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قسم الإنشاءات والأساسات

Prediction of Ultimate Shear Strength of Reinforced Concrete Deep Beams Using Artificial Neural Networks

M. Sc. Thesis

Submitted to the Faculty of Engineering
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بسم الله الرحمن الرحيم

"قالوا سبحانك لا علم لنا إلا ما علمتنا إنك أنت العليم الحكيم"

البقرة- 32

"رب إني لما أنزلت إلي من خير فقير"

القصص- 24

الملخص

تم استخدام طريقة الشبكات العصبية الصناعية والتي هي إحدى طرق الذكاء الصناعي لتطوير عدة نماذج بغرض تخمين قوة القص القصوى للكمرات المسلحة العميقة.

استخدمت في هذه الدراسة قاعدة بيانات واسعة لتجارب مختبريه تم تجميعها بعناية من دراسات سابقة. احتوت قاعدة البيانات المستخدمة على تجارب مختبريه لعدد 161 كمرة مسلحة عميقة ذات خرسانة عادية المقاومة وعدد 42 كمرة مسلحة عميقة ذات خرسانة عالية المقاومة.

تم تدريب النماذج المطورة على تخمين مقاومة القص القصوى باستخدام قاعدة البيانات بعد مرورها بعدة مراحل من المعالجة والتدقيق.

من خلال دراسة الأبحاث السابقة التي نشرت في هذا الموضوع، تم اعتماد عدد سبعة متغيرات كمدخلات لنموذج الشبكات العصبية في كلا الحالتين الكمرات ذات الخرسانة العادية والعالية المقاومة، أما المخرجات فكانت مخرج واحد هو قوة القص القصوى للكمرات في الحالتين .

لتدريب الشبكة العصبية تم استخدام تقنية feed forward back propagation لبناء الشبكة العصبية المطلوبة وباستخدام طريقة المحاولة والخطأ، تم تحديد الشكل المعماري للشبكة العصبية المناسبة والذي احتوى على أربعة طبقات، طبقة المدخلات وبها سبعة خلايا عصبية neurons ، وطبقتين مخفيتين كل منهما بها خمسة خلايا وطبقة المخرجات وبها خلية واحدة وذلك في كلا الحالتين الخرسانة العادية والخرسانة عالية المقاومة.

أظهرت عملية التدريب أن النسبة بين قوة القص النهائية لكمرات مفحوصة سابقا إلي قوة القص المخمنة بواسطة الشبكة العصبية المطورة تساوى 1.04فى حالة الخرسانة عادية المقاومة وتساوى 1.002 في حالة الخرسانة عالية المقاومة.

قورنت هذه القيم مع قيم لكمرات مماثلة محسوبة باستخدام معادلات معهد الخرسانة الأمريكي (ACI) فكانت القيم كما يلي:2.78 في حالة الخرسانة العادية و 1.228 في حالة الخرسانة العالية المقاومة. هذه المقارنة تظهر مدى قوة الشبكات العصبية التي تم تطويرها في تخمين قوة القص القصوى للشبكات العصبية.

استخدمت أيضا الشبكات العصبية المطورة في إجراء دراسة لتأثير المدخلات (المتغيرات) كل علي حده علي المخرجات (قوة القص القصوى) وقد لوحظ أن shear span to depth ratio تعطي التأثير الأكبر علي قوة القص القصوى والعامل الآخر الذي يؤثر بشكل فعال علي قوة القص القصوى هو قوة تحمل الضغط للخرسانة.

ABSTRACT

The artificial neural networks (ANN) was used to develop a number of models in order to predict the ultimate shear strength of reinforced concrete deep beams for both normal and high concrete compressive strength. In this study a large number of experimental results database was collected carefully from previous studies. This database contained 161 and 42 experimental results for normal and high strength respectively.

From the performed literature review a number of 7 variables were identified as input parameters for the ANN model for both normal and high strength concrete, whereas the output parameter was the ultimate shear strength.

The feed forward back propagation neural network was used to build up the required model. Using the trial and error technique the topology of the neural networks was obtained.

The ANN model was found to successfully predict the ultimate shear strength of deep beams within the range of the considered input parameters. The average ratio of the experimental shear strength to predicted shear strength using the ANN model is 1.04 for normal strength concrete and 1.002 for high strength concrete. The ANN shear strength predicted results were also compared to those obtained using the American Concrete Institute (ACI) code 318.02. The results show that ANN have strong potential as a feasible tool for predicting the ultimate shear strength of both normal and high strength RC deep beams within the range of input parameters.

The trained neural network model was used to perform a parametric study to evaluate the effect of the input parameters on the utilized ultimate shear strength of deep beams .

DEDICATION

TO MY PARENTS

THE MARTYR : DR. IBRAHIM AL-MAQADMAH

AND

THE PALESTINIAN PRESONERS

I DEDICATE THIS WORK

ACKNOWLEDGMENTS

First of all, all thanks and appreciations go to Allah for his unlimited blessings and for giving me the strength to complete this thesis.

The work presented in this thesis was carried out in the Department of Civil and Structural Engineering at the Islamic University of Gaza, under the supervision of Dr.Mamoun Al Qedra and Dr. Mohammed Arafa, many thanks for them as they were patience and advisable to me.

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Finally, I present my thanks for all people who helped me in completing this work .

