	500	700	35	3926.991	25	8	1	12.52763
1395.833	283.8473	179.9647	500	700	35	3926.991	25	8	1	10.96593
1790.775	344.0856	231.9147	500	700	35	5890.486	25	12	1	6.509395
1850.606	403.5981	265.3565	500	700	35	7853.982	25	16	1	0.100122
1941.107	354.5821	214.7223	500	800	35	3926.991	25	8	1	1.869671
1251.016	350.0624	170.6636	500	800	35	3926.991	25	8	1	5.319184
2520	312.0922	217.3898	500	800	35	3926.991	25	8	1	2.751202
1563.333	352.1079	193.7957	500	800	35	3926.991	25	8	1	3.898101
2045.114	423.305	249.7786	500	800	35	5890.486	25	12	1	0.890169
1695	425.0349	231.7123	500	800	35	5890.486	25	12	1	4.237101
2104.954	492.6638	283.7594	500	800	35	7853.982	25	16	1	3.983072
1707.125	244.7849	247.4862	600	600	35	3926.991	25	8	1	8.182055
2094.167	224.5833	251.2664	600	600	35	3926.991	25	8	1	14.05988
1487.5	243.3346	229.304	600	600	35	3926.991	25	8	1	12.24181
1798.903	293.2938	292.0819	600	600	35	5890.486	25	12	1	6.219919
1858.784	342.9476	334.0929	600	600	35	7853.982	25	16	1	1.779694
2007.426	315.8288	272.8275	600	700	35	3926.991	25	8	1	3.155971
2675	275.1347	274.4969	600	700	35	3926.991	25	8	1	7.924274
2106.432	374.453	318.0729	600	700	35	5890.486	25	12	1	5.495727
2166.262	433.9654	360.9782	600	700	35	7853.982	25	16	1	0.495292
2305.513	394.2411	297.8656	600	800	35	3926.991	25	8	1	5.386719
1519.555	387.1416	237.325	600	800	35	3926.991	25	8	1	1.995625
2875	354.7363	300.3903	600	800	35	3926.991	25	8	1	1.036872

2409.52	462.964	343.5471	600	800	35	5890.486	25	12	1	1.180009
2700	439.6453	346.2843	600	800	35	5890.486	25	12	1	6.468511
2469.36	532.3228	387.124	600	800	35	7853.982	25	16	1	1.510413
2323.082	346.1961	358.2834	700	700	35	3926.991	25	8	1	1.593237
1528.32	338.575	282.7431	700	700	35	3926.991	25	8	1	6.143187
2885	313.5913	360.8038	700	700	35	3926.991	25	8	1	4.175364
2422.088	404.8203	414.3244	700	700	35	5890.486	25	12	1	0.85152
3072.5	361.2565	415.4794	700	700	35	5890.486	25	12	1	10.53575
2481.919	464.3327	466.7556	700	700	35	7853.982	25	16	1	4.519833
2773.926	502.623	448.7639	700	800	35	5890.486	25	12	1	1.348055
2833.767	571.9818	501.9849	700	800	35	7853.982	25	16	1	1.141238
3121.099	608.8787	482.841	700	900	35	5890.486	25	12	1	1.968773
1973.705	607.2946	381.8339	700	900	35	5890.486	25	12	1	0.591639
3182.904	688.2167	536.693	700	900	35	7853.982	25	16	1	2.285664
1965.122	696.2683	430.9382	700	900	35	7853.982	25	16	1	6.052429
3466.857	723.7313	516.713	700	1000	35	5890.486	25	12	1	7.11792
2232.634	721.1281	412.3456	700	1000	35	5890.486	25	12	1	4.972092
3530.248	813.0467	571.057	700	1000	35	7853.982	25	16	1	5.673491
2228.117	821.7221	456.2652	700	1000	35	7853.982	25	16	1	9.046086
4170.833	748.9754	573.2474	700	1000	35	7853.982	25	16	1	3.385306
137.5018	12.20766	9.988083	200	200	35	1017.876	18	4	1	15.67802
254.1667	10.51647	11.10819	200	200	35	1017.876	18	4	1	3.168877
191.6667	11.42248	10.45024	200	200	35	1017.876	18	4	1	5.849633
235.8333	10.78223	10.9689	200	200	35	1017.876	18	4	1	3.201203
166.6667	11.78488	10.0329	200	200	35	1017.876	18	4	1	9.048808
127.0444	15.91589	13.02209	200	200	35	2035.752	18	8	1	3.30843
208.3333	14.92219	12.32917	200	200	35	2035.752	18	8	1	11.25246
158.3333	15.53341	12.70915	200	200	35	2035.752	18	8	1	7.928082
246.984	26.40768	12.72022	200	300	35	1017.876	18	4	1	2.19157
294.1667	25.00805	13.35995	200	300	35	1017.876	18	4	1	2.781059
205	26.14443	11.8799	200	300	35	1017.876	18	4	1	2.640726
270.3064	34.08425	14.75072	200	300	35	2035.752	18	8	1	11.32429
362.5	31.6343	16.16703	200	300	35	2035.752	18	8	1	11.10214
292.1209	43.93737	17.83349	200	300	35	3053.628	18	12	1	3.37004
375	41.68638	18.95099	200	300	35	3053.628	18	12	1	2.680815
220.8333	38.4	18.47547	200	300	35	3053.628	18	12	0.929079	22.1256
347.7277	43.00345	15.5969	200	400	35	1017.876	18	4	1	0.93771
449.1667	38.76567	16.6318	200	400	35	1017.876	18	4	1	6.013192
291.6667	36.4	14.74117	200	400	35	1017.876	18	4	0.918099	30.44576
384.559	54.615	17.97778	200	400	35	2035.752	18	8	1	14.99627

510	49.71227	19.4452	200	400	35	2035.752	18	8	1	14.08425
291.6667	49.4	16.8016	200	400	35	2035.752	18	8	0.947877	32.627
420.9192	69.69861	21.06134	200	400	35	3053.628	18	12	1	7.423415
331.6667	64.5	20.14534	200	400	35	3053.628	18	12	0.955738	21.36569
450.8709	85.48026	24.16047	200	400	35	4071.504	18	16	1	0.037042
446.7255	62.04708	18.37824	200	500	35	1017.876	18	4	1	1.092877
313.0663	61.18214	15.40958	200	500	35	1017.876	18	4	1	10.20775
508.3333	58.81788	19.05448	200	500	35	1017.876	18	4	1	1.709862
596.6667	46.3	19.48845	200	500	35	1017.876	18	4	0.914918	23.39218
360	58.9	17.11193	200	500	35	1017.876	18	4	0.976427	13.40987
490.9535	77.5863	20.92773	200	500	35	2035.752	18	8	1	15.18191
562.5	73.97169	21.76979	200	500	35	2035.752	18	8	1	15.42065
630	70.56151	22.37592	200	500	35	2035.752	18	8	1	13.89431
380	74.5	19.17724	200	500	35	2035.752	18	8	0.978247	27.3103
535.2802	97.9109	24.21706	200	500	35	3053.628	18	12	1	7.487991
611.6667	93.61643	25.19625	200	500	35	3053.628	18	12	1	7.176308
389.1667	96.4	22.27144	200	500	35	3053.628	18	12	0.985844	16.85314
566.1964	118.8576	27.44393	200	500	35	4071.504	18	16	1	0.127814
395.8333	120.4	26.08756	200	500	35	4071.504	18	16	0.998852	4.420117
569.6961	26.97145	31.32075	300	300	35	1017.876	18	4	1	1.417124
369.3465	31.93495	29.89141	300	300	35	1017.876	18	4	1	15.66823
450	29.93683	30.98862	300	300	35	1017.876	18	4	1	3.928882
333.3333	31.59712	28.05207	300	300	35	1017.876	18	4	1	13.20442
500	28.69812	31.30163	300	300	35	1017.876	18	4	1	0.1347
392.6689	39.61152	35.19189	300	300	35	2035.752	18	8	1	7.75811
549.1667	35.89586	37.84547	300	300	35	2035.752	18	8	1	14.93575
414.4834	49.46464	42.05025	300	300	35	3053.628	18	12	1	4.431941
528.3333	46.62088	44.90652	300	300	35	3053.628	18	12	1	8.073749
436.8314	59.90398	49.1309	300	300	35	4071.504	18	16	1	1.409494
763.0434	44.34029	37.14216	300	400	35	1017.876	18	4	1	10.35787
518.8402	52.89363	36.28641	300	400	35	1017.876	18	4	1	5.94654
665	47.77431	37.5817	300	400	35	1017.876	18	4	1	7.723509
472.5	52.43763	34.93127	300	400	35	1017.876	18	4	1	3.873215
555.6715	64.50518	42.21008	300	400	35	2035.752	18	8	1	15.54183
713.3333	59.0304	44.20848	300	400	35	2035.752	18	8	1	22.39468
417.5	63.97846	36.72865	300	400	35	2035.752	18	8	1	17.88165
592.0317	79.58879	49.88622	300	400	35	3053.628	18	12	1	10.33778
621.9834	95.37043	57.65939	300	400	35	4071.504	18	16	1	2.00899
545	95.64397	55.21666	300	400	35	4071.504	18	16	1	4.925645
710.816	93.07061	48.71659	300	500	35	2035.752	18	8	1	17.47416

954.1667	82.1849	50.84723	300	500	35	2035.752	18	8	1	23.62322
619.1667	92.6576	46.61113	300	500	35	2035.752	18	8	1	19.43363
755.1427	113.3952	56.77273	300	500	35	3053.628	18	12	1	13.57047
535.8333	114.0099	49.20968	300	500	35	3053.628	18	12	1	16.89001
786.0589	134.3419	64.8378	300	500	35	4071.504	18	16	1	6.222573
535.8333	135.9165	57.80696	300	500	35	4071.504	18	16	1	9.874556
862.5393	125.3125	55.02712	300	600	35	2035.752	18	8	1	15.71218
1086.667	113.1964	57.01033	300	600	35	2035.752	18	8	1	20.54813
625	124.0187	47.35192	300	600	35	2035.752	18	8	1	20.73752
911.882	150.8805	63.29745	300	600	35	3053.628	18	12	1	14.02231
720.8333	151.5087	58.2176	300	600	35	3053.628	18	12	1	17.2458
942.934	176.9514	71.54298	300	600	35	4071.504	18	16	1	8.107673
726.784	74.39536	72.54257	400	400	35	2035.752	18	8	1	15.97921
958.3333	67.09739	75.10996	400	400	35	2035.752	18	8	1	25.10263
610.8333	73.68227	65.70293	400	400	35	2035.752	18	8	1	17.36618
763.1442	89.47897	85.31207	400	400	35	3053.628	18	12	1	16.02601
1033.333	79.94297	88.74348	400	400	35	3053.628	18	12	1	23.26199
610.8333	89.38092	75.98906	400	400	35	3053.628	18	12	1	16.99238
793.0959	105.2606	97.99752	400	400	35	4071.504	18	16	1	11.6846
611.6667	105.4893	86.30945	400	400	35	4071.504	18	16	1	14.19198
930.6785	108.5549	83.93934	400	500	35	2035.752	18	8	1	16.78947
1184.167	98.24779	86.19176	400	500	35	2035.752	18	8	1	24.9965
833.3333	107.8477	79.75742	400	500	35	2035.752	18	8	1	18.6558
975.0052	128.8795	97.19052	400	500	35	3053.628	18	12	1	17.91946
833.3333	128.8302	90.65354	400	500	35	3053.628	18	12	1	19.29692
1005.921	149.8262	110.331	400	500	35	4071.504	18	16	1	14.7232
833.3333	150.3541	101.4133	400	500	35	4071.504	18	16	1	16.48232
1131.152	147.6222	95.06934	400	600	35	2035.752	18	8	1	11.68752
1360.833	136.3106	97.12831	400	600	35	2035.752	18	8	1	17.26033
936.6667	145.9627	86.77993	400	600	35	2035.752	18	8	1	15.77907
1180.494	173.1902	108.5854	400	600	35	3053.628	18	12	1	15.89858
1488.333	155.7287	110.9013	400	600	35	3053.628	18	12	1	22.36526
1045	173.125	104.0129	400	600	35	3053.628	18	12	1	17.5997
1211.546	199.2611	122.0053	400	600	35	4071.504	18	16	1	14.30503
1382.628	222.4134	119.7541	400	700	35	3053.628	18	12	1	10.81542
1100	222.1529	108.5152	400	700	35	3053.628	18	12	1	14.77468
1413.587	253.5873	133.3603	400	700	35	4071.504	18	16	1	11.31059
1581.959	276.4988	130.7919	400	800	35	3053.628	18	12	1	3.695593
995.5539	275.6189	103.8192	400	800	35	3053.628	18	12	1	10.32161
1407.5	276.237	126.7005	400	800	35	3053.628	18	12	1	6.441715

