ARTIFICIAL INTELLIGENCE FOR DESIGN OF BRIDGES

by

B. V. D. N. Chandrasiri

1. INTRODUCTION

Design of Bridges or Buildings or any other structure, is generally said and recognized to be of cyclic nature, which requires initial assumptions, analysis, designs and validation, in an iterative manner, to achieve an optimum solution to a given problem. This process, generally called the "top down" is the most popular technique among the general designers of today, since the other available options of Bottom up approach and case based reasoning being more of reflective nature, in comparison to the rationality of the top down decomposition.

The availability of computers and software designed to analyze structural problems has immensely simplified the analysis (rational) phase of the design. However the initial phase of any design, which involves decision making (rather than technical rationality) has not been addressed by available literature/software to the same extent as the analysis. This probably is due to the ill-structured nature of the problem, which is not readily suited for the conventional programming techniques, adopted by software developers.

In a practical design, the initial design decisions are taken, based on the designer's experience and intuition, which could only be conveniently computerized through the process of Artificial Intelligence. It is intended to present some possible techniques in this approach, adopted over in bridge design environment, during this paper.

2. ARTIFICIAL INTELLIGENCE

Generally, 02 Artificial Intelligence techniques are available, for making design decisions.

(1) Expert Systems

(2) Neural networks

2.1 EXPERT SYSTEMS

Expert Systems attempt to model the problem solving expertise of a human expert. This will require the knowledge of the expert, to be stored on a database in the computer. Here generally the knowledge is directed towards rationally eliminating **probable solutions** to a given problem. ("What if –then – else" situation) these guidelines are called facts and rules, inside the knowledge base, and hence the name, rule based or knowledge based expert systems. The problem solving mechanism involves drawing inferences and controlling the reasoning process. These strategies are compiled through what is called the inference engine of the expert system.

Generally, the knowledge base includes two different type of knowledge; factual and heuristic. Factual knowledge is the documented theories, found in textbooks and other references and hence can be termed common knowledge. The heuristic knowledge is the knowledge exclusive to the expert, gained through experience, thumb rules etc.

Figure I below show the mechanism involved in an expert system.

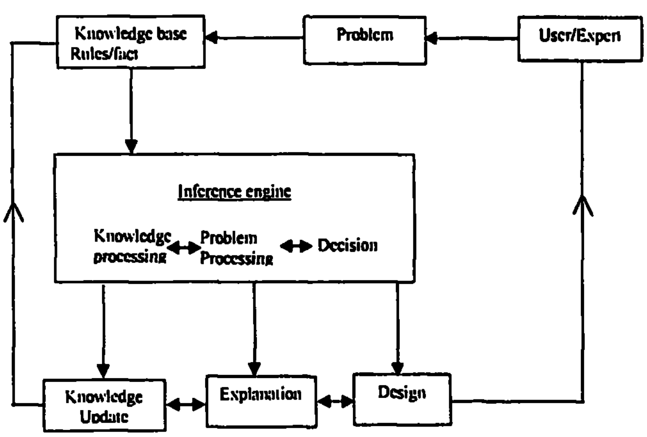


Figure 1 - Representation of an Expert System

Eng. B.V.D.N. Chandrasiri BSc (Eng)., CEng., MIE (SL), Director (Maintenance Management & Construction), Road Development Authority.

One of the important aspects of an expert system is that the rationale for arriving at end result is also transparent to the user (explanation) with a probabilistic confidence rating.

2.2 NEURAL NETWORKS

This approach can best be described by visualizing, that the expert codifies case studies, where he got involved, instead of his knowledge. These case histories may have similarities, with a given problem, which may not be obvious even to the naked eye of the expert. The computer will establish relationships between these inputs/outputs, which could be termed the training phase of a Neural Network. Once such training is accomplished, the trained Network could be presented with fresh data representing new problems, to which the computer could respond by presenting the probable response of an expert (or case histories) to a given design brief.