LIST OF ABBREVIATIONS (NOTATIONS)

Symbol	Notation
a	Shear span.
ACI	The American Concrete Institute.
$A_{s,\min}$	Minimum amount of flexural reinforcement.
A_v	Total area of vertical reinforcement spaced at s_v in the horizontal direction at both faces of the beam.
A_{vh}	Total area of horizontal reinforcement spaced at s_h in the vertical direction at both faces of the beam.
A_c	The cross- sectional area at one end of the strut.
b	Width of the beam.
b_w	Web width.
d	Effective depth; distance from extreme compression fiber to centroid of tension reinforcement.
f_y	Specified yield strength of non pre stressed reinforcement.
f_{yh}	yield stress of horizontal web reinforcement
f_{yv}	yield stress of vertical web reinforcement
F_u	The force in a strut or tie, or the force acting on one face of a nodal zone, due to the factored loads.
F_n	The nominal strength of the strut, tie, or nodal zone.
$\sqrt{f_c'}$	Square root of specified compressive strength of concrete.
h	Over all depth of the beam
l	Span length of the beam.
l_e	Effective span length.

P	Variable value.
$P_{\min}$	Minimum value of the variable.
$P_{\max}$	Maximum value of the variable.
S	The normalized value.
s	Spacing of shear or tension reinforcement measured in a direction parallel to longitudinal reinforcement.
s_v	Spacing of vertical web shear reinforcement.
s_h	Spacing of horizontal web shear reinforcement.
V_u	The factored shear force.
V_c	The normal shear resisting force of the plain concrete.
V_s	The force resisted by the shear reinforcement :
V_n	Nominal shear strength.
x	The distance of the failure plane from the face of the support.
ρ_t	Longitudinal steel reinforcement ratio.
ρ_v	Vertical shear reinforcement ratio.
ρ_h	Horizontal shear reinforcement ratio.
ϕ	The strength reduction factor.

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1. INTRODUCTION

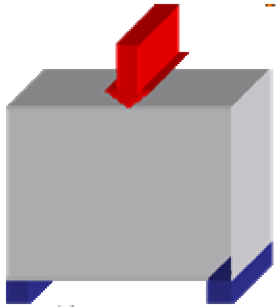
1.1 BACKGROUND

Reinforced concrete (RC) deep beams are used for load distribution in a wide range of structures; for example in tall buildings, offshore gravity structures, as transfer girders, pile caps, folded plates, and foundation walls, also shear walls are considered as cantilever deep beam. Deep beams are often located on the perimeter of framed structures where they provide stiffness against horizontal loads.

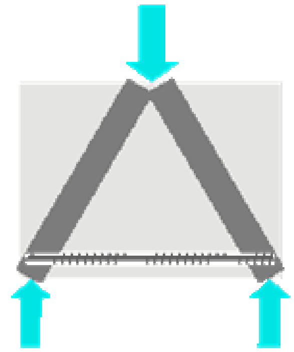
By increasing the depth of the beam while keeping the span length constant, the member becomes so stiff that the applied load is effectively carried through tension and compression zones, see Fig 1.1, rather than by bending and shear. This can be referred to as ***membrane action*** although historically such members are known as ***deep beam*** [29,71, 74].

The structural behavior of deep beams differs from that of shallow beams because of the small ratio between shear span and the depth. In contrast to shallow beams, the response is characterized by nonlinear strain distribution even in the elastic range [7].

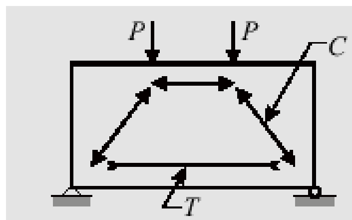
The ultimate shear strength of deep beams can be predicted using various methods. These methods comprise the ACI code and Strut-and-Tie model which is also included on the ACI 318-02 Code.



(a) Deep beam[74].



(b) Strut-and –tie behavior (membrane action) [74].



(c) Tension and compression zones [71].

Figure 1-1: Deep Beam (Short Beam)

1.2 NEURAL NETWORKS IN CIVIL ENGINEERING

Artificial Neural Networks (ANN) are one of the artificial intelligence methods, they are widely used to approximate complex systems that are difficult to model using conventional modeling techniques such as mathematical modeling [26,35,41]. They are applied in several civil engineering problems such as structural, geotechnical, management etc.

1.3 PROBLEM STATEMENT

The basic problem of deep beams emerges from the fact that a number of parameters affecting shear behavior have led to a limited understanding of shear failure mechanism and predicting of exact shear strength [60]. Although there were a large number of researches carried out, there is no agreed rational procedure to predict the strength of reinforced concrete deep beams [8,7]. This is mainly due to the highly nonlinear behavior associated with the failure of the reinforced concrete beams.

Ashour, et al [8] mentioned that the design of deep beams has not yet been covered by the British Standards Institution (BS8110). He mentioned that comparisons between experimental results and predictions from other codes, such as ACI, show poor agreement in prediction of ultimate shear strength. Therefore, the author believes that there is still a strong need to introduce the ability to predict the ultimate shear strength of deep beams.

1.4 RESEARCH OBJECTIVES

The objectives of this study are summarized as follows:

- Develop a neural network model which can predict the ultimate shear strength of deep beams.
- Carry out a parametric study using the trained neural network to obtain the significance of each parameter affecting the shear strength of deep beams.
- Compare the predicted strength of deep beams using neural networks with those calculated from ACI 318-02 equations.

1.5 RESEARCH METHODOLOGY

The objectives of this study will be achieved through performing the following tasks:

- Conduct a literature survey to obtain the necessary researches in strength and behavior of RC deep beams .This will enhance the understanding of the physical problem. The Islamic University-Gaza (IUG) library, the Internet facilities and the connections with people abroad have been used to carry out the literature survey.
- Conduct a literature survey on the use of artificial neural networks (ANN) in civil engineering applications, paying special attention on the use of ANN in deep beams.