1613.589	312.8166	144.5382	400	800	35	4071.504	18	16	1	6.486068
990.0305	316.2587	116.6432	400	800	35	4071.504	18	16	1	9.867057
1150.541	124.0393	126.3275	500	500	35	2035.752	18	8	1	13.91441
1486.667	111.3869	128.6322	500	500	35	2035.752	18	8	1	20.55767
833.3333	121.1101	104.5349	500	500	35	2035.752	18	8	1	17.8237
1194.868	144.3639	145.0403	500	500	35	3053.628	18	12	1	18.55789
1472.5	132.3797	147.5476	500	500	35	3053.628	18	12	1	24.95217
950	143.6874	128.3351	500	500	35	3053.628	18	12	1	20.7439
1225.784	165.3105	163.1376	500	500	35	4071.504	18	16	1	17.40223
1449.107	195.4999	162.6469	500	600	35	3053.628	18	12	1	14.59145
1925	170.4087	163.9736	500	600	35	3053.628	18	12	1	20.17158
1480.159	221.5708	181.1181	500	600	35	4071.504	18	16	1	15.96539
1313.333	221.7633	171.656	500	600	35	4071.504	18	16	1	17.92267
1699.99	252.7797	179.9856	500	700	35	3053.628	18	12	1	5.628071
2129.167	226.2836	181.651	500	700	35	3053.628	18	12	1	9.284227
1730.95	283.9536	198.7063	500	700	35	4071.504	18	16	1	10.24965
1463.333	284.3258	184.388	500	700	35	4071.504	18	16	1	13.44977
1979.702	352.4707	216.0782	500	800	35	4071.504	18	16	1	2.001072
1259.827	353.4081	172.1643	500	800	35	4071.504	18	16	1	7.085495
1669.167	352.8751	200.7946	500	800	35	4071.504	18	16	1	6.064299
1717.719	217.8096	225.2713	600	600	35	3053.628	18	12	1	8.135091
2299.167	188.9703	225.0177	600	600	35	3053.628	18	12	1	10.92243
1528.333	216.7727	211.2973	600	600	35	3053.628	18	12	1	12.36119
1748.771	243.8805	248.8043	600	600	35	4071.504	18	16	1	11.46653
2320	213.118	249.5687	600	600	35	4071.504	18	16	1	17.06283
2048.312	314.3199	273.9854	600	700	35	4071.504	18	16	1	6.854099
1304.768	313.206	216.7955	600	700	35	4071.504	18	16	1	10.59537
2702.5	273.313	273.6462	600	700	35	4071.504	18	16	1	11.1738
1754.167	313.8793	253.8856	600	700	35	4071.504	18	16	1	10.79679
2345.814	392.1248	298.9176	600	800	35	4071.504	18	16	1	1.284341
1529.624	390.5575	239.4217	600	800	35	4071.504	18	16	1	3.944735
2989.167	346.3538	298.9766	600	800	35	4071.504	18	16	1	2.289961
2146.667	391.7424	288.0709	600	800	35	4071.504	18	16	1	1.493535
2365.675	344.6862	359.1143	700	700	35	4071.504	18	16	1	2.287407
1538.639	341.5404	285.4959	700	700	35	4071.504	18	16	1	7.692039
3073.333	302.4389	357.6079	700	700	35	4071.504	18	16	1	7.226871
2146.667	343.8532	341.081	700	700	35	4071.504	18	16	1	5.867915
832.0579	29.16415	37.48161	300	300	35	1963.495	25	4	1	1.947695
644.9054	36.30595	41.61169	300	300	35	1963.495	25	4	1	2.84656
850	28.32998	36.73639	300	300	35	1963.495	25	4	1	1.607473

730.8333	33.02691	40.10974	300	300	35	1963.495	25	4	1	1.097411
885.4335	46.32541	54.62313	300	300	35	3926.991	25	8	1	1.51262
683.3333	51.71838	53.79084	300	300	35	3926.991	25	8	1	2.191008
1249.713	33.6495	32.37174	300	400	35	1963.495	25	4	1	18.98332
1060.638	46.45558	41.65406	300	400	35	1963.495	25	4	1	12.35829
840.8296	58.88536	47.42503	300	400	35	1963.495	25	4	1	5.657935
1130	41.75768	38.48494	300	400	35	1963.495	25	4	1	15.27681
940.8333	53.23032	45.44043	300	400	35	1963.495	25	4	1	9.67519
1103.51	74.2326	60.18075	300	400	35	3926.991	25	8	1	0.354462
835	85.02228	60.20524	300	400	35	3926.991	25	8	1	4.58113
1074.167	105.35	76.67741	300	400	35	5890.486	25	12	1	12.76501
1191.667	100.37	77.16239	300	400	35	5890.486	25	12	1	14.56801
1500	44.4697	34.94277	300	500	35	1963.495	25	4	1	26.00264
1287.242	65.80821	45.85966	300	500	35	1963.495	25	4	1	16.91614
1034.2	84.52431	53.21362	300	500	35	1963.495	25	4	1	7.986426
1148.333	76.08248	50.8425	300	500	35	1963.495	25	4	1	12.54861
1308.943	105.1892	65.79385	300	500	35	3926.991	25	8	1	7.19159
1488.333	92.86086	62.33665	300	500	35	3926.991	25	8	1	6.722606
1049.167	118.8549	66.94865	300	500	35	3926.991	25	8	1	9.294241
1551.466	131.5561	81.53239	300	500	35	5890.486	25	12	1	9.561267
1169.167	153.5441	82.53498	300	500	35	5890.486	25	12	1	6.64633
1305.833	145.6837	83.32046	300	500	35	5890.486	25	12	1	7.99786
1454.167	178.6168	99.18569	300	500	35	7853.982	25	16	1	21.3967
1750	55.72937	36.12299	300	600	35	1963.495	25	4	1	29.28047
1678.018	69.41428	41.91874	300	600	35	1963.495	25	4	1	23.07927
1513.097	87.22618	50.07711	300	600	35	1963.495	25	4	1	15.8648
1226.589	113.2262	59.00869	300	600	35	1963.495	25	4	1	5.720129
1586.667	79.28046	46.5694	300	600	35	1963.495	25	4	1	19.35885
1889.331	106.3668	60.40562	300	600	35	3926.991	25	8	1	11.21056
1508.9	139.2002	71.4659	300	600	35	3926.991	25	8	1	10.14642
1670	125.2964	68.34844	300	600	35	3926.991	25	8	1	10.27106
1315	151.6434	73.52016	300	600	35	3926.991	25	8	1	11.07182
1752.161	172.2321	87.06637	300	600	35	5890.486	25	12	1	2.836581
1369.167	199.7339	89.16304	300	600	35	5890.486	25	12	1	2.158471
1610	234.7276	105.4452	300	600	35	7853.982	25	16	1	15.97595
1583.333	35.02179	48.80789	400	400	35	1963.495	25	4	1	24.46094
1321.263	54.40256	70.62225	400	400	35	1963.495	25	4	1	17.85841
1062.361	68.28231	80.51899	400	400	35	1963.495	25	4	1	10.55288
1441.667	46.38669	62.37963	400	400	35	1963.495	25	4	1	22.03415
1395.833	49.43804	65.63435	400	400	35	1963.495	25	4	1	20.69751

1689.065	65.70988	87.86371	400	400	35	3926.991	25	8	1	10.51617
1325.041	83.62955	100.8208	400	400	35	3926.991	25	8	1	14.60437
1462.5	76.86291	96.80985	400	400	35	3926.991	25	8	1	14.08704
1100	92.03869	101.6428	400	400	35	3926.991	25	8	1	16.96038
1565.702	103.3033	125.6482	400	400	35	5890.486	25	12	1	2.342536
1358.333	111.614	127.0996	400	400	35	5890.486	25	12	1	4.387868
1395	140.5014	152.3037	400	400	35	7853.982	25	16	1	6.51415
1875	53.02273	57.57312	400	500	35	1963.495	25	4	1	18.09975
1622.867	77.59267	78.1122	400	500	35	1963.495	25	4	1	20.19735
1319.481	98.92251	90.77042	400	500	35	1963.495	25	4	1	11.44303
1758.333	65.87409	68.61436	400	500	35	1963.495	25	4	1	22.90482
1475	87.98859	85.32917	400	500	35	1963.495	25	4	1	17.24466
1996.029	92.82008	94.89551	400	500	35	3926.991	25	8	1	18.69482
1594.224	119.5874	110.7483	400	500	35	3926.991	25	8	1	19.33747
2140	80.65711	84.8325	400	500	35	3926.991	25	8	1	19.60735
1815	104.8798	103.4625	400	500	35	3926.991	25	8	1	19.74045
1485.833	124.8659	112.4733	400	500	35	3926.991	25	8	1	20.13239
1836.747	145.9543	135.2966	400	500	35	5890.486	25	12	1	9.048797
2116.667	126.086	124.8423	400	500	35	5890.486	25	12	1	10.17831
1579.167	159.8609	138.2237	400	500	35	5890.486	25	12	1	10.49575
2076.443	172.6229	159.825	400	500	35	7853.982	25	16	1	2.951097
1640	197.6898	163.8161	400	500	35	7853.982	25	16	1	2.547101
2183.333	71.20933	63.64766	400	600	35	1963.495	25	4	1	2.92547
1923.722	103.5411	85.61468	400	600	35	1963.495	25	4	1	11.7533
1575.62	133.6523	101.0119	400	600	35	1963.495	25	4	1	4.012776
2072.5	87.77251	75.03625	400	600	35	1963.495	25	4	1	12.08275
1753.333	118.2799	94.68394	400	600	35	1963.495	25	4	1	9.117647
2537.531	97.88442	84.97163	400	600	35	3926.991	25	8	1	21.56255
2299.956	122.6818	102.1209	400	600	35	3926.991	25	8	1	19.28989
1857.932	159.6263	120.7629	400	600	35	3926.991	25	8	1	18.3693
2072.5	141.6926	113.5821	400	600	35	3926.991	25	8	1	19.31148
1565.833	176.925	123.9925	400	600	35	3926.991	25	8	1	18.94153
2101.192	192.6581	145.1142	400	600	35	5890.486	25	12	1	11.8939
2306.667	174.5259	137.6643	400	600	35	5890.486	25	12	1	13.04002
1695	219.8745	149.3537	400	600	35	5890.486	25	12	1	12.04433
2346.65	226.1496	169.4764	400	600	35	7853.982	25	16	1	1.690224
2074.167	245.4012	174.3395	400	600	35	7853.982	25	16	1	1.469117
2933.333	104.0819	79.57935	400	700	35	3926.991	25	8	1	22.6673
2828.117	127.3355	93.14261	400	700	35	3926.991	25	8	1	18.21936
2602.447	155.3016	109.4439	400	700	35	3926.991	25	8	1	15.60071

2118.801	203.7537	130.8431	400	700	35	3926.991	25	8	1	13.97609
2676.667	146.104	104.26	400	700	35	3926.991	25	8	1	16.56922
2323.333	183.2634	123.9805	400	700	35	3926.991	25	8	1	14.95215
1841.667	222.9114	135.0373	400	700	35	3926.991	25	8	1	14.80846
2932.153	183.5539	128.8122	400	700	35	5890.486	25	12	1	12.21071
2362.388	243.4345	155.0395	400	700	35	5890.486	25	12	1	11.18684
2676.667	210.4048	143.0292	400	700	35	5890.486	25	12	1	12.29102
1941.667	276.7614	160.4948	400	700	35	5890.486	25	12	1	10.80848
2611.83	283.7433	179.269	400	700	35	7853.982	25	16	1	3.197811
2229.167	315.5421	185.8163	400	700	35	7853.982	25	16	1	2.489502
3225	133.0943	88.36888	400	800	35	3926.991	25	8	1	16.20414
2904.156	190.684	116.8233	400	800	35	3926.991	25	8	1	9.312785
2378.017	251.9751	140.9721	400	800	35	3926.991	25	8	1	7.542422
2990.833	178.2697	110.7158	400	800	35	3926.991	25	8	1	10.39811
2675	217.3789	130.5717	400	800	35	3926.991	25	8	1	8.285573
2100	273.8149	146.0587	400	800	35	3926.991	25	8	1	8.666462
3235.56	223.6368	136.1025	400	800	35	5890.486	25	12	1	9.370991
2621.754	298.295	165.0394	400	800	35	5890.486	25	12	1	8.139196
3315	212.475	130.6879	400	800	35	5890.486	25	12	1	9.616338
2935	260.1943	153.1316	400	800	35	5890.486	25	12	1	9.300803
2874.112	345.4171	189.1597	400	800	35	7853.982	25	16	1	1.734514
3216.667	303.1319	176.3799	400	800	35	7853.982	25	16	1	3.812747
2666.667	73.60074	103.4581	500	500	35	3926.991	25	8	1	22.50891
2331.654	104.6045	139.7284	500	500	35	3926.991	25	8	1	20.56564
1879.505	133.9856	163.3311	500	500	35	3926.991	25	8	1	21.28364
2480	92.17517	126.121	500	500	35	3926.991	25	8	1	21.32563
2100	119.6576	153.1055	500	500	35	3926.991	25	8	1	22.06441
1639.167	144.9323	165.8449	500	500	35	3926.991	25	8	1	22.63371
2655.726	123.431	166.2897	500	500	35	5890.486	25	12	1	15.0947
2122.029	160.3525	196.5987	500	500	35	5890.486	25	12	1	15.42843
2283.333	149.1934	188.8841	500	500	35	5890.486	25	12	1	16.39049
1858.333	173.8054	200.4873	500	500	35	5890.486	25	12	1	16.54849
2361.725	187.0211	230.2285	500	500	35	7853.982	25	16	1	5.6155
2675	165.3035	214.6931	500	500	35	7853.982	25	16	1	8.329099
2133.333	199.5269	234.5221	500	500	35	7853.982	25	16	1	5.756348
3041.667	100.0961	115.029	500	600	35	3926.991	25	8	1	15.63809
2987.531	110.3584	124.7616	500	600	35	3926.991	25	8	1	16.39713
2710.581	138.9967	151.0869	500	600	35	3926.991	25	8	1	18.09639
2206.963	180.0523	178.9843	500	600	35	3926.991	25	8	1	18.76164
2791.667	130.612	143.6946	500	600	35	3926.991	25	8	1	18.26752