The knowledge contained in an ANN is implicit, when compared to the expert system's explicit knowledge. The ANN approach is more natural to the human beings, since we use large amounts of implicit knowledge in our day to day activities. However it should be recognized that ANN knowledge is restrictive, in that it depends only on implicit case studies. A diagrammatic representation of an ANN is given in figure 2.

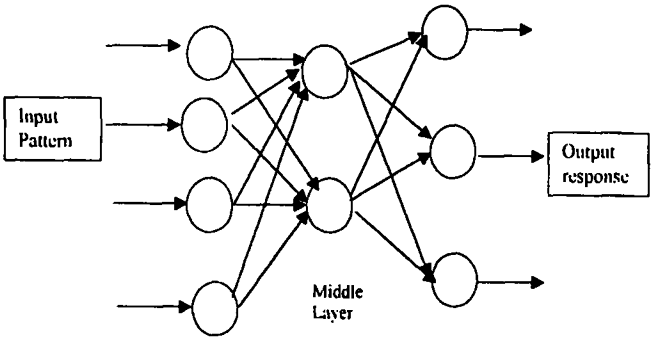


Figure 2 - Representation of an ANN

3. USING ARTIFICIAL INTELLIGENCE IN BRIDGE DESIGN

3.1 IMPLEMENTING AN EXPERT SYSTEM

Implementing an expert system in bridge design first requires identifying the knowledge of the bridge design process, to use to build and develop a knowledge base. Possible steps in the bridge design process are shown in figure 3.

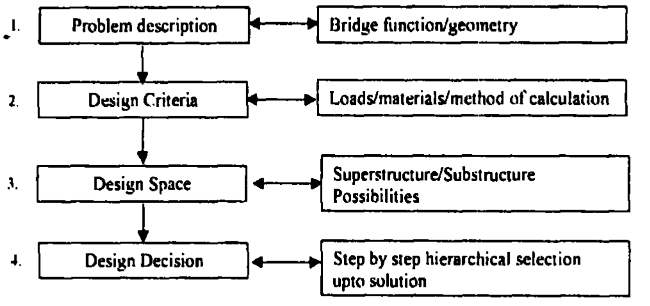


Figure 3 - Design Procedure

On the above procedure, the steps 1 and 2 does not require the inferencing knowledge of the expert system, if considered in our context. The bridge geometry, the function, and the loads/materials/method of calculation can be case specific; and hence could be rigidly implanted in the expert system.

However the third step will require establishing all possible bridge configurations, (within a reasonable space) each of which needs to be considered and discarded in a systematic (breadth first or depth first) way in arriving at a final structural configuration with suitable articulation. This will require both factual and heuristic knowledge of the expert system.

The final step can again be represented on a top down order as shown in figure 04.

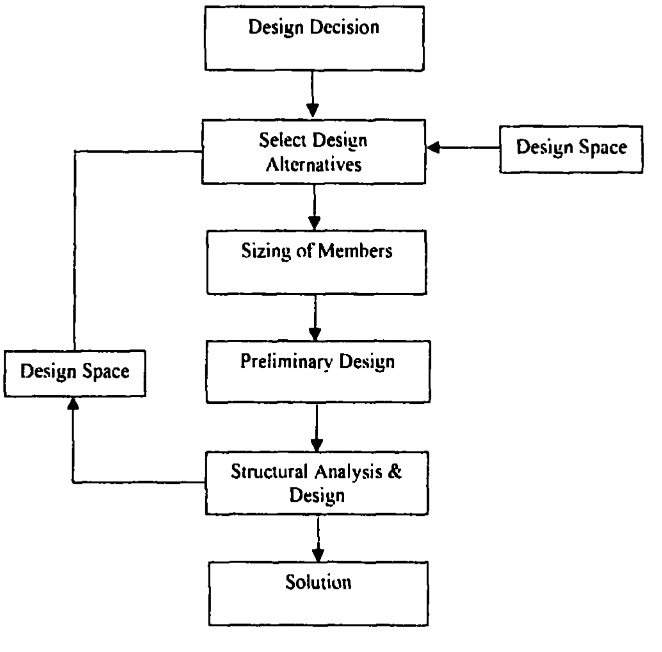


Figure 4 - Representation of Design Process

From above, it can be seen that the design decision, process would again involve both factual (in structural analysis) and heuristic (in sizing) knowledge of the expert system. However the design achieved by one designer may change from another, due to different weightages given to aesthetics, environment, economic factors and the different optimization techniques involved (least weight, least cost etc.).