- Obtain as much experimental test results as possible from the previous reliable studies. These experimental results are used for training the neural network model.
- MATLAB software toolbox of the neural networks was used in modeling a neural network

1.6 THESIS LAYOUT

The current study was divided into six chapters as follows :

Chapter one is an introductory chapter defines the problem statement, the objectives of this study, the methodology and an overview of this study.

Chapter two presents the definitions of deep beams, their problem, behavior, strength, and the previous studies performed.

Chapter three deals with the fundamentals of ANN showing their definition, the terminology used, as well as the advantages and disadvantages of them. The mechanism of ANN, their architecture types, algorithms used for training them are also reviewed. Finally, several applications of ANN used by researchers in civil engineering are included.

Chapter four explains the modeling of deep beams using artificial neural networks. This chapter also discusses the collection stage of the experimental data, pre processing of the training data, training and the performance of the developed model .

Chapter five presents a parametric study in which the influence of each parameter on the ultimate strength of deep beams in both cases the normal and high concrete compressive strength.

Chapter six presents conclusions and recommendations for future work.

2. STRENGTH AND BEHAVIOR OF DEEP BEAMS

2.1 INTRODUCTION

A deep beam is a beam in which a significant amount of the load is transferred to the supports by a compression thrust joining the load and the reaction [2].

The transition from reinforced concrete shallow beam behavior to that of deep beam is imprecise. For example, while the ACI code [10], CEB-FIP model code [11] and CIRIA Guide 2 [12] use the span/depth ratio limit to define RC deep beams, the Canadian code [13] employs the concept of shear span/ depth ratio. CEB-FIP model code treats simply supported and continuous beams of span/depth ratios less than 2 and 2.5, respectively, as deep beams [8].

ACI code 318-95 classifies the beam as a deep beam for flexural if the clear-span/overall-depth ratio is < 1.25 for simply supported beams and 2.5 for continuous beams and as deep beams for shear if the clear-span /effective-depth ratio is <5 for simply supported beams loaded on one face and supported on the opposite face so that compression struts can develop between loads and supports [7].

ACI code 318-02 defines deep beams as members loaded on one face and supported on the opposite face so that compression struts can develop between the loads and the supports, and have either: clear spans equal to or less than four times the overall member depth; or regions loaded with concentrated loads within twice the member depth from the face of the support [6].

The span–to-depth ratios in the definition of deep beams in the 1999 and earlier codes were based on papers published in 1946 and 1953. The definitions of deep beams given in clause 10.7.1 and 11.8.1 of these earlier codes were different from each other and different from the 2002 code definition that based on D- region behavior [6].

The Euro code defines a beam as a deep beam if the cross sectional depth to the effective span length is greater than the following limits [9], see Fig 2.1 :

- for simple beam $h/l_e > 0.5$
- for end span of continuous beams $h/l_e > 0.4$
- for inner spans of continuous beams $h/l_e > 0.3$
- for cantilever beams $h/l_e > 1.0$

Where:

h = depth of the beam.

l_e = effective span length.

Deep beams can be classified according to their concrete compressive strength as normal or high. The high strength concrete is a type of high performance concrete. ACI defines a high strength concrete as concrete that has a specific compressive strength for design of 41MPa (6000psi) or greater, other countries use a higher compressive strength in their definitions of high strength concrete with 48MPa (7000psi) minimum [78,79].

A comparison between deep beams and ordinary beams is shown in table 2.1 [3]:

Table 2-1: Comparison between Deep Beams and Ordinary Beams

No.	Deep Beam	Ordinary beam
1	Plane section before bending does not remain plane after bending.	Plane section before bending remains plane after bending.
2	Shear deformations become significant compared to pure flexure.	Shear deformation is neglected.
3	The stress block is non linear even at elastic stage.	The stress block can be considered linear at elastic stage.
4	It is subjected to two dimensional state of stress.	It is subjected to one dimensional state of stress.
5	The resulting strain is non linear.	The strain is linear.

2.2 PROBLEM OF DEEP BEAMS

The behavior and design of reinforced concrete beams in shear remains an area of concern for structural engineers due to the sudden and brittle failure of reinforced concrete beams dominated by shear action and due to the lack of rational design equations in building codes. The shear failure modes, the resisting mechanisms at cracked stages, and the role of various parameters are presently under discussion and subject to debates among researchers [40].

Although there were a large number of researches carried out, there is no agreed rational procedure to predict the strength of RC deep beams. This is mainly due to the highly nonlinear behavior associated with the failure of the reinforced concrete beams [7,8].

Unfortunately, no accurate theory exists for predicting the ultimate shear strength of deep reinforced concrete beams. Also the great number of parameters that affect the beam strength has led to a limited understanding of shear failure. In addition of existing several equations, none of them produce an accurate result [7]. Neural networks were successfully used by many researches as a molding technique. Therefore, this thesis aims at using the neural networks technique in studying and predicting the ultimate shear strength of deep beams.

2.3 BEHAVIOR OF DEEP BEAMS

In deep beams a significant amount of load is carried to supports by a compression thrust joining the load and the reaction. This compression in the diagonal direction combined with the tension along the beam bars constitute the basis for the strut-and-tie model. This tied arch action is recognized as the force-transferring mechanism of deep beams. The failure of a deep beam may occur because of crushing of a compression strut or loss of a beam bar anchorage [54].

In general, deep beams are governed by shear, rather than flexural. A large amount of compressive forces are directly transferred to supports by “Arch action". A linear elastic analysis is only valid while the deep beam remains un-cracked. However in practice tensile cracks develop in most deep beams between one-third and one-half of the ultimate loads. Therefore, tension reinforcement governs the design of the deep beams. Since the main loads and reactions act in the plane of the member, a state of plane stress in the concrete can be calculated approximately [4].