2399.167	164.3836	170.0293	500	600	35	3926.991	25	8	1	19.57828
1996.667	191.6885	182.6301	500	600	35	3926.991	25	8	1	20.03771
3037.977	162.5417	177.4032	500	600	35	5890.486	25	12	1	16.72857
2450.224	213.0842	212.0321	500	600	35	5890.486	25	12	1	17.37029
3155	150.7073	166.9803	500	600	35	5890.486	25	12	1	16.43883
2813.333	181.8594	192.7567	500	600	35	5890.486	25	12	1	18.01144
2130	233.2773	217.7932	500	600	35	5890.486	25	12	1	18.12866
2695.681	246.5757	245.4058	500	600	35	7853.982	25	16	1	10.56042
3089.167	212.4334	224.9046	500	600	35	7853.982	25	16	1	12.2789
3416.667	130.0907	126.6435	500	700	35	3926.991	25	8	1	3.505128
3088.072	176.8401	162.5747	500	700	35	3926.991	25	8	1	9.152865
2531.582	231.2343	194.7254	500	700	35	3926.991	25	8	1	10.75449
3208.333	162.0817	151.4404	500	700	35	3926.991	25	8	1	8.601163
2951.667	190.173	173.1875	500	700	35	3926.991	25	8	1	9.873613
3726.388	167.91	160.0386	500	700	35	5890.486	25	12	1	12.10388
3417.778	205.0924	188.7167	500	700	35	5890.486	25	12	1	13.26635
2775.169	270.9151	227.6034	500	700	35	5890.486	25	12	1	14.07113
3565	187.3546	175.3996	500	700	35	5890.486	25	12	1	12.97639
3120.833	235.5085	209.3907	500	700	35	5890.486	25	12	1	14.643
2351.667	302.3943	235.412	500	700	35	5890.486	25	12	1	14.55319
3761.058	234.7635	216.299	500	700	35	7853.982	25	16	1	10.02368
3024.611	311.2238	260.776	500	700	35	7853.982	25	16	1	9.974336
3525	259.2718	233.7004	500	700	35	7853.982	25	16	1	10.94877
2748.333	332.9622	268.1845	500	700	35	7853.982	25	16	1	10.10628
3791.667	163.5701	138.2885	500	800	35	3926.991	25	8	1	7.945401
3464.781	218.1389	174.1373	500	800	35	3926.991	25	8	1	1.951302
2854.548	287.5368	210.5307	500	800	35	3926.991	25	8	1	0.517198
3648.333	192.1079	156.8835	500	800	35	3926.991	25	8	1	3.873069
3140	255.0742	196.5853	500	800	35	3926.991	25	8	1	0.295191
4250	170.759	145.5015	500	800	35	5890.486	25	12	1	10.22678
4090.483	209.9946	172.7477	500	800	35	5890.486	25	12	1	7.768277
3796.185	251.0917	200.1491	500	800	35	5890.486	25	12	1	8.152825
3098.285	333.8567	243.2692	500	800	35	5890.486	25	12	1	8.640769
3973.333	226.3539	183.9391	500	800	35	5890.486	25	12	1	8.094479
3541.667	281.2754	219.3194	500	800	35	5890.486	25	12	1	8.976352
4140.248	285.7831	227.5558	500	800	35	7853.982	25	16	1	7.078587
3350.644	380.9788	276.2786	500	800	35	7853.982	25	16	1	6.795744
4283.333	265.4813	214.3583	500	800	35	7853.982	25	16	1	6.940765
3895.833	315.25	246.516	500	800	35	7853.982	25	16	1	7.755661
3081.667	405.0945	284.6125	500	800	35	7853.982	25	16	1	6.86518

3481.667	114.3768	159.2963	600	600	35	3926.991	25	8	1	1.768728
3121.206	155.3117	207.4315	600	600	35	3926.991	25	8	1	9.173941
2555.994	200.4784	246.0791	600	600	35	3926.991	25	8	1	11.93135
3246.667	142.4298	193.1941	600	600	35	3926.991	25	8	1	7.902051
2933.333	170.3248	221.822	600	600	35	3926.991	25	8	1	11.56736
3815.859	141.8575	198.2608	600	600	35	5890.486	25	12	1	11.34182
3448.602	178.8566	240.5476	600	600	35	5890.486	25	12	1	13.35835
2799.255	233.5103	287.7444	600	600	35	5890.486	25	12	1	14.07893
3600	163.6041	223.7294	600	600	35	5890.486	25	12	1	13.08916
3065	211.1433	270.6176	600	600	35	5890.486	25	12	1	15.15828
2399.167	257.4206	295.5134	600	600	35	5890.486	25	12	1	14.859
3790.725	203.5044	275.703	600	600	35	7853.982	25	16	1	9.396055
3044.712	267.0017	330.2039	600	600	35	7853.982	25	16	1	8.642468
3498.333	228.3915	299.6687	600	600	35	7853.982	25	16	1	10.67447
2669.167	291.0514	338.9942	600	600	35	7853.982	25	16	1	8.746354
3975	139.408	165.1068	600	700	35	3926.991	25	8	1	21.28007
3878.117	161.2925	188.2713	600	700	35	3926.991	25	8	1	10.40322
3573.697	198.3785	224.0448	600	700	35	3926.991	25	8	1	0.027921
2944.363	258.7149	268.7923	600	700	35	3926.991	25	8	1	5.398208
3714.167	181.2658	207.9563	600	700	35	3926.991	25	8	1	3.090248
3203.333	233.8865	252.7382	600	700	35	3926.991	25	8	1	5.034233
4391.667	154.6568	184.7058	600	700	35	5890.486	25	12	1	6.519243
4251.388	184.8885	216.7925	600	700	35	5890.486	25	12	1	9.017326
3903.403	226.6308	256.9372	600	700	35	5890.486	25	12	1	11.76742
3187.95	298.3957	310.2798	600	700	35	5890.486	25	12	1	13.23959
4044.167	209.7456	241.1812	600	700	35	5890.486	25	12	1	11.23756
3640.833	252.9684	279.3158	600	700	35	5890.486	25	12	1	13.49133
2905.833	318.2354	317.8616	600	700	35	5890.486	25	12	1	14.30924
4246.683	256.3019	291.7929	600	700	35	7853.982	25	16	1	11.02658
3437.393	338.7044	352.4691	600	700	35	7853.982	25	16	1	11.31662
4450	231.5545	268.4848	600	700	35	7853.982	25	16	1	10.60775
3858.333	295.844	324.2896	600	700	35	7853.982	25	16	1	12.68952
2981.667	372.8574	364.0999	600	700	35	7853.982	25	16	1	11.38837
4416.667	179.0922	183.9822	600	800	35	3926.991	25	8	1	30.83595
4321.02	203.9756	206.0008	600	800	35	3926.991	25	8	1	22.85213
4025.406	245.5939	240.7473	600	800	35	3926.991	25	8	1	12.31726
3331.079	323.0985	291.5835	600	800	35	3926.991	25	8	1	4.684756
4126.667	231.3378	229.1628	600	800	35	3926.991	25	8	1	14.85004
3747.5	276.6153	264.5676	600	800	35	3926.991	25	8	1	7.404046
4808.333	202.7874	209.4205	600	800	35	5890.486	25	12	1	2.039995

4690.483	232.1706	234.9124	600	800	35	5890.486	25	12	1	4.116952
4356.81	278.5466	273.472	600	800	35	5890.486	25	12	1	7.010806
3574.817	369.4184	332.9265	600	800	35	5890.486	25	12	1	8.720041
4531.667	254.2439	253.6737	600	800	35	5890.486	25	12	1	6.080109
3155	403.1197	343.9359	600	800	35	5890.486	25	12	1	9.81578
5060.623	262.5023	265.9017	600	800	35	7853.982	25	16	1	9.23522
4700.873	313.238	308.1013	600	800	35	7853.982	25	16	1	9.514934
3827.175	416.5405	374.8988	600	800	35	7853.982	25	16	1	9.534227
4824.167	295.8499	294.0458	600	800	35	7853.982	25	16	1	9.554854
4434.167	344.7723	332.4724	600	800	35	7853.982	25	16	1	10.54062
3480	446.1445	386.0837	600	800	35	7853.982	25	16	1	9.961787
4475	161.9192	224.6095	700	700	35	3926.991	25	8	1	34.5476
4403.117	178.271	245.8001	700	700	35	3926.991	25	8	1	24.09625
4059.322	219.9169	293.8323	700	700	35	3926.991	25	8	1	6.366994
3357.144	286.1954	352.9896	700	700	35	3926.991	25	8	1	0.785874
4194.167	203.5824	275.5272	700	700	35	3926.991	25	8	1	10.78646
3805.833	243.8437	317.3831	700	700	35	3926.991	25	8	1	1.144491
4866.667	182.1836	254.5987	700	700	35	5890.486	25	12	1	3.166766
4776.388	201.867	280.1662	700	700	35	5890.486	25	12	1	6.632373
4389.028	248.1693	333.4601	700	700	35	5890.486	25	12	1	10.47324
3600.732	325.8763	403.0423	700	700	35	5890.486	25	12	1	10.30585
4586.667	224.5449	306.9186	700	700	35	5890.486	25	12	1	9.762531
4055.833	281.0142	365.7349	700	700	35	5890.486	25	12	1	11.91436
5149.665	227.273	317.2082	700	700	35	7853.982	25	16	1	11.80642
4732.308	277.8404	375.5774	700	700	35	7853.982	25	16	1	10.74938
3850.174	366.185	454.2967	700	700	35	7853.982	25	16	1	8.419599
5231.667	209.6512	294.3039	700	700	35	7853.982	25	16	1	13.81356
4914.167	255.8062	350.8471	700	700	35	7853.982	25	16	1	11.42498
4423.333	308.7838	406.3181	700	700	35	7853.982	25	16	1	11.3134
5416.667	222.5528	270.0821	700	800	35	5890.486	25	12	1	4.510263
5290.483	254.3466	304.6424	700	800	35	5890.486	25	12	1	2.04436
4917.435	306.0015	356.0536	700	800	35	5890.486	25	12	1	8.023089
4051.348	404.9801	433.9821	700	800	35	5890.486	25	12	1	9.670612
5100	280.7223	331.4306	700	800	35	5890.486	25	12	1	6.283246
4691.667	331.8029	379.6434	700	800	35	5890.486	25	12	1	9.759773
3752.5	427.8233	443.8064	700	800	35	5890.486	25	12	1	10.7869
5833.333	241.7257	295.0418	700	800	35	7853.982	25	16	1	12.7592
5660.623	284.6783	342.0864	700	800	35	7853.982	25	16	1	12.91442
5261.498	340.6929	397.8965	700	800	35	7853.982	25	16	1	12.58799
4303.706	452.1023	484.9664	700	800	35	7853.982	25	16	1	10.86649

5741.667	264.523	321.1719	700	800	35	7853.982	25	16	1	13.69082
5435	316.343	374.2114	700	800	35	7853.982	25	16	1	13.04252
5005	370.5285	424.9579	700	800	35	7853.982	25	16	1	13.15771
5933.333	275.6068	295.2159	700	900	35	5890.486	25	12	1	9.601394
5806.971	311.7384	328.7948	700	900	35	5890.486	25	12	1	3.987308
5444.974	368.6736	378.755	700	900	35	5890.486	25	12	1	2.756492
4500.836	491.255	465.0119	700	900	35	5890.486	25	12	1	5.62177
5656.667	335.3784	349.9794	700	900	35	5890.486	25	12	1	0.237987
5169.167	404.4828	408.4532	700	900	35	5890.486	25	12	1	5.203377
4171.667	519.317	476.9882	700	900	35	5890.486	25	12	1	6.882377
6375	290.4099	312.767	700	900	35	7853.982	25	16	1	9.457403
6174.663	347.0148	366.5401	700	900	35	7853.982	25	16	1	11.33366
5789.6	408.3831	420.3825	700	900	35	7853.982	25	16	1	11.42557
4755.419	545.1877	515.7751	700	900	35	7853.982	25	16	1	9.2834
6283.333	316.3102	339.1362	700	900	35	7853.982	25	16	1	11.21014
5958.333	381.4917	397.2748	700	900	35	7853.982	25	16	1	11.77878
5415	457.9363	460.0784	700	900	35	7853.982	25	16	1	11.89375
6475	326.0781	313.1296	700	1000	35	5890.486	25	12	1	14.76823
6325.141	374.0235	352.7229	700	1000	35	5890.486	25	12	1	10.15694
5971.939	436.1886	401.5302	700	1000	35	5890.486	25	12	1	3.302668
4949.582	584.7052	496.1091	700	1000	35	5890.486	25	12	1	0.421324
6176.667	400.1556	373.6228	700	1000	35	5890.486	25	12	1	6.608106
5620.833	487.1933	439.7084	700	1000	35	5890.486	25	12	1	0.061586
4655.833	612.2482	508.7768	700	1000	35	5890.486	25	12	1	1.555519
6908.333	345.4435	332.9405	700	1000	35	7853.982	25	16	1	6.145142
6690.87	414.2579	390.7015	700	1000	35	7853.982	25	16	1	8.622103
6316.986	480.9146	442.9835	700	1000	35	7853.982	25	16	1	9.183999
5205.917	645.4464	546.6874	700	1000	35	7853.982	25	16	1	6.090414
6461.667	455.1207	423.1559	700	1000	35	7853.982	25	16	1	9.389904
4889.167	677.1277	561.0467	700	1000	35	7853.982	25	16	1	6.501254
375	8.251041	10.45388	200	200	35	1017.876	18	4	1	4.132334
275.6307	10.20532	11.21919	200	200	35	1017.876	18	4	1	3.82394
378.6297	12.84044	14.36429	200	200	35	2035.752	18	8	1	6.887754
430.8333	12.00882	14.27788	200	200	35	2035.752	18	8	1	4.034615
325	13.49603	14.00296	200	200	35	2035.752	18	8	1	10.67102
266.6667	14.20911	13.32968	200	200	35	2035.752	18	8	1	12.52299
558.3333	15.56767	11.64274	200	300	35	1017.876	18	4	1	8.397918
519.7094	17.39459	12.56537	200	300	35	1017.876	18	4	1	5.856261
409.6836	21.58135	13.89568	200	300	35	1017.876	18	4	1	4.245641
458.3333	19.7301	13.6022	200	300	35	1017.876	18	4	1	4.887943