3.2 IMPLEMENTING AN ARTIFICIAL NEURAL NETWORK

ANN knowledge as stated earlier is of implicit nature; and hence is better suited for case histories in a design environment. If sufficient numbers of case histories are found, to represent a wider domain, of a problem, a relationship can be found through ANN, which could be used, for future decision making. This implies the knowledge lean nature of an ANN, compared to an expert system.

In the bridge design process, number of initial assumptions, or decisions have to be made, in finding a solution. For example, the type of foundation, number of spans, type of structure are all decisions, that could depend on several factors extraneous to structural requirements. However these decisions are major decisions, which could affect the final solution to a great extent, if not selected intelligently.

In a design office, where such decision have been taken for large number of projects in the past representing a wider range of bridge layout and geometry, these case histories can be fed to an ANN, to establish possible pattern in the decisions hitherto taken. This phase is called the training of the Network. The efficiency of the training depends on the type of Network selected (i.e. No. Of middle layers, function type etc.) And the number of training data available for a given bridge configuration.

Once the ANN is trained, using case histories, the same ANN can be used to provide solution to future problems; (based on the trained data) thus providing a decision making tool.

It may be construed that the above approach is somewhat analogues to multiple regression approach in a mathematical design process, though it has been shown, that ANN provides more probable decisions (for structural design) than the conventional regression based approach. (4)

4.0 APPLICATION EXAMPLE

4.1 FORMULATION OF ANN

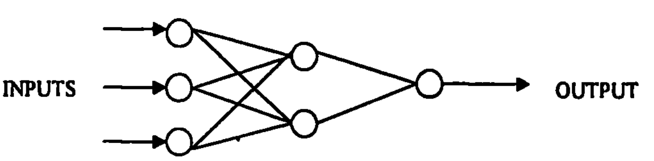
In the Sri Lankan bridge industry, the scope being limited, due to economy and the geometrics, the emphasis is more for small to medium scale spans, which are mostly decked with precast prestressed beams to form slabs or beam and slab superstructures, posing hardly any engineering challenges.

However, especially for these small span bridges, the substructure including foundations presents formidable engineering problems where considerable engineering judgement has to be exercised.

This subjective judgement can present an opportunity for forming either an Expert system or an ANN as a supporting tool for the decision-maker. However since an Expert system will be somewhat difficult to achieve, due to practicalities of the profession, an ANN can be easily trained based on the large number of already taken decisions in the past of the bridge industry.

The foundation type is generally decided, based on soil type, (representing allowable bearing capacity) span and height of substructure, (representing applied loads). Hence the ANN was considered for deciding an abutment foundation type representing span, abutment height to scoured bed level and average standard penetration test (SPT) value of the soil for a depth of 5.0m below scoured bed. The output required being a single foundation type, represented by a number.

The ANN was designed so, with 3 input nodes and one output node with a single intermediate level of 2 nodes. The data was collected to represent the domain of common design situations as far as possible, to better represent the random nature of the problem. The internal transformation function was selected to be the sigmoid function.



The minimum number of training examples required is (2x3+2+1) 9.

Hence the minimum number of historical data sets required are about 15, considering 2/3 of data as training and 1/3 for testing.

For the example, 34 data sets were used, with 12 reserved for testing and balance 22 taken for training. (See attached lists)

4.2 TRAINING AND EVALUATION

While training the learning and momentum parameters a,b respectively were changed to control training instability. Final values of these variables are being 0.9 and 0.05.