The basic parameters that control the shear strength of deep beams, based on previous research works as in [7], are shown in Fig. 2.1. These parameters are: The effective span of beam (l_e), width of beam (b), effective depth of beam (d), shear span (a), cylinder compressive strength of concrete ($f_c^{\backslash}$), yield strength of horizontal steel (f_{yh}), yield strength of vertical steel (f_{yv}), reinforcement ratio of horizontal steel (ρ_h), reinforcement ratio of total horizontal tensile steel (ρ_t), and reinforcement ratio of transverse steel (ρ_v).

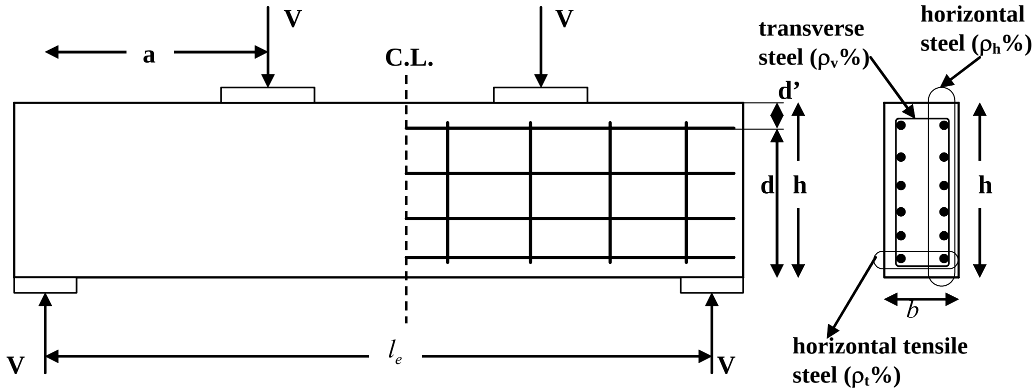


Figure 2-1: Basic parameters for shear strength prediction of simply supported deep beam: (a) Deep beam; (b) Cross section[7].

In addition to those listed above, there are more parameters that are also critical in deep beam behavior. These are anchorage of longitudinal steel into supports and size of bearing and loading areas [7]. Tests have shown that vertical shear reinforcement is more effective than horizontal shear reinforcement [6]. Crack shape in deep beam would almost be vertical or follow the direction of the compression trajectories, with the beam almost shearing off from the support in a total shear failure. Hence, in the case of deep beams, horizontal reinforcement to resist the vertical crack is needed throughout the height of the beam, in addition to vertical shear reinforcement along the span.

To resist the high tensile stresses at the lower regions of the deep beam, it is needed to concentrate horizontal reinforcing bars in the lower fiber. The allowable concrete shear resistance V_c of the deep beam is higher than of ordinary beam because of the great ratio of depth/ span [3].

2.4 <u>REVIEW OF PREVIOUS STUDIES</u>

Siao [51] used the strut-and-tie approach, to examine the ability of it in the analysis of shear strength of deep beams with web openings. The results showed that it could be used. On the other hand strut-and-tie model can be applied to beams with rectangular openings whose horizontal dimensions ranges from 0.1 to 0.4 times the clear span and vertical dimension ranges from 0.1 to 0.4 times the beam height, moreover when the opening is small, a more accurate prediction is obtained, this aspect has not been conclusively dealt with by earlier researchers .

Goh [42] used the artificial neural network ANN to predict the ultimate shear strength of deep beams. The neural network predictions were more reliable than predictions using other conventional methods such as ACI and Strut-and-Tie model.

Tan et al [52] studied the variations of the effective span and shear span on the high strength concrete deep beams.

Foster and Gilbert [53] studied the crack patterns and failure mechanisms of high strength concrete deep beams by the aid of experimental data.

Tan and Lu [54] investigated the shear behavior of large reinforced concrete deep beams experimentally and a comparison with different codes of practice was made.

Ashour and Rishi [55] tested reinforced concrete continuous deep beams with openings, the modes of failure were observed, depending on the position of the web openings.

Hwang and et al [56] predicted the shear strength of deep beams using strut-and–tie model in order to improve the current deep beam design procedure.

Teng et al [57]investigated experimentally the shear strength of concrete deep beams under fatigue loading, the investigation showed that the relevant ACI equations can be applied to deep beams under fatigue or repeated loading once the properties of the concrete and reinforcement are adjusted to take account of the effect of fatigue loading.

Oh and Shin [60] tested reinforced high strength deep beams to determine their diagonal cracking and ultimate shear capacities.

Sanad and Saka [7] used the artificial neural network in predicting the ultimate shear strength of reinforced-concrete deep beams and the results obtained were compared with the experimental values and with those determined from the ACI code method, strut –and-tie method, and Mau-Hsu method. It was clear that the performance of the neural network in predicting the shear strength is much more accurate than the methods considered. It is noticed that, although the average ratio of actual and predicted shear strength was 2.08 in the ACI code method, the same ratio is only 0.97 in the neural network.

Aguilar et al [59] evaluated experimentally the design procedure for the shear strength of deep reinforced concrete beams, the behavior of the beep beams was described in terms of cracking pattern, load-versus-deflection response, failure mode, and strain in steel reinforcement and concrete .

Zararis [59] described theoretically the shear compression failure in reinforced concrete deep beams.

Ashour et al [8] performed an empirical modeling of shear strength of reinforced concrete deep beam by genetic programming (GP), which is a new form of artificial intelligence, good agreement between the model predictions and experiments has been achieved. The GP model predicts the following behavior between the shear strength and the influencing parameters:

- The shear span to depth and main longitudinal bottom reinforcement ratios have the most significant effect on the shear strength of RC deep beams.