537.5729	26.98192	17.02345	200	300	35	2035.752	18	8	1	2.287026
583.3333	25.44627	16.80814	200	300	35	2035.752	18	8	1	0.782021
436.6667	29.6634	16.88401	200	300	35	2035.752	18	8	1	7.985596
482.5	38.76669	20.33541	200	300	35	3053.628	18	12	1	0.271125
557.5	36.7297	20.92675	200	300	35	3053.628	18	12	1	2.711679
666.6667	20.4	14.59099	200	400	35	1017.876	18	4	0.847236	24.11916
671.3106	27.65893	14.47943	200	400	35	1017.876	18	4	1	7.856856
539.2809	35.001	16.5559	200	400	35	1017.876	18	4	1	5.144829
624.1667	22.4	15.55288	200	400	35	1017.876	18	4	0.851363	26.68776
833.3333	28.4	17.63663	200	400	35	2035.752	18	8	0.888204	15.76724
677.5892	43.16221	19.64822	200	400	35	2035.752	18	8	1	5.963803
760.8333	32.5	19.06413	200	400	35	2035.752	18	8	0.903577	16.31607
590.8333	40.1	19.87894	200	400	35	2035.752	18	8	0.918903	26.03542
802.7293	53.60841	23.48555	200	400	35	3053.628	18	12	1	2.473202
602.5	62.04646	23.3029	200	400	35	3053.628	18	12	1	3.382547
702.5	50.4	23.78602	200	400	35	3053.628	18	12	0.92458	9.455069
565	80.33413	25.96603	200	400	35	4071.504	18	16	1	2.43537
653.3333	76.35115	26.97724	200	400	35	4071.504	18	16	1	4.494456
722.5	73.2324	27.55422	200	400	35	4071.504	18	16	1	6.225205
830.8333	60.4	27.81057	200	400	35	4071.504	18	16	0.931458	2.606631
791.6667	32.5	17.13044	200	500	35	1017.876	18	4	0.874931	25.89554
667.7344	50.46283	19.23094	200	500	35	1017.876	18	4	1	0.51046
958.3333	44.6	20.18229	200	500	35	2035.752	18	8	0.922673	14.58714
811.7534	61.37913	22.29687	200	500	35	2035.752	18	8	1	6.015327
952.5	44.5	20.30678	200	500	35	2035.752	18	8	0.917754	15.73779
685.8333	63.2	22.64149	200	500	35	2035.752	18	8	0.960346	19.82658
937.6525	75.28939	26.11183	200	500	35	3053.628	18	12	1	1.898462
1035.833	58.4	25.35884	200	500	35	3053.628	18	12	0.915811	2.769159
713.3333	87.90069	26.16	200	500	35	3053.628	18	12	1	4.822487
823.3333	78.6	26.51601	200	500	35	3053.628	18	12	0.977228	4.487391
1063.119	89.37207	29.9804	200	500	35	4071.504	18	16	1	8.735913
657.5	113.44	28.73391	200	500	35	4071.504	18	16	1	0.989041
720.8333	109.682	29.4513	200	500	35	4071.504	18	16	1	2.275186
833.3333	103.0067	30.39533	200	500	35	4071.504	18	16	1	5.541765
933.3333	90.2	30.55727	200	500	35	4071.504	18	16	0.957929	3.139598
708.3333	22.09688	28.28833	300	300	35	1017.876	18	4	1	5.11346
633.3333	24.73587	30.15674	300	300	35	1017.876	18	4	1	4.580459
892.9849	26.09188	34.37635	300	300	35	2035.752	18	8	1	3.77465
697.5854	32.37202	38.30016	300	300	35	2035.752	18	8	1	11.28768
950	23.58815	31.85406	300	300	35	2035.752	18	8	1	3.496583

796.6667	29.18755	36.65219	300	300	35	2035.752	18	8	1	8.597417
602.5	34.62959	38.21672	300	300	35	2035.752	18	8	1	14.64948
820.3032	39.32802	47.01018	300	300	35	3053.628	18	12	1	2.424067
954.1667	34.65999	44.2913	300	300	35	3053.628	18	12	1	0.324249
702.5	42.27052	46.96359	300	300	35	3053.628	18	12	1	6.913165
933.9004	46.32669	55.5565	300	300	35	4071.504	18	16	1	2.417253
620.8333	54.87803	53.91871	300	300	35	4071.504	18	16	1	1.560699
746.6667	51.44093	55.45636	300	300	35	4071.504	18	16	1	1.059024
1083.333	18.8	25.13247	300	400	35	1017.876	18	4	0.915194	67.18988
934.5606	35.47514	32.56918	300	400	35	1017.876	18	4	1	15.66947
1035.833	28.7524	27.65509	300	400	35	1017.876	18	4	1	12.74469
896.6667	35.67	34.22671	300	400	35	1017.876	18	4	0.971526	16.94081
1126.212	41.4884	38.33931	300	400	35	2035.752	18	8	1	19.59049
901.3517	52.5015	43.99506	300	400	35	2035.752	18	8	1	20.99869
1208.333	36.17327	34.48896	300	400	35	2035.752	18	8	1	21.36836
1025	46.44551	41.63496	300	400	35	2035.752	18	8	1	20.70896
1292.435	48.96138	45.31753	300	400	35	3053.628	18	12	1	8.307263
1026.492	62.9477	52.52631	300	400	35	3053.628	18	12	1	10.94519
1183.333	54.69919	49.0315	300	400	35	3053.628	18	12	1	9.796768
837.5	70.18664	53.12668	300	400	35	3053.628	18	12	1	14.79167
1147.657	73.49074	60.98062	300	400	35	4071.504	18	16	1	0.161346
870.8333	85.01275	61.57805	300	400	35	4071.504	18	16	1	4.514706
1541.667	40.9208	32.75388	300	500	35	2035.752	18	8	1	27.26084
1354.387	58.94975	42.48004	300	500	35	2035.752	18	8	1	24.17718
1099.266	75.69424	49.7283	300	500	35	2035.752	18	8	1	22.49065
1473.333	48.8945	36.69574	300	500	35	2035.752	18	8	1	27.02769
1231.667	67.00432	47.10505	300	500	35	2035.752	18	8	1	23.28107
1523.081	68.87491	49.37387	300	500	35	3053.628	18	12	1	16.55952
1225.165	89.6045	58.14493	300	500	35	3053.628	18	12	1	16.5224
1361.667	80.10646	55.12474	300	500	35	3053.628	18	12	1	16.72807
1006.667	100.664	59.43093	300	500	35	3053.628	18	12	1	18.58598
1350.631	103.6872	66.52485	300	500	35	4071.504	18	16	1	7.48061
1508.333	92.64671	63.09249	300	500	35	4071.504	18	16	1	7.166026
1185	112.6805	68.27993	300	500	35	4071.504	18	16	1	9.314062
1750	58.5	38.22025	300	600	35	2035.752	18	8	0.992863	28.96104
1581.194	78.48016	46.66438	300	600	35	2035.752	18	8	1	23.40551
1294.626	101.9543	55.49647	300	600	35	2035.752	18	8	1	19.49544
1666.667	69.59603	42.51438	300	600	35	2035.752	18	8	1	26.20052
1435.833	90.38735	52.65675	300	600	35	2035.752	18	8	1	20.95975
1751.478	90.84878	53.50505	300	600	35	3053.628	18	12	1	19.53904

1420.822	119.3159	63.82691	300	600	35	3053.628	18	12	1	17.53456
1859.167	79.86729	48.38247	300	600	35	3053.628	18	12	1	21.88258
1585	105.1813	60.10886	300	600	35	3053.628	18	12	1	18.24302
1275	128.3598	65.89968	300	600	35	3053.628	18	12	1	18.41105
1929.124	103.8162	60.46082	300	600	35	4071.504	18	16	1	11.48523
1549.038	136.9343	72.14781	300	600	35	4071.504	18	16	1	11.18096
1754.167	119.0608	67.47599	300	600	35	4071.504	18	16	1	10.87763
1370	148.755	74.50212	300	600	35	4071.504	18	16	1	12.33117
1595.856	36.05253	50.26216	400	400	35	2035.752	18	8	1	24.83007
1389.462	49.30461	65.15455	400	400	35	2035.752	18	8	1	24.77393
1125.114	61.84079	74.63058	400	400	35	2035.752	18	8	1	24.39123
1498.333	42.31425	57.60814	400	400	35	2035.752	18	8	1	26.59902
1250	55.91833	70.69927	400	400	35	2035.752	18	8	1	25.72849
1555.685	56.77759	75.64609	400	400	35	3053.628	18	12	1	19.85373
1250.254	72.287	87.74372	400	400	35	3053.628	18	12	1	21.29901
1666.667	49.82868	68.19847	400	400	35	3053.628	18	12	1	20.38679
1458.333	61.72099	80.09362	400	400	35	3053.628	18	12	1	21.13558
1371.419	82.83003	100.8902	400	400	35	4071.504	18	16	1	15.20934
1519.167	75.3103	95.93633	400	400	35	4071.504	18	16	1	14.67509
1055.833	95.07021	102.3193	400	400	35	4071.504	18	16	1	17.49819
1916.667	49.50068	54.29239	400	500	35	2035.752	18	8	1	14.66748
1692.637	70.55552	72.51811	400	500	35	2035.752	18	8	1	26.21277
1386.778	90.00935	84.75627	400	500	35	2035.752	18	8	1	24.76681
1815.833	60.2449	63.79867	400	500	35	2035.752	18	8	1	25.2597
1510	82.17196	80.75725	400	500	35	2035.752	18	8	1	26.51865
2125	56.01456	61.85469	400	500	35	3053.628	18	12	1	28.88825
1861.331	80.48068	82.88426	400	500	35	3053.628	18	12	1	26.54739
1512.678	103.9196	97.7202	400	500	35	3053.628	18	12	1	25.14153
1981.667	70.59712	74.61285	400	500	35	3053.628	18	12	1	27.77975
1750	87.96515	88.74251	400	500	35	3053.628	18	12	1	26.65193
1398.333	109.2277	99.49267	400	500	35	3053.628	18	12	1	25.88462
2038.129	90.84268	93.78343	400	500	35	4071.504	18	16	1	19.97136
1638.144	118.0023	110.7415	400	500	35	4071.504	18	16	1	20.85197
1445	127.7245	113.3968	400	500	35	4071.504	18	16	1	22.13568
2208.333	69.98863	63.16281	400	600	35	2035.752	18	8	1	3.240937
1994.444	94.56848	79.95037	400	600	35	2035.752	18	8	1	16.7445
1645.889	122.2718	94.92777	400	600	35	2035.752	18	8	1	16.53326
2094.167	84.31361	72.87616	400	600	35	2035.752	18	8	1	14.72504
1783.333	111.3477	90.36069	400	600	35	2035.752	18	8	1	17.74559
2416.667	77.88273	70.62014	400	600	35	3053.628	18	12	1	23.69829

2164.728	106.9371	90.23549	400	600	35	3053.628	18	12	1	24.03855
1772.084	139.6335	107.7838	400	600	35	3053.628	18	12	1	21.93715
2321.667	91.03282	79.19917	400	600	35	3053.628	18	12	1	24.97396
1989.167	121.5565	99.69219	400	600	35	3053.628	18	12	1	23.5889
2569.625	96.56791	84.61117	400	600	35	4071.504	18	16	1	22.54835
2342.374	119.9045	101.0179	400	600	35	4071.504	18	16	1	20.87821
1900.3	157.2519	120.709	400	600	35	4071.504	18	16	1	20.38406
2426.667	111.2484	95.14169	400	600	35	4071.504	18	16	1	21.60272
2205.833	131.4397	108.989	400	600	35	4071.504	18	16	1	20.83869
1666.667	171.5019	124.4372	400	600	35	4071.504	18	16	1	21.33391
2708.333	103.0961	79.43446	400	700	35	3053.628	18	12	1	15.75226
2466.988	136.154	97.64504	400	700	35	3053.628	18	12	1	16.8415
2029.991	179.4381	117.9046	400	700	35	3053.628	18	12	1	14.84828
2525	129.173	93.62809	400	700	35	3053.628	18	12	1	17.29263
2306.667	152.0337	107.3606	400	700	35	3053.628	18	12	1	16.14787
1880.833	189.3399	121.5044	400	700	35	3053.628	18	12	1	15.36602
2958.333	104.263	80.44244	400	700	35	4071.504	18	16	1	23.54226
2860.588	125.4536	92.75959	400	700	35	4071.504	18	16	1	19.67431
2645.166	151.7247	108.3455	400	700	35	4071.504	18	16	1	17.55322
2160.112	200.5895	130.7534	400	700	35	4071.504	18	16	1	16.38928
2707.5	144.1229	103.9828	400	700	35	4071.504	18	16	1	18.24229
2366.667	179.781	123.2103	400	700	35	4071.504	18	16	1	17.18854
1941.667	216.0976	135.1814	400	700	35	4071.504	18	16	1	17.31236
3000	131.6502	88.2827	400	800	35	3053.628	18	12	1	6.827471
2768.598	168.1353	105.0884	400	800	35	3053.628	18	12	1	6.753848
2287.048	223.3389	128.0655	400	800	35	3053.628	18	12	1	5.450655
2915	147.7579	94.67281	400	800	35	3053.628	18	12	1	7.013666
2655.833	180	112.6655	400	800	35	3053.628	18	12	0.996403	6.575199
2108.333	236.813	132.6298	400	800	35	3053.628	18	12	1	6.349242
3250	133.0489	89.20466	400	800	35	4071.504	18	16	1	17.58014
3153.78	157.166	100.7482	400	800	35	4071.504	18	16	1	13.66396
2947.138	186.3079	115.7278	400	800	35	4071.504	18	16	1	11.63812
2418.565	248.0216	140.8518	400	800	35	4071.504	18	16	1	10.3412
3049.167	171.9192	108.4777	400	800	35	4071.504	18	16	1	12.73666
2760	208.1572	127.729	400	800	35	4071.504	18	16	1	10.78139
2320	250	143.9654	400	800	35	4071.504	18	16	0.985939	12.90295
2291.667	58.10752	80.65302	500	500	35	2035.752	18	8	1	11.07305
2030.887	82.16128	108.8256	500	500	35	2035.752	18	8	1	16.27311
1674.291	104.3245	127.253	500	500	35	2035.752	18	8	1	18.52437
2229.167	65.68065	90.22442	500	500	35	2035.752	18	8	1	4.563844