The training was conducted on windows neural network (WINNN), software environment, where 90% of the data got trained.

Once the network got trained, test data were fed through the trained network and the results were obtained to find the error involved.

The accuracy of the test set can be measured by following indices.

1.0 Mean Absolute Error (MAE)
2.0 Standard deviation of the ratio between predicted and desired (RSTD)
3.0 Absolute difference between unity and the average ratio between predicted and desired. (1-RAVG)

The results of the training run, test run, are attached with the graphical co-relation between the assumed pattern and the actual and the assigned weightage distribution through back-propagation.

Further, a multiple regression analysis too was performed using the training set of data, to arrive at a representative exponential function, using Microsoft Excel spreadsheet to compare the results of ANN with regression analysis. The equation and the comparison are also attached.

5.0 CONCLUSION

The Decisions/Analysis required in a design space, can be supplemented through Artificial Intelligence techniques to provide an easy to use, uniform set of solutions to a given problem, through sharing of the knowledge of the expert and codifying available experience in a computerized environment. However since it has been found that the probability of making an expert imparting his entire knowledge is not very high, ANN provides better prospects in a design office environment, for initial design decisions.

The example presented demonstrates the flexibility of the ANN method to enhance the quality of judgement in a conventional design office environment.

The comparison between regression analysis and the ANN results clearly shows that ANN, is the better tool in predicting non- linear relationships. However the disadvantage of ANN is that analysis of significance are not very easy or straightforward, when compared with regression.

6.0 ACKNOWLEDGEMENT

The author wishes to thank the entire RDA management for allowing the publication of this document and wishes especially to thank Prof. Priyan Dias of the University of Moratuwa, for imparting his knowledge selflessly and Eng. D.P.Mallawaarachi of the Road Development Authority, for encouraging the engineers on more and more research works.

REFERENCES:

1. Structural Design of Bridges - Transportation Research Board National Research Council (Transportation Research Record 1072) Washington D.C. 1986, pp 65-70
2. Expert Systems - Jean – Louis Ermine Prentice Hall of India Pvt. Ltd.
3. Course Notes for 'Design Methodology" M.Eng in Structural Engineering. - Prof. Priyan Dias – University of Moratuwa
4. Analysis of Bridge Cindition Rating data using Neural Networks - Cattan J. & Mohammadi J., 1997 Microcomputers in Civil Engineering - pp. 419-429.
5. A knowledge based wxport system application in structural safety assessment of concrete bridges - Miyamoto, A., et. al., Japan 1993, - Bridge Management 2, Edited by J. E. Harding et. al., pp 96-108.
6. Analysis of Bridge Condition Rating data using Neural Networks A knowledge based expert system application in structural safety assessment of concrete bridges.

Name of Bridge	Span	Abutment height to Scour Level	Avg. N. for (0.0-5.0) below scour	Type of Fdn.
131/4 on CRWB road	3.3	7.3	32	03
116/10 on CRWB road	6.6	3.2	09	02
117/10 on CRWB road	5.0	3.35	07	02
126/3 on CRWB road	7.5	3.45	09	03
144/3 on CRWB road	18.59	5.46	05	02
Idanpitiya Bridge on Padiyapelella Elamulla Rd	6.615	13.57	>50	01
Nawala Rd - Pagoda Rd Connection	10.34	3.88	07	02
2/4 Pitakotte Talawatugoda Rd	7.0	3.29	07	02
12/16 Matara Hakmana Rd	4.15	2.96	13	02
154/2 CGH	10.3	3.5	08	02
59/2 PNR	6.65	3.1	12	02
59/2 PNR	6.65	5.5	20	01
92/2 CRWB	11.82	4.935	13	02
92/2 CRWB	11.82	4.935	32	01
1/5 Kaluaggala Labugama Rd	15.77	4.925	18	02
- do -	15.77	4.925	25	01
Obesekarapura	10.31	4.955	02	2
- do -	10.31	4.955	08	2
25/4 PNR	13.0	7.7	34	01
- do -	13.0	5.45	20	02
62/4 Colombo Puttalam Rd	27.129	8.332	47	1
Lewella Bridge	22.14	7.57	>50	1
Muhuwadiya Bridge	22.14	7.63	11.5	2
43/3 Colombo Puttalam Rd	22.14	7.03	09	2
Halwatura Bridge	27.129	8.918	>50	1
Getambe Bridge	27.129	6.123	>50	1
1/1 Akurana Kamburupitiya	18.59	6.316	08	2
8/1 Ambepussa Kurunegala Trincomalee Rd	18.59	11.973	>50	1
Ragama Flyover	18.59	6.875	14	1
51/1 CGH Rd	18.59	1.38	05	2
88/1 CRWB Rd	18.59	6.13	07	2
1/1 Veyangoda Ruwanwella Rd	15.8	4.315	18	1
- do -	15.8	4.315	07	1
43/1 CRWB (Kalunggala)	13.0	6.33	12	2