- The shear strength is inversely proportional to the shear span-depth ratio; the higher the shear span to depth ratio, the less the shear strength.
- The shear strength increases with the increase of the main longitudinal bottom reinforcement ratio up to a certain limit beyond which no improvement can be achieved.
- The effect of the beam span to depth ratio and web reinforcement on the shear strength is very small.

2.5 PREDICTION OF THE ULTIMATE SHEAR STRENGTH OF DEEP BEAMS

The ultimate shear strength of deep beams can be predicted using various methods. Some of these methods are explained in the following subsections:

2.5.1 Shear Strength of Deep Beams from ACI 2002 Code

According to the ACI 318-02, deep beams shall be designed either taking into account nonlinear distribution of strain, or by using Appendix A which deals with the Strut-and-Tie model. Lateral buckling shall be considered. While the critical section for calculating the factored shear force Vu is taken at distance d from the face of the support in normal beams, the shear plane in deep beams is considerably steeper in inclination and closer to the support [50].

The factored shear force Vu has to satisfy the following condition:

$$V_u \le \phi\left(10\sqrt{f_c'}\,b_w d\right) \qquad \textbf{(2.1)}$$

Where:

$\sqrt{f'_c}$ = square root of specified compressive strength of concrete, (psi)

b_w = web width, (in.)

d = distance from extreme compression fiber to centroid of longitudinal tension reinforcement, but need not be less than 0.80h for circular sections and pre-stressed members, (in.)

If the condition is not satisfied, the section has to be enlarged .The strength reduction factor $\phi = 0.75$. The present ACI Code does not give guidance on determining the shear value Vu of the plain concrete or the maximum permissible value, although the shear capacity of the plain concrete in the deep beam has to be considerably higher than in normal beams as previously discussed. A value of $V_c \le 6.0\sqrt{f_c^{'}}b_w d$

can be used for deep beams as compared to the limit value of $V_c \le 3.5\sqrt{f_c^{'}}b_w d$

in normal beams.

In the strut-and –tie approach given in section 6.11 of the Code, compressive force in the strut and tensile force in the ties are used for determining the necessary reinforcement in lieu of the approach presented in this section.

The normal shear resisting force V_c of the plain concrete can be taken as

$$V_c = (3.5 - 2.5\frac{M_u}{V_u d})(1.9\sqrt{f_c^{\backslash}} + 25000\ \rho w\frac{V_u d}{M_u})b_w d \le 6\sqrt{f_c^{\backslash}}b_w d \qquad \textbf{(2.2a)}$$

where $1.0 < 3.5 - 2.5\left(M_u / V_u d \right) \le 2.5$ .This factor is a multiplier of the basic equation for V_c in normal beams to account for the higher resisting capacity of deep beams. If some minor unsightly cracking is not tolerated, the designer can use

$$V_c = 2\sqrt{f_c^{\backslash}}b_w d \qquad \textbf{(2.2b)}$$

When the factored shear V_u exceeds ϕV_c, shear reinforcement has to be provided such that $V_u \le \phi(V_c + V_s)$, where V_s is the force resisted by the shear reinforcement:

$$V_s = \left[\frac{A_v}{s_v} \left(\frac{1 + l_n/d}{12} \right) + \frac{A_{vh}}{s_h} \left(\frac{11 - l_n/d}{12} \right) \right] f_y d \qquad \textbf{(2.3)}$$

where:

A_v = total area of vertical reinforcement spaced at s_v in the horizontal direction at both faces of the beam;

A_{vh} = total area of horizontal reinforcement spaced at s_h in the vertical direction at both faces of the beam .

Maximum spacing $s_v \le \dfrac{d}{5}$ or 12 in. **(2.4a)**

whichever is smaller

Maximum spacing $s_h \le \dfrac{d}{5}$ or 12 in **(2.4b)**

and

minimum $A_{vh} = 0.0015 b s_h$

minimum $A_v = 0.0025 b s_v$

The shear reinforcement required at the critical section must be provided throughout the deep beams.

In the case of continuous deep beams, because of the large stiffness and the negligible rotation of the beam section at the supports, the continuity factor at the first interior support has a value close to 1.0. Consequently, the same reinforcement for shear can be used in all spans for all practical purpose if all the spans are equal and similarly loaded [50].

2.5.2 Strut-and-Tie Model from ACI 2002

The strut-and-tie model STM has been introduced in the new AASHTO LRFD Specifications (1994), which was its first appearance in a design specification in the US. It was also included in ACI 318-02 Appendix A [14].

The Strut-and-Tie is a unified approach that considers all load effects (Bending moment, normal force, shear force, and tension force) simultaneously. It is a powerful tool for the design of what is known as "discontinuity" or "disturbed" regions in reinforced and pre stressed concrete structures. These regions are normally referred to as the D-regions. These are regions where a complex state of stress and strain develops. Examples of D-regions include corbels, deep beams, joints, walls with openings, anchorage zones and so on, see Fig 2.2.