1917.5	89.20852	115.4055	500	500	35	2035.752	18	8	1	18.85108
2500	64.56282	90.35261	500	500	35	3053.628	18	12	1	17.89094
2199.581	92.08644	122.7145	500	500	35	3053.628	18	12	1	24.37432
1800.19	118.2347	144.7272	500	500	35	3053.628	18	12	1	24.15916
2341.667	80.45752	109.8755	500	500	35	3053.628	18	12	1	23.95911
2027.5	103.3527	133.2064	500	500	35	3053.628	18	12	1	25.50622
2657.206	79.20583	110.8546	500	500	35	4071.504	18	16	1	21.7933
2376.379	102.4484	137.4245	500	500	35	4071.504	18	16	1	22.28423
1925.656	132.3174	162.4455	500	500	35	4071.504	18	16	1	23.18584
2481.667	93.73431	127.8757	500	500	35	4071.504	18	16	1	22.62348
2203.333	113.916	148.2009	500	500	35	4071.504	18	16	1	23.62861
1713.333	142.3266	165.6413	500	500	35	4071.504	18	16	1	24.64194
2875	88.65841	101.9544	500	600	35	3053.628	18	12	1	0.789503
2824.965	98.10548	111.1458	500	600	35	3053.628	18	12	1	8.082406
2577.978	123.0254	134.2527	500	600	35	3053.628	18	12	1	16.67384
2123.347	159.951	160.4924	500	600	35	3053.628	18	12	1	18.54071
2683.333	112.3955	124.6975	500	600	35	3053.628	18	12	1	14.91084
2352.5	141.339	148.8428	500	600	35	3053.628	18	12	1	19.10654
3083.333	97.17898	112.1849	500	600	35	4071.504	18	16	1	16.3054
2755.624	135.9928	148.7997	500	600	35	4071.504	18	16	1	20.008
2251.563	177.5694	178.0706	500	600	35	4071.504	18	16	1	21.12795
2969.167	114.193	128.7603	500	600	35	4071.504	18	16	1	18.72739
2625	146.7671	158.0735	500	600	35	4071.504	18	16	1	20.95975
2108.333	185.7393	181.4756	500	600	35	4071.504	18	16	1	22.18231
3250	116.2334	113.5944	500	700	35	3053.628	18	12	1	17.46336
3192.948	128.9494	123.5462	500	700	35	3053.628	18	12	1	9.058931
2955.238	157.4178	145.864	500	700	35	3053.628	18	12	1	1.576904
2445.003	206.7847	176.3249	500	700	35	3053.628	18	12	1	6.426295
3083.333	142.077	134.083	500	700	35	3053.628	18	12	1	2.400687
2758.333	176.469	159.9242	500	700	35	3053.628	18	12	1	4.897237
3475	122.7446	120.3382	500	700	35	4071.504	18	16	1	3.138758
3385.588	142.4321	136.3545	500	700	35	4071.504	18	16	1	7.752102
3133.416	172.9886	160.2967	500	700	35	4071.504	18	16	1	11.33402
2575.124	227.9362	193.794	500	700	35	4071.504	18	16	1	13.51758
3208.333	163.9106	153.408	500	700	35	4071.504	18	16	1	10.91239
2306.667	245.7504	199.6927	500	700	35	4071.504	18	16	1	15.36528
3833.333	159.1199	135.3902	500	800	35	4071.504	18	16	1	6.106649
3753.78	179.342	148.7234	500	800	35	4071.504	18	16	1	3.241404
3510.388	213.4404	171.8655	500	800	35	4071.504	18	16	1	0.598708
2897.327	283.4239	209.5856	500	800	35	4071.504	18	16	1	3.704503

3625	197.3836	161.188	500	800	35	4071.504	18	16	1	0.556185
2666.667	300.78	216.0852	500	800	35	4071.504	18	16	1	5.437856
3291.667	107.3894	148.6084	600	600	35	3053.628	18	12	1	21.13567
2991.228	139.1137	185.5232	600	600	35	3053.628	18	12	1	1.164234
2474.609	180.2686	221.9097	600	600	35	3053.628	18	12	1	8.253181
3140	124.1524	168.7556	600	600	35	3053.628	18	12	1	5.615998
2722.5	160.5211	205.9511	600	600	35	3053.628	18	12	1	7.392294
3541.667	107.9277	150.9117	600	600	35	4071.504	18	16	1	3.696318
3469.625	121.5159	168.6303	600	600	35	4071.504	18	16	1	3.199062
3168.874	152.0812	203.8335	600	600	35	4071.504	18	16	1	11.40063
2602.825	197.887	244.1833	600	600	35	4071.504	18	16	1	14.65105
3338.333	134.859	184.4485	600	600	35	4071.504	18	16	1	8.61005
3002.5	165.5445	217.1125	600	600	35	4071.504	18	16	1	13.74926
3958.333	148.7774	175.9138	600	700	35	4071.504	18	16	1	12.83726
3621.666	194.2525	220.4583	600	700	35	4071.504	18	16	1	2.330397
2990.137	255.2828	266.8986	600	700	35	4071.504	18	16	1	8.456901
3778.333	175.3595	202.4572	600	700	35	4071.504	18	16	1	1.850605
3433.333	212.4527	236.6294	600	700	35	4071.504	18	16	1	5.746261
4416.667	185.3684	190.6307	600	800	35	4071.504	18	16	1	25.16741
4073.638	240.5728	237.1683	600	800	35	4071.504	18	16	1	9.725668
3376.09	318.8263	289.6941	600	800	35	4071.504	18	16	1	1.247607
4253.333	215.5213	216.3542	600	800	35	4071.504	18	16	1	15.40916
3822.5	268.7463	259.3662	600	800	35	4071.504	18	16	1	4.837744
4500	161.9193	224.6708	700	700	35	4071.504	18	16	1	30.82073
4109.916	215.5163	288.8162	700	700	35	4071.504	18	16	1	4.003244
3405.149	282.6295	350.0375	700	700	35	4071.504	18	16	1	4.106017
4398.333	180.8649	248.8207	700	700	35	4071.504	18	16	1	18.59383
3988.333	227.0943	300.7017	700	700	35	4071.504	18	16	1	0.774542
2203.333	68.48799	98.71639	400	400	30	5890.486	25	12	1	3.300196
1835.833	89.61202	120.8021	400	400	30	5890.486	25	12	1	1.610114
1804.676	123.5673	156.1479	400	400	30	7853.982	25	16	1	4.564069
2212.5	102.1998	140.2761	400	400	30	7853.982	25	16	1	3.925269
1875	54.38895	61.45396	400	500	30	1963.495	25	4	1	20.0944
2291.667	66.81315	75.85577	400	500	30	3926.991	25	8	1	8.754968
2000.495	93.11734	99.24829	400	500	30	3926.991	25	8	1	9.862634
2133.333	81.88636	89.42028	400	500	30	3926.991	25	8	1	10.66545
1861.667	102.3612	106.6832	400	500	30	3926.991	25	8	1	9.983259
2708.333	78.10767	88.98703	400	500	30	5890.486	25	12	1	2.09422
2326.969	112.0585	119.1951	400	500	30	5890.486	25	12	1	6.438878
2537.5	94.82439	104.1001	400	500	30	5890.486	25	12	1	6.783961

2138.333	125.4404	129.4683	400	500	30	5890.486	25	12	1	4.991583
2669.62	131.7992	140.1323	400	500	30	7853.982	25	16	1	1.223574
2084.853	173.1907	166.4378	400	500	30	7853.982	25	16	1	7.650816
2204.167	164.7453	162.3071	400	500	30	7853.982	25	16	1	5.74873
1861.667	185.9979	170.3877	400	500	30	7853.982	25	16	1	7.990981
2625	84.94438	78.98259	400	600	30	3926.991	25	8	1	11.91892
2304.438	123.0543	106.9743	400	600	30	3926.991	25	8	1	9.437283
2425	110.4606	97.98133	400	600	30	3926.991	25	8	1	10.12965
3083.333	92.91616	86.55362	400	600	30	5890.486	25	12	1	2.630034
2923.945	117.2768	105.3869	400	600	30	5890.486	25	12	1	7.299361
2634.242	146.7419	126.7845	400	600	30	5890.486	25	12	1	8.565868
2783.333	131.5781	116.0829	400	600	30	5890.486	25	12	1	8.97044
2320.833	174.3866	143.6539	400	600	30	5890.486	25	12	1	6.604225
2978.763	171.5407	147.5291	400	600	30	7853.982	25	16	1	3.128699
2355.125	226.8588	176.9088	400	600	30	7853.982	25	16	1	4.355719
3222.5	146.3379	129.5587	400	600	30	7853.982	25	16	1	4.664004
2700	196.2676	163.1178	400	600	30	7853.982	25	16	1	0.171593
2546.667	209.8686	169.7558	400	600	30	7853.982	25	16	1	1.905124
2898.333	115.3631	90.73054	400	700	30	3926.991	25	8	1	8.550431
2833.321	127.6734	97.39827	400	700	30	3926.991	25	8	1	6.019054
2606.938	155.7494	114.7849	400	700	30	3926.991	25	8	1	5.008398
2898.333	115.3631	90.73054	400	700	30	3926.991	25	8	1	8.550431
3375	121.4022	95.48989	400	700	30	5890.486	25	12	1	3.528431
3209.327	151.3959	114.4463	400	700	30	5890.486	25	12	1	5.75721
2939.058	184.1724	134.5048	400	700	30	5890.486	25	12	1	6.98264
3037.5	172.234	127.4253	400	700	30	5890.486	25	12	1	7.173417
2685	210.8628	149.6347	400	700	30	5890.486	25	12	1	5.883178
3750	147.2602	114.9342	400	700	30	7853.982	25	16	1	1.094593
3574.665	178.2545	133.41	400	700	30	7853.982	25	16	1	4.035794
3275.433	197	155.7818	400	700	30	7853.982	25	16	0.950106	1.212387
2611.83	280	187.7903	400	700	30	7853.982	25	16	0.988669	1.853659
3666.667	160	126.1164	400	700	30	7853.982	25	16	0.991465	0.099792
3335.833	207.7215	151.4439	400	700	30	7853.982	25	16	1	3.66783
3086.667	235.0637	167.854	400	700	30	7853.982	25	16	1	0.682576
3213.333	141.0423	96.48332	400	800	30	3926.991	25	8	1	6.360693
3037.5	172.7392	112.8821	400	800	30	3926.991	25	8	1	0.070389
3648.333	157.0015	107.0381	400	800	30	5890.486	25	12	1	2.314506
3498.31	188.3816	123.2314	400	800	30	5890.486	25	12	1	2.0059
3242.475	224.3585	142.2991	400	800	30	5890.486	25	12	1	2.853361
4083.333	174.6563	118.131	400	800	30	7853.982	25	16	1	0.863485