Types of Foundations
1 Spread / Caission
2 Pile / Cylinders
3 Raft / BoxCulvert

Complete Data Set

TRAINING DATA

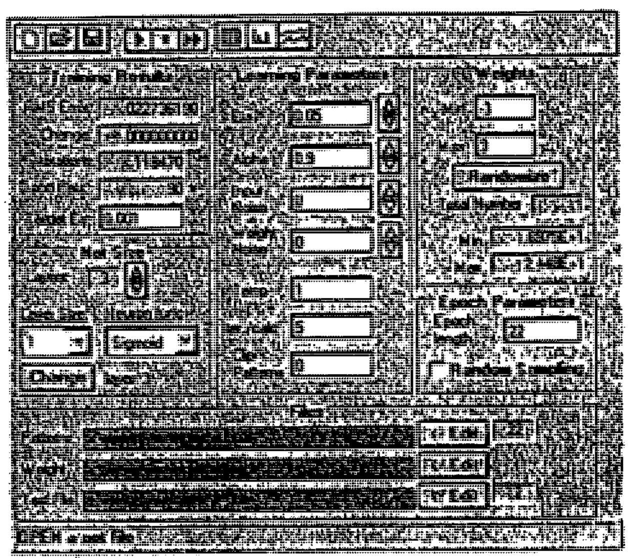
Name of Bridge	Span	Abutment height to Scour Level	Avg. N. for (0.0-5.0) below scour	Type of Fdn.
131/4 on CRWB road	3.3	7.3	32	03
116/10 on CRWB road	6.6	3.2	09	02
144/3 on CRWB road	18.59	5.46	05	02
Idanpitiya Bridge on Padiyapelella Elamulla Rd	6.615	13.57	>50	01
Nawala Rd - Pagoda Rd Connection	10.34	3.88	07	02
2/4 Pitakotte Talawatugoda Rd	7.0	3.29	07	02
154/2 CGH	10.3	3.5	08	02
59/2 PNR	6.65	5.5	20	01
92/2 CRWB	11.82	4.935	13	02
1/5 Kaluaggala Labugama Rd	15.77	4.925	18	02
- do -	15.77	4.925	25	01
Obesekarapura	10.31	4.955	02	2
25/4 PNR	13.0	7.7	34	01
62/4 Colombo Puttalam Rd	27.129	8.332	47	1
Lewella Bridge	22.14	7.57	>50	1
Muhuwadiya Bridge	22.14	7.63	11.5	2
Halwatura Bridge	27.129	8.918	>50	1
1/1 Akurana Kamburupitiya	18.59	6.316	08	2
8/1 Ambepussa Kurunegala Trincomalee Rd	18.59	11.973	>50	1
51/1 CGH Rd	18.59	1.38	05	2
1/1 Veyangoda Ruwanwella Rd	15.8	4.315	18	1
43/1 CRWB (Kalunggala)	13.0	6.33	12	2