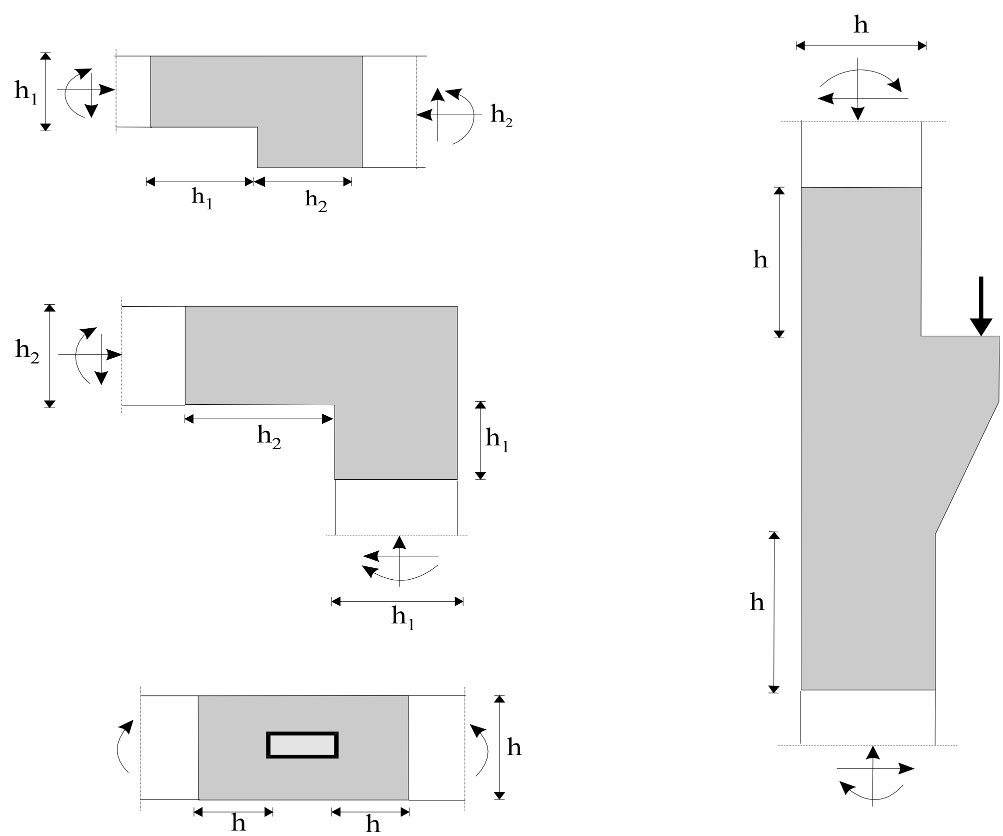
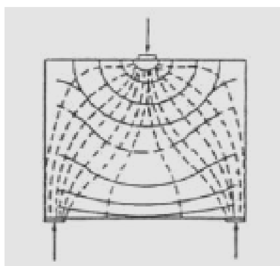


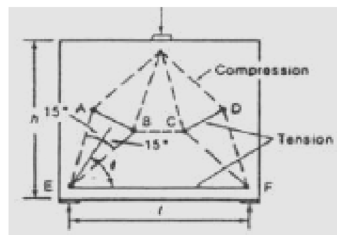
Figure 2-2: D-regions (shaded areas) with nonlinear strain distribution due to (a) Geometrical discontinuities. (b) Statically and/or geometrical discontinuities [5,6].

The STM idealizes the D-region by a system of truss members that serve to carry the load to the boundaries of the D-region. The truss model consists of compression struts (concrete) and tension ties (reinforcing bars). So this model provides a rational approach by representing a complex structural member with an appropriate simplified truss models. Although there is no single, unique STM for most design situations encountered, there are, however, some techniques and rules, which help the designer develop an appropriate model [5, 6,14].

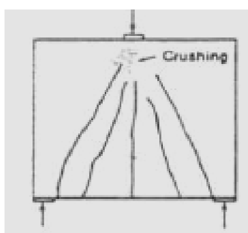
The deep beam stress and its Strut-and-Tie model is shown in Fig 2.3.



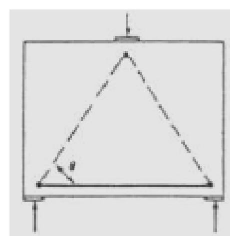
(a) Stress trajectories



(b)Truss model



(c) Crack pattern in test



(d) Simplified truss

Figure 2-3: Deep beam stresses and its STM model [14]

Strut –and-tie model design procedure according to ACI 318-02 :

It shall be permitted to design structural concrete members, or D-region in such members, by modeling the member or region as an idealized truss. The strut-and-tie model shall be in equilibrium with the applied loads and the reactions. The angle between the axes of any strut and tie entering a single node shall not be taken as less than 25 degrees. Design of struts, ties, and nodal zones shall be on

$$\phi F_n \geq F_u$$

where:

Fu is the force in a strut or tie, or the force acting on one face of a nodal zone, due to the factored loads, **Fn** is the nominal strength of the strut, tie, or nodal zone; and Φ is the strength reduction factor 0.75.

Strength of Struts

The nominal compressive strength of a strut without longitudinal reinforcement shall be taken as the smaller value of

$$F_{ns} = f_{cu} A_c$$

at the two ends of the strut, where A_c is the cross- sectional area at one end of the strut, and f_{cu} is the smaller of (a) and (b):

(a)- The effective compressive strength of the concrete in the strut shall be taken as

$$f_{cu} = 0.85 \beta_s f_c^{'}$$

(b)- The effective compressive strength of the concrete in a nodal zone shall not exceed the value given by:

$$f_{cu} = 0.85 \beta_n f_c^{'}$$

where the value of β_n is given in Table 2.2.

The use of compression reinforcement shall be permitted to increase the strength of a strut. Compression reinforcement shall be properly anchored, parallel to the axes of the strut, located within the strut. The strength of a longitudinally reinforced strut is:

$$F_{ns} = f_{cu} A_c + A_s^{'} f_s^{'}$$

Strength of ties

The nominal strength of a tie shall be taken as

$$F_{nt} = A_{st} f_y + A_{ps}\left(f_{se} + \Delta f_p\right)$$

where $\left(f_{se} + \Delta f_p\right)$ shall not exceed f_{py} and A_{ps} is zero for non pre stressed members.