3871.151	218.8777	141.5949	400	800	30	7853.982	25	16	1	0.989668
3588.952	259.2612	162.8189	400	800	30	7853.982	25	16	1	0.280315
3935	204	136.5589	400	800	30	7853.982	25	16	0.995339	0.785328
3694.167	244.2047	155.1121	400	800	30	7853.982	25	16	1	1.036796
3286.667	296.5597	181.4737	400	800	30	7853.982	25	16	1	2.279021
2708.333	69.89823	102.7389	500	500	30	3926.991	25	8	1	9.80728
2336.12	104.9018	146.5139	500	500	30	3926.991	25	8	1	7.433377
2500	91.16141	130.4406	500	500	30	3926.991	25	8	1	8.175997
3125	81.3952	120.4575	500	500	30	5890.486	25	12	1	3.543808
3019.277	94.74611	138.6665	500	500	30	5890.486	25	12	1	5.174491
2662.594	123.8429	173.5374	500	500	30	5890.486	25	12	1	7.488314
2851.667	108.4191	155.6607	500	500	30	5890.486	25	12	1	7.7083
3405.361	110.4855	162.3232	500	500	30	7853.982	25	16	1	3.344617
3005.245	143.5837	202.111	500	500	30	7853.982	25	16	1	3.212486
2370.134	187.5889	240.5674	500	500	30	7853.982	25	16	1	5.901609
3176.667	129.4035	185.7472	500	500	30	7853.982	25	16	1	4.909954
2851.667	154.2248	212.943	500	500	30	7853.982	25	16	1	1.938353
3058.333	100.0352	119.6451	500	600	30	3926.991	25	8	1	9.480124
2992.837	110.6256	130.5346	500	600	30	3926.991	25	8	1	7.289842
2851.667	125.2337	145.1841	500	600	30	3926.991	25	8	1	7.854922
3525	106.3897	128.2205	500	600	30	5890.486	25	12	1	6.144611
3373.945	129.7508	153.1481	500	600	30	5890.486	25	12	1	7.68064
3044.867	163.0569	185.4634	500	600	30	5890.486	25	12	1	9.968065
3190	148.3679	171.662	500	600	30	5890.486	25	12	1	9.881731
3950	120.2659	145.2005	500	600	30	7853.982	25	16	1	3.417006
3754.167	150.3674	177.4237	500	600	30	7853.982	25	16	1	6.521566
3389.388	187.8557	213.7623	500	600	30	7853.982	25	16	1	6.772917
3591.667	167.0675	194.1138	500	600	30	7853.982	25	16	1	7.678271
3025.833	219.3863	239.3063	500	600	30	7853.982	25	16	1	4.556405
3425	131.9678	133.5387	500	700	30	3926.991	25	8	1	5.159285
3247.5	158.2611	155.4565	500	700	30	3926.991	25	8	1	2.423357
3900	138.0732	140.4232	500	700	30	5890.486	25	12	1	6.75648
3734.327	168.3744	167.0407	500	700	30	5890.486	25	12	1	5.682989
3424.683	205.7108	197.5637	500	700	30	5890.486	25	12	1	7.427096
3525.833	193.5143	187.9106	500	700	30	5890.486	25	12	1	7.334266
4315	156.6627	159.105	500	700	30	7853.982	25	16	1	3.990635
3770.37	235.5632	225.6751	500	700	30	7853.982	25	16	1	6.165089
3945	214.1705	208.6438	500	700	30	7853.982	25	16	1	6.560112
3441.667	269.6763	250.2706	500	700	30	7853.982	25	16	1	5.236639
3845.833	156.0428	137.4716	500	800	30	3926.991	25	8	1	3.043923

3726.145	182.2094	157.1108	500	800	30	3926.991	25	8	1	2.907248
4240.833	180.4764	158.7764	500	800	30	5890.486	25	12	1	5.752773
3803.1	251.8134	209.7637	500	800	30	5890.486	25	12	1	3.054222
3935.833	233.2639	196.9262	500	800	30	5890.486	25	12	1	3.072964
4683.333	196.443	172.4844	500	800	30	7853.982	25	16	1	3.853524
4471.151	241.0537	205.5882	500	800	30	7853.982	25	16	1	2.852388
4149.577	286.7162	237.7377	500	800	30	7853.982	25	16	1	3.169389
4516.667	230	200.8364	500	800	30	7853.982	25	16	0.996084	2.273032
4252.5	272.1014	227.731	500	800	30	7853.982	25	16	1	3.426016
3751.667	334.6711	267.9165	500	800	30	7853.982	25	16	1	2.592948
3500	113.8162	165.8859	600	600	30	3926.991	25	8	1	2.900944
3933.333	125.1534	183.8222	600	600	30	5890.486	25	12	1	6.083507
3823.945	142.2248	206.9681	600	600	30	5890.486	25	12	1	4.401602
3455.492	179.3718	251.9967	600	600	30	5890.486	25	12	1	5.372236
3587.5	166.0629	236.4387	600	600	30	5890.486	25	12	1	5.560658
4398.333	132.7268	196.6084	600	600	30	7853.982	25	16	1	3.979796
4204.167	162.8414	237.7196	600	600	30	7853.982	25	16	1	3.2835
3800.013	204.1706	287.8489	600	600	30	7853.982	25	16	1	3.306217
3988.333	184.9128	265.1779	600	600	30	7853.982	25	16	1	4.103946
3415	236.9278	320.9519	600	600	30	7853.982	25	16	1	2.075125
3981.667	142.8592	176.6811	600	700	30	3926.991	25	8	1	1.368261
4398.333	159.7309	198.2724	600	700	30	5890.486	25	12	1	9.188147
4259.327	185.3529	226.6951	600	700	30	5890.486	25	12	1	6.310587
3910.308	227.2493	269.492	600	700	30	5890.486	25	12	1	6.784293
3990.833	217.583	259.9706	600	700	30	5890.486	25	12	1	6.869016
4833.333	174.576	217.3988	600	700	30	7853.982	25	16	1	8.061425
4635.339	210.8946	257.9848	600	700	30	7853.982	25	16	1	6.143313
4255.995	257.1016	305.1019	600	700	30	7853.982	25	16	1	6.616479
4440.833	234.5869	282.6835	600	700	30	7853.982	25	16	1	6.839165
3893.333	294.0147	337.8558	600	700	30	7853.982	25	16	1	6.782668
4875	195.1869	210.189	600	800	30	5890.486	25	12	1	10.44733
4698.31	232.7336	245.9664	600	800	30	5890.486	25	12	1	5.138689
4552.5	253.0132	264.2892	600	800	30	5890.486	25	12	1	4.759942
5291.667	216.5526	233.213	600	800	30	7853.982	25	16	1	10.0251
5071.151	263.2297	277.6504	600	800	30	7853.982	25	16	1	5.488203
4710.202	314.1711	322.5411	600	800	30	7853.982	25	16	1	5.376168
4861.667	292.7946	304.1338	600	800	30	7853.982	25	16	1	5.601264
4916.667	177.7889	260.1379	700	700	30	5890.486	25	12	1	11.94532
4784.327	202.3314	293.3782	700	700	30	5890.486	25	12	1	7.103138
4608.333	223.3822	319.7837	700	700	30	5890.486	25	12	1	5.768986

5375	188.2537	277.3467	700	700	30	7853.982	25	16	1	12.35227
5160.339	227.8731	331.2607	700	700	30	7853.982	25	16	1	5.469388
4741.62	278.64	393.3746	700	700	30	7853.982	25	16	1	3.85415
4861.667	264.0852	376.1455	700	700	30	7853.982	25	16	1	4.463188
5458.333	220.7238	280.0494	700	800	30	5890.486	25	12	1	12.95888
5298.31	254.9096	319.3915	700	800	30	5890.486	25	12	1	8.04459
5875	242.0242	307.7842	700	800	30	7853.982	25	16	1	14.85781
5671.151	285.4057	357.7487	700	800	30	7853.982	25	16	1	7.849317
5270.827	341.626	417.1999	700	800	30	7853.982	25	16	1	5.981551
5453.333	315.9954	390.665	700	800	30	7853.982	25	16	1	6.761757
5981.667	272.0386	304.6703	700	900	30	5890.486	25	12	1	10.97007
6425	290.0517	325.4946	700	900	30	7853.982	25	16	1	16.53239
6185.075	347.8709	383.7622	700	900	30	7853.982	25	16	1	7.268789
6285.833	323.5894	360.9243	700	900	30	7853.982	25	16	1	10.96438
6025	373.3989	408.0237	700	900	30	7853.982	25	16	1	5.854992
6500	329.6726	330.6103	700	1000	30	5890.486	25	12	1	7.565956
6916.667	357.2552	358.2066	700	1000	30	7853.982	25	16	1	14.45324
6701.189	415.2436	409.4461	700	1000	30	7853.982	25	16	1	5.551815
391.6667	7.87773	10.58306	200	200	30	1017.876	18	4	1	7.78137
458.3333	11.64415	14.69353	200	200	30	2035.752	18	8	1	2.368992
416.6667	12.30704	14.88907	200	200	30	2035.752	18	8	1	3.97343
380.6382	12.88023	14.94582	200	200	30	2035.752	18	8	1	5.581616
558.3333	15.66375	12.23098	200	300	30	1017.876	18	4	1	3.971172
726.6667	20.58591	15.31666	200	300	30	2035.752	18	8	1	4.744734
624.1667	24.22909	17.23922	200	300	30	2035.752	18	8	1	0.455187
666.6667	17.4	16.6161	200	300	30	2035.752	18	8	0.865208	9.653327
663.4931	34.05228	21.68894	200	300	30	3053.628	18	12	1	2.550799
764.1667	30.39275	21.00649	200	300	30	3053.628	18	12	1	0.255184
865	27.4	17.71492	200	400	30	2035.752	18	8	0.891309	7.457165
778.3333	30.4	19.63152	200	400	30	2035.752	18	8	0.88192	14.93511
1032.733	41.30876	21.17495	200	400	30	3053.628	18	12	1	4.933272
806.0089	53.77859	24.47108	200	400	30	3053.628	18	12	1	1.227114
969.1667	38.4	22.57766	200	400	30	3053.628	18	12	0.916177	0.882138
928.2176	64.37727	28.43836	200	400	30	4071.504	18	16	1	2.258939
1074.167	50.6	27.13055	200	400	30	4071.504	18	16	0.938331	1.887517
805.8333	65.3	28.97219	200	400	30	4071.504	18	16	0.960816	2.07448
958.3333	46.3	21.16988	200	500	30	2035.752	18	8	0.93867	6.085112
1141.667	54.3	24.26338	200	500	30	3053.628	18	12	0.935881	0.076034
940.9691	75.51518	27.28381	200	500	30	3053.628	18	12	1	1.347119
1016.667	69.99946	26.72546	200	500	30	3053.628	18	12	1	2.261491

1308.333	67.4	27.64082	200	500	30	4071.504	18	16	0.96049	1.034031
1067.492	89.67123	31.19079	200	500	30	4071.504	18	16	1	4.240677
1203.333	77.6	29.82065	200	500	30	4071.504	18	16	0.983311	3.385375
975	22.66722	32.1176	300	300	30	2035.752	18	8	1	1.219549
895.2665	26.17069	35.93839	300	300	30	2035.752	18	8	1	0.588834
1175	26.31403	37.7023	300	300	30	3053.628	18	12	1	4.316024
1059.884	31.20591	43.07912	300	300	30	3053.628	18	12	1	1.65449
1103.333	29.35953	41.1364	300	300	30	3053.628	18	12	1	2.103626
945	35.20899	46.47595	300	300	30	3053.628	18	12	1	0.693009
1231.501	36.37835	50.52071	300	300	30	4071.504	18	16	1	1.066228
938.1228	46.47895	57.79363	300	300	30	4071.504	18	16	1	0.560956
1055.833	42.42634	55.47615	300	300	30	4071.504	18	16	1	0.835044
1115	40.38931	53.99	300	300	30	4071.504	18	16	1	1.070834
844.1667	49.04193	58.14938	300	300	30	4071.504	18	16	1	2.114662
1333.333	26.94532	28.40987	300	400	30	2035.752	18	8	1	16.81045
1128.519	41.60622	40.17611	300	400	30	2035.752	18	8	1	11.52441
1240.833	34.33217	34.47645	300	400	30	2035.752	18	8	1	12.57835
1503.658	36.08246	36.75044	300	400	30	3053.628	18	12	1	0.879471
1295.983	49.12497	47.25376	300	400	30	3053.628	18	12	1	3.980509
1418.333	41.44107	41.27956	300	400	30	3053.628	18	12	1	3.228565
1170	55.74704	51.70898	300	400	30	3053.628	18	12	1	4.394433
1472.484	56.92644	54.45209	300	400	30	4071.504	18	16	1	2.847844
1151.98	73.71656	63.66469	300	400	30	4071.504	18	16	1	4.205347
1585.833	49.7239	48.94439	300	400	30	4071.504	18	16	1	2.151311
1514.208	45.783	36.30185	300	500	30	2035.752	18	8	1	18.24406
1443.333	51.7785	40.15486	300	500	30	2035.752	18	8	1	16.30423
1750	46.3	40.04084	300	500	30	3053.628	18	12	0.966982	8.241708
1526.647	69.09206	51.59576	300	500	30	3053.628	18	12	1	8.916205
1654.167	58.55872	45.20866	300	500	30	3053.628	18	12	1	8.710638
1399.167	77.95866	56.82455	300	500	30	3053.628	18	12	1	8.114978
1958.333	52.4	45.54392	300	500	30	4071.504	18	16	0.95892	7.167408
1704.683	79.51776	58.70928	300	500	30	4071.504	18	16	1	3.152157
1820.833	69.78691	52.92873	300	500	30	4071.504	18	16	1	3.72412
1535.833	91.33294	65.25272	300	500	30	4071.504	18	16	1	1.400808
1750	55.3	40.16997	300	600	30	2035.752	18	8	0.950487	29.78525
1666.667	64.3	44.72824	300	600	30	2035.752	18	8	0.951351	23.87326
2000	62.28258	42.05769	300	600	30	3053.628	18	12	1	15.03656
1833.333	83.13076	52.08214	300	600	30	3053.628	18	12	1	9.886054
1755.054	91.11946	56.00406	300	600	30	3053.628	18	12	1	9.297935
2166.667	72.4	50.93206	300	600	30	4071.504	18	16	0.958074	1.631251