Types of Foundations
1 Spread / Caission
2 Pile / Cylinders
3 Raft / BoxCulvert

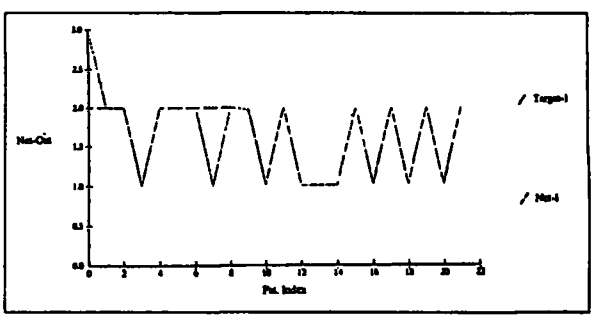
TESTING DATA

Name of Bridge	Span	Abutment height to Scour Level	Avg. N. for (0.0-5.0) below scour	Type of Fdn.
117/10 on CRWB road	5.0	3.35	07	02
126/3 on CRWB road	7.5	3.45	09	03
12/16 Matara Hakmana Rd	4.15	2.96	13	02
59/2 PNR	6.65	3.1	12	02
92/2 CRWB	11.82	4.935	32	01
Obeysekarapura	10.31	4.955	08	2
25/4 PNR	13.0	5.45	20	02
43/3 Colombo Puttalam Rd	22.14	7.03	09	2
Getambe Bridge	27.129	6.123	>50	1
Ragama Flyover	18.59	6.875	14	1
88/1 CRWB Rd	18.59	6.13	07	2
1/1 Veyangoda Ruwanwella Rd	15.8	4.315	07	1

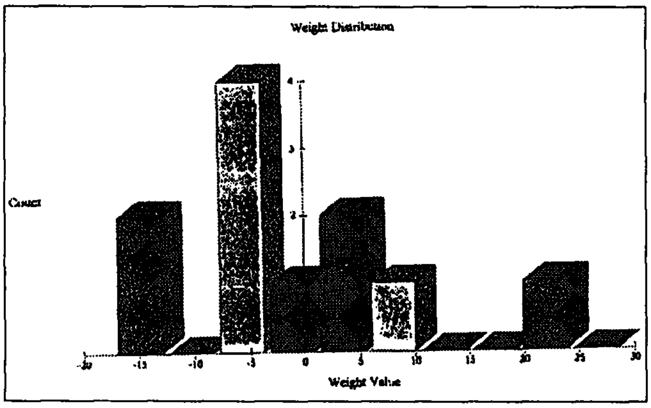
Types of Foundations
1 Spread / Caission
2 Pile / Cylinders
3 Raft / BoxCulvert



Neural Network Panei of "WINNN" at the end of training



Graphical representation of the accuracy of trained Network



Final anigned weight distribution in the trained Network

RESULTS OF THE TRAINING RUN

RMS ERROR 0.022736
GOOD PATTERNS 90.9%

	Output Results	Pesired Results	RMS ERROR
0001)	2.001958	3.000000	0.249022 -
0002)	2.001992	2.000000	0.000001 +
0003)	2.001992	2.000000	0.000001 +
0004)	1.004219	1.000000	0.000004 +
0005)	2.001992	2.000000	0.000001 +
0006)	2.001992	2.000000	0.000001 +
0007)	2.001992	2.000000	0.000001 +
0008)	2.001992	1.000000	0.250997 -
0009)	2.001992	2.000000	0.000001 +
0010)	1.978089	2.000000	0.000120 +
0011)	1.000007	1.000000	0.000000 +
0012)	2.001992	2.000000	0.000001 +
0013)	1.000003	1.000000	0.000000 +
0014)	1.000000	1.000000	0.000000 +
0015)	1.000000	1.000000	0.000000 +
0016)	1.998445	2.000000	0.000001 +
0017)	1.000000	1.000000	0.000000 +
0018)	2.001988	2.000000	0.000001 +
0019)	1.000000	1.000000	0.000000 +
0020)	2.001226	2.000000	0.000000 +
0021)	1.013068	1.000000	0.000043 +
0022)	2.001992	2.000000	0.000001 +