Table 2-2: Stress Limits and Strength Reduction Factors According to ACI 318-02 Appendix A [1,7]

Stress Limits, f_{cu}	
	Struts: $f_{cu} = 0.85\beta_s f_c^{'}$
where:	$\beta_s = 1.00$ for prismatic struts in un cracked compression zones $\beta_s = 0.40$ for struts in tension members $\beta_s = 0.75$ struts may be bottle shaped and crack control reinforcement is included $\beta_s = 0.60$ struts may be bottle shaped and crack control reinforcement is not included $\beta_s = 0.60$ for all other cases $f_c^{'}$ = specified concrete compressive strength
Note:	Crack control reinforcement requirement is $\sum \rho_{vi} \sin\gamma_i \ge 0.003$, where ρ_{vi} = steel ratio of the i-th layer of reinforcement crossing the strut under review, and γ_i = angle between the axis of the strut and the bars.
	Nodes: $f_{cu} = 0.85\beta_n f_c^{'}$
where:	$\beta_n = 1.00$ when nodes are bounded by struts and/or bearing areas $\beta_n = 0.80$ when nodes anchor only one tie $\beta_n = 0.60$ when nodes anchor more than one tie
Strength Reduction Factors, ϕ	
	$\phi = 0.75$ for struts, ties, and nodes

3. ARTIFICIAL NEURAL NETWORKS

3.1 INTRODUCTION

Artificial Neural Networks (ANN) are widely used to approximate complex systems that are difficult to model using conventional modeling techniques such as mathematical modeling [26,35,41]. They are applied in several civil engineering problems structural, geotechnical, management etc.

This chapter presents the fundamentals of ANN showing the history, definition, terminology used, as well as advantages and disadvantages. The mechanism of ANN, architecture classes, algorithms used for training are also reviewed. Finally, several applications of ANN used in civil engineering are included.

3.2 DEFINITION OF ARTIFICIAL NEURAL NETWORKS

An artificial neural network is an assembly (network) of a large number of highly connected processing units, the so-called nodes or neurons. The neurons are connected by unidirectional communication channels (connections). The strength of the connections between the neurons is represented by numerical values which normally are called weights. Knowledge is stored in the form of a collection of weights. Each neuron has an activation value that is a function of the sum of inputs received from other nodes through the weighted connections [28,41].

Also ANN can be defined as a form of artificial intelligence, which by means of their architecture, attempt to simulate the biological structure of the human brain and nervous system [22,26].

3.3 TERMINOLOGY USED IN ARTIFICIAL NEURAL NETWORK

The definition of the terms used in Figure 3.1 is presented in the following paragraphs:

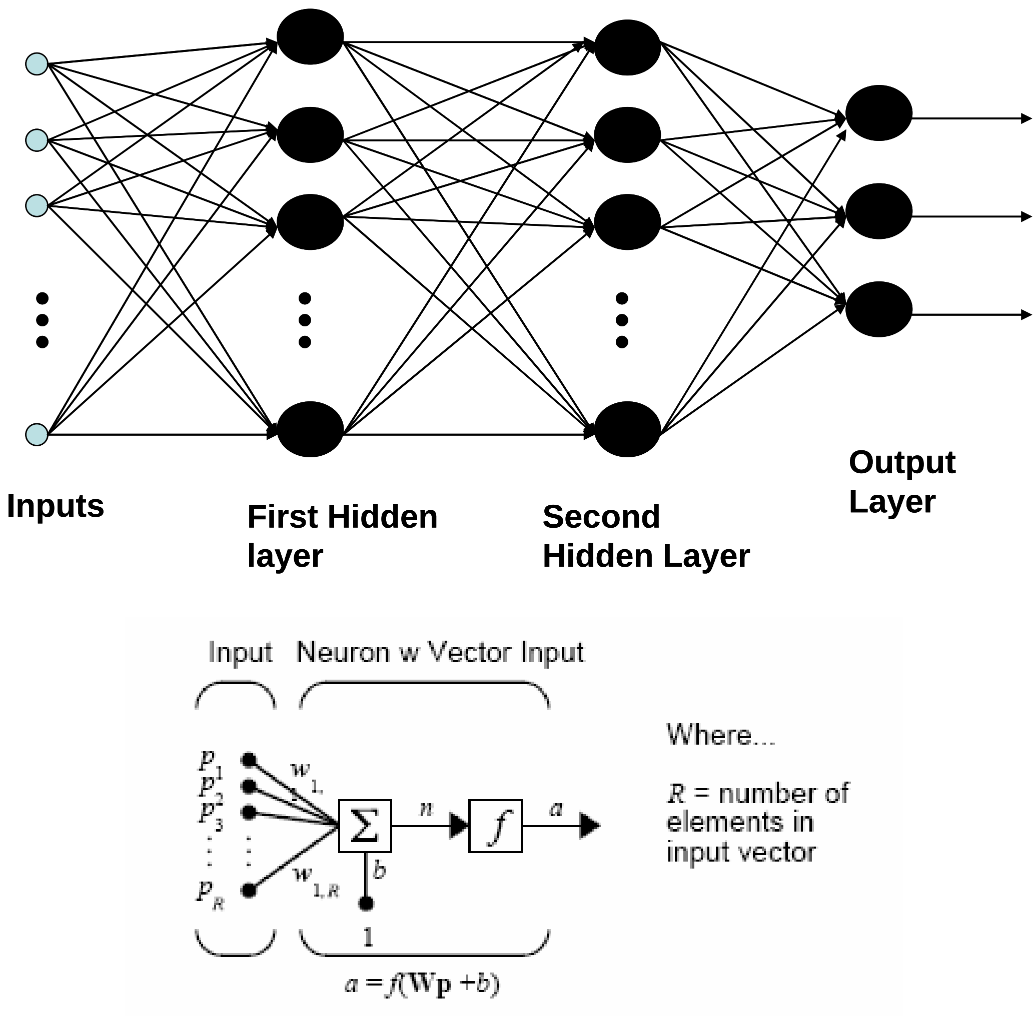


Figure 3-1: Typical Structure of ANN[21,35]

Neuron (artificial): A simple model of a biological neuron used in neural networks to perform a small part of some overall computational problem. It has inputs from other neurons, with each of which is associated a weight - that is, a number which indicates the degree of importance which this neuron attaches to that input. It also has an activation function, and a bias. It is the processing element in ANN and they are called nodes also [23,30].