1933.944	104.1662	63.0694	300	600	30	4071.504	18	16	1	5.837692
2074.167	89.6381	55.93337	300	600	30	4071.504	18	16	1	5.719224
1722.5	122.5824	71.57085	300	600	30	4071.504	18	16	1	4.231089
1625	33.33409	48.77158	400	400	30	2035.752	18	8	1	22.37815
1510	41.82682	59.69467	400	400	30	2035.752	18	8	1	16.4111
1825	39.46301	57.95382	400	400	30	3053.628	18	12	1	8.433609
1559.233	56.94118	79.17157	400	400	30	3053.628	18	12	1	9.927927
1657.5	50.78416	72.18685	400	400	30	3053.628	18	12	1	10.10364
2041.667	44.08474	65.10566	400	400	30	4071.504	18	16	1	0.146354
1735.734	64.74265	90.43306	400	400	30	4071.504	18	16	1	5.226232
1858.333	56.98083	81.55249	400	400	30	4071.504	18	16	1	5.076129
1533.333	75.03902	99.95166	400	400	30	4071.504	18	16	1	6.507331
1900	52.98796	60.33658	400	500	30	2035.752	18	8	1	21.86824
2125	57.60259	65.84742	400	500	30	3053.628	18	12	1	18.07781
1864.897	80.69782	86.90306	400	500	30	3053.628	18	12	1	15.4088
1998.333	69.73074	77.09337	400	500	30	3053.628	18	12	1	16.24818
2324.167	66.06125	75.39823	400	500	30	4071.504	18	16	1	8.966116
2042.933	91.12352	98.00512	400	500	30	4071.504	18	16	1	11.47986
2169.167	80.61777	88.6729	400	500	30	4071.504	18	16	1	11.60029
2221.667	69.26576	65.11429	400	600	30	2035.752	18	8	1	15.72131
2441.667	75.9339	71.39117	400	600	30	3053.628	18	12	1	19.44557
2379.122	85.82923	78.7342	400	600	30	3053.628	18	12	1	14.88823
2666.667	82.43301	77.30289	400	600	30	4071.504	18	16	1	12.98163
2575.212	96.82343	88.2823	400	600	30	4071.504	18	16	1	10.33693
2347.194	120.2545	105.7391	400	600	30	4071.504	18	16	1	11.11861
2426.667	112.088	99.85526	400	600	30	4071.504	18	16	1	11.36538
2750	97.68373	78.10152	400	700	30	3053.628	18	12	1	16.06648
2672.032	112.2194	87.24438	400	700	30	3053.628	18	12	1	9.742009
2958.333	108.6487	86.36735	400	700	30	4071.504	18	16	1	11.95507
2866.081	125.7747	96.94854	400	700	30	4071.504	18	16	1	7.41739
2649.998	152.1439	113.5534	400	700	30	4071.504	18	16	1	6.971745
2730	142.381	107.5687	400	700	30	4071.504	18	16	1	7.310899
3040.833	125.5146	87.33739	400	800	30	3053.628	18	12	1	9.460011
3258.333	136.3544	94.26509	400	800	30	4071.504	18	16	1	9.520887
3159.202	157.5535	105.4384	400	800	30	4071.504	18	16	1	2.903035
3183.333	150.4	103.506	400	800	30	4071.504	18	16	0.992027	4.797846
3024.167	176.6092	115.9787	400	800	30	4071.504	18	16	1	1.699927
2500	66.21469	96.66833	500	500	30	3053.628	18	12	1	13.50199
2357.5	79.66306	114.014	500	500	30	3053.628	18	12	1	11.39062
2708.333	73.47679	107.6659	500	500	30	4071.504	18	16	1	9.566984

2381.183	102.7293	143.9841	500	500	30	4071.504	18	16	1	9.687068
2565	87.50637	125.9113	500	500	30	4071.504	18	16	1	9.597831
2891.667	88.32138	106.0232	500	600	30	3053.628	18	12	1	10.07646
2829.122	98.30323	116.5216	500	600	30	3053.628	18	12	1	8.036194
3083.333	100.0694	119.9998	500	600	30	4071.504	18	16	1	10.50365
2981.667	113.7455	134.0026	500	600	30	4071.504	18	16	1	9.20542
3241.667	120.8154	122.9258	500	700	30	3053.628	18	12	1	0.998852
3490.833	124.0942	126.4734	500	700	30	4071.504	18	16	1	8.570315
3391.081	142.7532	142.8084	500	700	30	4071.504	18	16	1	4.661096
3833.333	163.7727	144.7348	500	800	30	4071.504	18	16	1	3.123583
3731.667	183.5893	158.8185	500	800	30	4071.504	18	16	1	0.489647
3333.333	102.0702	148.5509	600	600	30	3053.628	18	12	1	3.895448
3533.333	112.4815	164.0663	600	600	30	4071.504	18	16	1	4.846995
3340.833	135.4357	193.8319	600	600	30	4071.504	18	16	1	3.501945
4016.667	140.8116	174.5646	600	700	30	4071.504	18	16	1	3.568925
3916.081	159.7317	195.7076	600	700	30	4071.504	18	16	1	1.754103
516.6667	10.84741	14.07549	200	200	35	1963.495	25	4	1	5.869794
485.1624	11.59672	14.65213	200	200	35	1963.495	25	4	1	6.834719
700	21.8262	15.31754	200	300	35	1963.495	25	4	1	4.202985
1083.333	48.6	24.23941	200	400	35	3926.991	25	8	0.937914	0.995919
881.9785	64.83564	26.17709	200	400	35	3926.991	25	8	1	1.82295
981.6667	59.59737	25.63211	200	400	35	3926.991	25	8	1	0.824411
1250	70.4	26.02188	200	500	35	3926.991	25	8	0.965977	1.160588
1166.667	76.4	27.51121	200	500	35	3926.991	25	8	0.96878	3.175389
1558.333	88.5	32.26806	200	500	35	5890.486	25	12	0.959065	4.664469
1266.185	117.1579	35.49761	200	500	35	5890.486	25	12	1	8.82579
1452.5	96.4	34.11483	200	500	35	5890.486	25	12	0.961388	6.7988
1100	120	35.89605	200	500	35	5890.486	25	12	0.965349	7.010199
975	22.5184	30.84266	300	300	35	1963.495	25	4	1	0.42428
1333.333	30.21958	42.27243	300	300	35	3926.991	25	8	1	6.552963
1183.714	36.5425	48.84822	300	300	35	3926.991	25	8	1	5.019788
1025	41.74795	52.56662	300	300	35	3926.991	25	8	1	2.988635
1670.073	42.15825	40.86292	300	400	35	3926.991	25	8	1	5.555318
1428.44	57.7629	52.34198	300	400	35	3926.991	25	8	1	1.755361
1565.833	48.89006	46.08617	300	400	35	3926.991	25	8	1	1.902039
1300	64.27312	56.49929	300	400	35	3926.991	25	8	1	1.236642
1747.337	71.85172	65.44255	300	400	35	5890.486	25	12	1	8.697567
1344.171	93.90636	76.10843	300	400	35	5890.486	25	12	1	15.75345
1933.333	60.38708	57.20797	300	400	35	5890.486	25	12	1	7.06243
1546.667	82.82913	71.81655	300	400	35	5890.486	25	12	1	12.48693

1933.333	54.04441	42.65296	300	500	35	3926.991	25	8	1	6.400362
1660.404	81.03561	56.31688	300	500	35	3926.991	25	8	1	7.12518
1822.5	67.18737	48.72151	300	500	35	3926.991	25	8	1	7.04313
2358.333	63.79347	50.41621	300	500	35	5890.486	25	12	1	12.64196
2260.992	77.14869	56.39268	300	500	35	5890.486	25	12	1	3.845295
1984.476	99.8621	69.23564	300	500	35	5890.486	25	12	1	3.713631
2139.167	87.15559	62.30334	300	500	35	5890.486	25	12	1	2.255031
2324.743	119.482	82.1953	300	500	35	7853.982	25	16	1	11.15818
1791.162	158.2247	97.04905	300	500	35	7853.982	25	16	1	21.08649
2419.167	111.5989	78.03226	300	500	35	7853.982	25	16	1	9.592443
2111.667	134.9532	89.88736	300	500	35	7853.982	25	16	1	15.76133
2166.667	70.92483	45.85839	300	600	35	3926.991	25	8	1	18.53885
2087.531	85.41042	50.90562	300	600	35	3926.991	25	8	1	12.20459
1980	96.78007	56.20293	300	600	35	3926.991	25	8	1	11.95277
2583.333	84.48924	54.56289	300	600	35	5890.486	25	12	1	4.380726
2465.859	104.4355	61.58253	300	600	35	5890.486	25	12	1	1.923048
2216.727	129.9118	73.20794	300	600	35	5890.486	25	12	1	2.143268
2321.667	119.1806	68.49621	300	600	35	5890.486	25	12	1	2.944613
2002.5	149.4271	81.31528	300	600	35	5890.486	25	12	1	0.779299
2843.302	124.9447	72.74207	300	600	35	7853.982	25	16	1	5.036982
2558.85	154.5595	86.06144	300	600	35	7853.982	25	16	1	6.968956
1997.619	205.7235	102.484	300	600	35	7853.982	25	16	1	15.81072
2700	139.8642	79.66465	300	600	35	7853.982	25	16	1	4.996084
2240	183.6271	97.22693	300	600	35	7853.982	25	16	1	12.75181
1975	47.11877	66.82184	400	400	35	3926.991	25	8	1	8.440436
1796.667	58.81453	80.55592	400	400	35	3926.991	25	8	1	10.3111
2416.667	52.23913	75.49755	400	400	35	5890.486	25	12	1	5.012374
2007.962	79.7987	107.787	400	400	35	5890.486	25	12	1	3.311371
2283.333	62.84356	89.05253	400	400	35	5890.486	25	12	1	0.213974
1739.167	94.08427	119.8309	400	400	35	5890.486	25	12	1	3.485062
2344.854	94.38429	128.8151	400	400	35	7853.982	25	16	1	2.413746
1796.374	123.141	150.39	400	400	35	7853.982	25	16	1	5.507349
2154.167	104.382	137.7718	400	400	35	7853.982	25	16	1	0.395115
2333.333	58.68243	64.87534	400	500	35	3926.991	25	8	1	26.34358
2250.62	71.31168	76.52705	400	500	35	3926.991	25	8	1	19.76408
2750	69.64535	77.67301	400	500	35	5890.486	25	12	1	6.137367
2635.992	85.81119	92.51526	400	500	35	5890.486	25	12	1	6.476018
2320.101	111.6466	114.5563	400	500	35	5890.486	25	12	1	9.724755
2396.667	105.3846	109.5343	400	500	35	5890.486	25	12	1	9.739967
3166.667	80.99059	90.65799	400	500	35	7853.982	25	16	1	5.181303

3019.237	101.4709	109.6587	400	500	35	7853.982	25	16	1	0.135411
2660.368	131.2665	135.2301	400	500	35	7853.982	25	16	1	1.80756
2881.667	112.8929	119.9163	400	500	35	7853.982	25	16	1	2.088804
2306.667	156.3173	151.9569	400	500	35	7853.982	25	16	1	0.48604
2625	81.53962	73.57048	400	600	35	3926.991	25	8	1	26.57953
3041.667	94.90204	86.13975	400	600	35	5890.486	25	12	1	14.12981
2915.859	116.9095	101.4238	400	600	35	5890.486	25	12	1	11.21241
2627.352	146.2267	121.6098	400	600	35	5890.486	25	12	1	12.82704
2715.833	137.2355	115.691	400	600	35	5890.486	25	12	1	12.84174
3458.333	109.0737	99.00159	400	600	35	7853.982	25	16	1	0.826836
3293.302	137.4187	118.99	400	600	35	7853.982	25	16	1	4.201371
2969.475	170.8745	142.0578	400	600	35	7853.982	25	16	1	5.352482
3116.667	155.6676	131.9267	400	600	35	7853.982	25	16	1	5.742927
2766.667	188.8735	153.4054	400	600	35	7853.982	25	16	1	4.404415
3333.333	123.4632	94.70519	400	700	35	5890.486	25	12	1	17.0468
3201.388	150.9315	109.9225	400	700	35	5890.486	25	12	1	11.8328
3041.667	170.2845	121.368	400	700	35	5890.486	25	12	1	12.30351
3750	140.4419	107.4571	400	700	35	7853.982	25	16	1	4.541494
3574.665	176.3375	127.7759	400	700	35	7853.982	25	16	1	5.338633
3275.433	213.225	149.1002	400	700	35	7853.982	25	16	1	6.264461
3666.667	157.5024	120.1423	400	700	35	7853.982	25	16	1	2.7858
3335.833	205.7793	144.9768	400	700	35	7853.982	25	16	1	6.450146
3086.667	233.2845	160.6822	400	700	35	7853.982	25	16	1	5.350177
3625	155.3278	103.3434	400	800	35	5890.486	25	12	1	16.26659
3490.483	187.8186	118.17	400	800	35	5890.486	25	12	1	9.980756
3525	178	115.6223	400	800	35	5890.486	25	12	0.994937	11.06535
4083.333	165.1852	109.5017	400	800	35	7853.982	25	16	1	8.280023
3860.623	218.1503	136.2293	400	800	35	7853.982	25	16	1	4.116055
3579.623	258.3281	156.2694	400	800	35	7853.982	25	16	1	4.630933
3957.5	195	128.9237	400	800	35	7853.982	25	16	0.99965	2.958759
3715.833	238.8526	146.778	400	800	35	7853.982	25	16	1	4.750634
3083.333	83.96279	119.5746	500	500	35	5890.486	25	12	1	14.19559
3010.992	94.47369	133.4162	500	500	35	5890.486	25	12	1	12.13835
2815	110.4488	152.1687	500	500	35	5890.486	25	12	1	14.53304
3541.667	89.14374	128.7487	500	500	35	7853.982	25	16	1	3.971491
3394.237	110.1334	156.7444	500	500	35	7853.982	25	16	1	5.207922
2995.993	143.0509	194.4292	500	500	35	7853.982	25	16	1	8.406219
3176.667	128.1171	178.0312	500	500	35	7853.982	25	16	1	8.21912
3500	105.403	122.7224	500	600	35	5890.486	25	12	1	18.01308
3365.859	129.3835	146.9981	500	600	35	5890.486	25	12	1	14.73361