RESULTS OF THE TEST RUN

RMS ERROR 0.062572
GOOD PATTERNS 75%

	Output Results	Pesired Results	RMS ERROR
0001)	2.001992	2.000000	0.000001 +
0002)	2.001992	3.000000	0.249005 -
0003)	2.001992	2.000000	0.000001 +
0004)	2.001992	2.000000	0.000001 +
0005)	1.000007	1.000000	0.000000 +
0006)	2.001992	2.000000	0.000001 +
0007)	2.001790	2.000000	0.000001 +
0008)	2.001494	2.000000	0.000001 +
0009)	1.000000	1.000000	0.000000 +
0010)	2.001704	1.000000	0.250853 -
0011)	2.001990	2.000000	0.000001 +
0012)	2.001992	1.000000	0.250997 -

<u>RESULTS OF THE TEST RUN (ANN)</u>

RMS ERROR 0.062572
) PATTERNS 75%

Serial No.	Tr.results Predicted	Actual Desired	RMS error	%error	Ratio Pred/Des.
0001)	2.001992	2.000000	0.000001	0.099501	1.000996
0002)	2.001992	3.000000	0.249005	-49.850749	0.667331
0003)	2.001992	2.000000	0.000001	0.099501	1.000996
0004)	2.001992	2.000000	0.000001	0 099501	1.000996
0005)	1.000007	1.000000	0.000000	0 000700	1.000007
0006)	2.001992	2.000000	0.000001	0 099501	1.000996
0007)	2.001790	2.000000	0.000001	0.089420	1.000895
0008)	2.001494	2.000000	0.000001	0.074644	1.000747
0009)	1.000000	1.000000	0.000000	0.000000	1.000000
0010)	2.001704	1.000000	0.250853	50.042564	2.001704
0011)	2.001990	2.000000	0.000001	0.099401	1.000995
0012)	2.001992	1.000000	0.250997	50.049750	2.001992

Mean Absolute Error(MAE) 0.509037
RSTD 0.413800
1-RAVG 0.139805

<u>Multiple regression analysis</u>

Results Predicted	Actual Desired	%Error	Ratio Pred/Desired
2.183977	2	8.423944	0.259258
2.183977	3	-37.364084	-0.058451
2.183977	2	8.423944	0.259258
2.183977	2	8.423944	0.259258
2.183977	1	54.211972	0.040286
2.183977	2	8.423944	0.259258
2.183977	2	8.423944	0.259258
2.183977	2	8.423944	0.259258
2.183977	1	54.211972	0.040286
2.183977	1	54.211972	0.040286
2.183977	2	8.423944	0.259258
2.183977	1	54.211972	0.040286

Mean Absolute Error(MAE) 19.870951
RSTD 0.400615
1-RAVG 0.840208

Multiple Regression Analysis
Of input variables

X1	X2	X3	Y
3.30	7.30	32.00	3.00
6.60	3.20	9.00	2.00
18.59	5.46	5.00	2.00
6.62	13.57	50.00	1.00
10.34	3.88	7.00	2.00
7.00	3.29	7.00	2.00
10.30	3.50	8.00	2.00
6.65	5.50	20.00	1.00
11.82	4.94	13.00	2.00
15.77	4.93	18.00	2.00
15.77	4.93	25.00	1.00
10.31	4.96	2.00	2.00
13.00	7.70	34.00	1.00
27.13	8.33	47.00	1.00
22.14	7.57	50.00	1.00
22.14	7.63	11.50	2.00
27.13	8.92	50.00	1.00
18.59	6.32	8.00	2.00
18.59	11.97	50.00	1.00
18.59	1.38	5.00	2.00
15.80	4.32	18.00	1.00
13.00	6.33	12.00	2.00

The equation to be used is

Y=A*P^X1*Q^X2*R^X3

Where A, P, Q, R, are constants

The results obtained are

R	Q	P	A
0.98267	1.0232275	0.9922873	2.1839769