3916.667	119.4497	139.828	500	600	35	7853.982	25	16	1	8.853181
3743.302	149.8927	170.8824	500	600	35	7853.982	25	16	1	8.565651
3380.1	187.1894	205.2171	500	600	35	7853.982	25	16	1	11.33907
3843.333	132.3271	154.0963	500	600	35	7853.982	25	16	1	8.486168
3525	172.3099	192.0196	500	600	35	7853.982	25	16	1	10.95927
3875	136.3553	134.0743	500	700	35	5890.486	25	12	1	14.87956
4291.667	153.2006	151.0337	500	700	35	7853.982	25	16	1	10.89415
4099.665	193.316	184.2994	500	700	35	7853.982	25	16	1	8.047841
3957.5	210.7178	198.1267	500	700	35	7853.982	25	16	1	9.293391
4633.333	198.4684	168.9901	500	800	35	7853.982	25	16	1	10.4624
4460.623	240.3263	197.2777	500	800	35	7853.982	25	16	1	6.36264
3891.667	128.0793	180.2874	600	600	35	5890.486	25	12	1	12.25622
4308.333	141.8155	201.469	600	600	35	7853.982	25	16	1	9.955275
4193.302	162.3667	228.4481	600	600	35	7853.982	25	16	1	7.55824
3986.667	183.4819	253.4039	600	600	35	7853.982	25	16	1	9.013059
4808.333	171.3137	205.7938	600	700	35	7853.982	25	16	1	12.56487
4624.665	210.2945	247.4471	600	700	35	7853.982	25	16	1	9.73719
5225	222.0848	230.2781	600	800	35	7853.982	25	16	1	11.84639
5333.333	187.8036	265.4663	700	700	35	7853.982	25	16	1	13.64709
475	11.30522	14.04493	200	200	35	2035.752	18	8	1	1.775787
708.3333	21.21392	15.09074	200	300	35	2035.752	18	8	1	0.276281
655	16.4	16.14205	200	300	35	2035.752	18	8	0.837312	21.89824
891.6667	25.38116	18.14733	200	300	35	3053.628	18	12	1	5.305954
868.121	26.37631	18.64031	200	300	35	3053.628	18	12	1	3.926565
660.2907	33.93792	20.89222	200	300	35	3053.628	18	12	1	3.281349
769.1667	29.97662	20.21369	200	300	35	3053.628	18	12	1	1.451834
945	36.5	22.15081	200	400	35	3053.628	18	12	0.882759	0.901591
1000	40	21.05205	200	400	35	3053.628	18	12	0.961206	1.986302
1166.667	46.3	24.37008	200	400	35	4071.504	18	16	0.94544	1.7051
923.8944	64.15145	27.41553	200	400	35	4071.504	18	16	1	6.253794
1000	60.01396	26.87663	200	400	35	4071.504	18	16	1	5.020721
1100	46.5	25.67247	200	400	35	4071.504	18	16	0.913007	5.23806
1141.667	52.4	23.24816	200	500	35	3053.628	18	12	0.921721	0.271528
1275	66.6	27.26781	200	500	35	4071.504	18	16	0.940799	6.26779
1124.167	84.92586	29.54113	200	500	35	4071.504	18	16	1	8.893441
1000	21.39248	29.46317	300	300	35	2035.752	18	8	1	3.20251
1208.333	24.6432	34.56773	300	300	35	3053.628	18	12	1	8.830226
1056.371	31.09597	41.43929	300	300	35	3053.628	18	12	1	3.710687
1107.5	28.92488	39.26912	300	300	35	3053.628	18	12	1	4.772765
1375	29.93987	42.0986	300	300	35	4071.504	18	16	1	5.892117

1226.779	36.23598	48.80752	300	300	35	4071.504	18	16	1	4.002783
1307.5	32.80712	45.28316	300	300	35	4071.504	18	16	1	4.259872
1040.833	42.64247	53.66541	300	300	35	4071.504	18	16	1	2.854945
1137.5	39.31195	51.36591	300	300	35	4071.504	18	16	1	3.284968
1295.856	30.50853	30.01542	300	400	35	2035.752	18	8	1	22.39717
1541.667	31.13277	32.06791	300	400	35	3053.628	18	12	1	10.65524
1499.263	35.98238	35.41117	300	400	35	3053.628	18	12	1	5.904287
1383.333	43.25728	41.18771	300	400	35	3053.628	18	12	1	7.898269
1750	36.42008	37.50059	300	400	35	4071.504	18	16	1	9.656884
1700.928	41.90646	41.14933	300	400	35	4071.504	18	16	1	6.611092
1467.707	56.71481	52.43152	300	400	35	4071.504	18	16	1	1.928415
1580.833	49.53189	47.21209	300	400	35	4071.504	18	16	1	2.313865
1315	64.7192	57.41338	300	400	35	4071.504	18	16	1	1.03042
1750	47.51407	38.14933	300	500	35	3053.628	18	12	1	22.36417
1665	57.16151	42.63537	300	500	35	3053.628	18	12	1	17.78817
1958.333	54.4625	43.53043	300	500	35	4071.504	18	16	1	4.890051
1907.206	61.88083	46.31162	300	500	35	4071.504	18	16	1	5.170669
1699.879	79.23692	56.38961	300	500	35	4071.504	18	16	1	6.883541
1753.333	74.76206	53.92731	300	500	35	4071.504	18	16	1	7.062897
1958.333	66.8	43.34632	300	600	35	3053.628	18	12	0.997244	27.82222
2208.333	68.26128	44.83594	300	600	35	4071.504	18	16	1	20.51812
2119.625	84.09391	51.15748	300	600	35	4071.504	18	16	1	12.12519
2046.667	91.64718	54.84316	300	600	35	4071.504	18	16	1	12.03455
1808.333	40.4556	57.06691	400	400	35	3053.628	18	12	1	21.97149
2000.928	47.45046	67.32639	400	400	35	4071.504	18	16	1	8.026256
1730.957	64.53102	86.7284	400	400	35	4071.504	18	16	1	11.49607
1875	55.41772	76.79643	400	400	35	4071.504	18	16	1	10.37923
2333.333	62.91277	69.6977	400	500	35	4071.504	18	16	1	23.8177
2282.206	70.54333	76.20235	400	500	35	4071.504	18	16	1	20.2318
2191.667	78.07327	82.99685	400	500	35	4071.504	18	16	1	20.35219
2641.667	83.38495	75.74656	400	600	35	4071.504	18	16	1	26.46493
2708.333	71.42133	100.6518	500	500	35	4071.504	18	16	1	23.48264
1544.914	61.73637	60.4559	300	400	25	4561.593	22	12	1	5.232203
1655.833	54.82794	55.00968	300	400	25	4561.593	22	12	1	3.769223
2208.333	46.73913	48.51293	300	400	25	6082.123	22	16	1	11.17146
2119.849	53.74773	54.94397	300	400	25	6082.123	22	16	1	7.807448
1809.874	73.29638	71.00533	300	400	25	6082.123	22	16	1	2.001313
1953.333	64.24908	63.94865	300	400	25	6082.123	22	16	1	1.793991
1750	47.4	41.9581	300	500	25	3041.062	22	8	0.955377	8.112693
2041.667	62.1	51.03771	300	500	25	4561.593	22	12	0.982595	2.825911

1778.946	86.11828	65.01089	300	500	25	4561.593	22	12	1	0.081653
1905.833	75.64526	58.55762	300	500	25	4561.593	22	12	1	1.078644
2389.167	69.2	56.88235	300	500	25	6082.123	22	16	0.98041	1.382013
2315.225	79.08888	61.43546	300	500	25	6082.123	22	16	1	0.236167
2046.407	101.6229	75.44885	300	500	25	6082.123	22	16	1	3.119554
2147.5	93.14863	70.3949	300	500	25	6082.123	22	16	1	2.099161
1904.167	111.8222	81.71389	300	500	25	6082.123	22	16	1	3.284748
2333.333	77.31623	50.86686	300	600	25	4561.593	22	12	1	1.593871
2224.363	90.53066	58.27073	300	600	25	4561.593	22	12	1	3.917855
2138.333	99.34106	62.97454	300	600	25	4561.593	22	12	1	4.934109
2583.333	98.3	63.57602	300	600	25	6082.123	22	16	0.995923	0.176291
2278.203	131.9938	80.05489	300	600	25	6082.123	22	16	1	0.08737
2454.167	113.665	70.91943	300	600	25	6082.123	22	16	1	0.577003
2111.667	146.9292	87.88261	300	600	25	6082.123	22	16	1	0.483963
2166.667	46.42556	70.49633	400	400	25	4561.593	22	12	1	2.502911
1954.167	60.45767	89.79362	400	400	25	4561.593	22	12	1	2.022837
2071.667	53.15278	80.36655	400	400	25	4561.593	22	12	1	0.125752
2500	52.9919	80.46721	400	400	25	6082.123	22	16	1	2.732871
2071.624	81.18783	117.6044	400	400	25	6082.123	22	16	1	2.208578
2296.667	67.03733	100.3834	400	400	25	6082.123	22	16	1	4.012004
1869.167	91.70214	128.1181	400	400	25	6082.123	22	16	1	0.107698
2416.667	72.6582	84.79484	400	500	25	4561.593	22	12	1	5.147349
2750	81.73384	94.87492	400	500	25	6082.123	22	16	1	4.983109
2383.157	113.3313	125.4947	400	500	25	6082.123	22	16	1	2.786463
2565	98.18308	111.4259	400	500	25	6082.123	22	16	1	5.144705
3041.667	110.538	104.2946	400	600	25	6082.123	22	16	1	6.6394
2860.833	130.559	120.2518	400	600	25	6082.123	22	16	1	7.429288
3382.5	135.5767	107.922	400	700	25	6082.123	22	16	1	5.159091
3208.333	82.13924	124.7269	500	500	25	6082.123	22	16	1	2.804214
3065.225	96.41388	146.2637	500	500	25	6082.123	22	16	1	4.144868
3120	90.95024	138.1062	500	500	25	6082.123	22	16	1	4.103111
3541.667	117.0697	144.3038	500	600	25	6082.123	22	16	1	7.715557
1125	48.5	24.36536	200	400	30	3926.991	25	8	0.954129	6.567317
1541.667	88.3	33.72274	200	500	30	5890.486	25	12	0.945653	2.06584
1401.667	107.7822	35.91488	200	500	30	5890.486	25	12	1	1.957012
1391.667	28.07963	40.96242	300	300	30	3926.991	25	8	1	3.693216
1675.719	42.28999	42.27628	300	400	30	3926.991	25	8	1	4.95336
2074.505	52.39499	52.17683	300	400	30	5890.486	25	12	1	6.677657
1754.17	72.1603	67.63421	300	400	30	5890.486	25	12	1	5.282286
1874.167	64.75626	62.20296	300	400	30	5890.486	25	12	1	4.063535

2269.277	77.42111	58.22384	300	500	30	5890.486	25	12	1	2.971256
2102.5	91.13426	66.58513	300	500	30	5890.486	25	12	1	1.792602
2655.361	93.16049	69.19446	300	500	30	7853.982	25	16	1	6.994017
2333.995	120.0148	84.82518	300	500	30	7853.982	25	16	1	6.899102
2501.667	106.0037	76.95772	300	500	30	7853.982	25	16	1	6.217135
2148.333	133.4864	92.11941	300	500	30	7853.982	25	16	1	8.802651
2854.167	125.4194	75.02156	300	600	30	7853.982	25	16	1	5.016837
2568.138	155.2258	89.01523	300	600	30	7853.982	25	16	1	5.610622
2703.333	141.1374	82.61084	300	600	30	7853.982	25	16	1	4.597127
2374.505	57.93899	85.60034	400	400	30	5890.486	25	12	1	1.967434
2875	58.85101	88.35165	400	400	30	7853.982	25	16	1	2.665044
2769.316	68.88668	102.2253	400	400	30	7853.982	25	16	1	2.322293
2354.047	94.78354	133.1221	400	400	30	7853.982	25	16	1	6.013959
2536.667	83.39508	120.2437	400	400	30	7853.982	25	16	1	7.372003
3166.667	84.9799	97.14038	400	500	30	7853.982	25	16	1	2.247782
3030.361	101.823	113.2267	400	500	30	7853.982	25	16	1	1.221813
2843.333	117.3643	127.656	400	500	30	7853.982	25	16	1	2.915045
3500	108.1332	100.3109	400	600	30	7853.982	25	16	1	0.27378
3558.333	91.32459	136.0601	500	500	30	7853.982	25	16	1	0.749018
899.1667	25.32153	18.65029	200	300	30	3053.628	18	12	1	8.079396
1209.234	49.11024	24.3377	200	400	30	4071.504	18	16	1	5.568107
1375	30.2783	43.72779	300	300	30	4071.504	18	16	1	0.435069
1706.824	42.03581	42.54885	300	400	30	4071.504	18	16	1	6.084891
2108.333	42.4	48.53274	300	400	35	5890.486	25	12	0.934351	27.33337
2750	78.58133	61.66612	300	500	35	7853.982	25	16	1	17.81566
2644.237	92.80844	67.27255	300	500	35	7853.982	25	16	1	10.09849
2673.333	84.2	65.80323	300	500	35	7853.982	25	16	0.96831	15.57907
3000	98.8122	63.16827	300	600	35	7853.982	25	16	1	13.07338
2841.667	59.74805	87.32579	400	400	35	7853.982	25	16	1	7.74877
2757.822	68.65229	99.34305	400	400	35	7853.982	25	16	1	3.056379
2600	78.48615	111.2795	400	400	35	7853.982	25	16	1	2.02046