Weight: A weight, in an artificial neural network, is a parameter associated with a connection from one neuron, M, to another neuron N. It determines how much notice the neuron N pays to the activation it receives from neuron M [30].

Input unit: An input unit -in a neural network- is a neuron with no input connections of its own. Its activation thus comes from outside the neural net [30].

Output unit: An output unit in a neural network is a neuron with no output connections of its own. Its activation thus serves as one of the output values of the neural net [30].

Bias: In feed-forward and some other neural networks, each hidden unit and each output unit is connected via a trainable weight to a unit (the bias unit) that always has an activation level of -1[30].

Epoch: In training a neural net, the term epoch is used to describe a complete pass through all of the training patterns. The weights in the neural net may be updated after each pattern is presented to the net, or they may be updated just once at the end of the epoch. Frequently used as a measure of speed of learning - as in "training was complete after x epochs"[30].

Hidden layer: Neurons or units in a feed forward net are usually structured into two or more layers. The input units constitute the input layer. The output units constitute the output layer. Layers in between the input and output layers (that is, layers that consist of hidden units) are termed hidden layers.

In layered nets, each neuron in a given layer is connected by trainable weights to each neuron in the next layer [30].

Hidden unit / node: A hidden unit in a neural network is a neuron which is neither an input unit nor an output unit [30].

A learning algorithm is a systematic procedure for adjusting the weights in the network to achieve a desired input/output relationship, i.e. supervised learning [26].

Note: The most popular and successful learning algorithm used to train multilayer neural networks is currently the back-propagation routine [26].

3.4 ADVANTAGES AND DISADVANTAGES OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks have many advantages that made it increasingly used in several applications by many researchers. Some of these **advantages** can be summarized below:

1- ANN are well suited to model complex problems where the relationship between the model variables is unknown [26].

2- Neural networks has the capability of producing correct or nearly correct outputs when presented with partially incorrect or incomplete inputs [28].

3- ANN do not need any prior knowledge about the nature of the relationship between the input/output variables, which is one of the benefits that ANN have compared with most empirical and statistical methods [26].

4- ANN can always be updated to obtain better results by presenting new training examples as new data become available [26].

5- Artificial Neural Networks have the advantage that it gives you the output without the need to perform any manual work such as using tables, charts, or equations [22].

6- It is often faster to use neural networks than a conventional approach [23].

7- Engineers often deal with incomplete and noisy data which is one area where ANN are most applicable [69].

8- ANN can learn and generalize form examples to produce meaningful solutions to problems [69].

9- Data presented for training ANN can be theoretical data, experimental data, empirical data based on good and reliable experience or a combination of these [69].

Although the artificial neural networks have advantages, on the other hand there are **disadvantages**. Some of these are listed below:

1- The principal disadvantage being that they give results without being able to explain how they arrive at their solutions. Their accuracy depends on the quality of the trained data and the ability of the developer to choose truly representative sample inputs [62].

2- There is no exact available formula to decide what architecture of ANN and which training algorithm will solve a given problem. The best solution is obtained by trial and error. One can get an idea by looking at a problem and decide to start with simple networks; going on to complex ones till the solution is within the acceptable limits of error [35].

3- The individual relations between the input variables and the output variables are not developed by engineering judgment so that the model tends to be a black box or input/output table without analytical basis [63].

The advantages appear to outweigh the disadvantages [63].

3.5 MECHANISM OF ARTIFICIAL NEURAL NETWORKS

Briefly neural networks are composed of simple elements operating in parallel. The network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below Fig 3.2. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target.

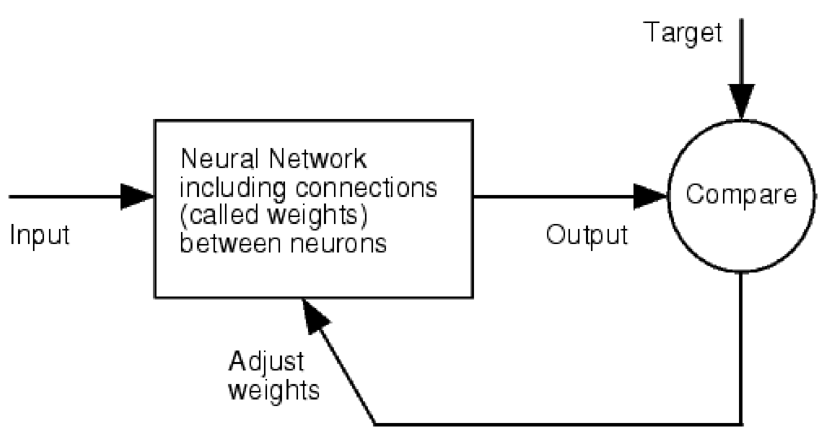


Figure 3-2: Neural Networks Concept [21].

Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as "on line" or "adaptive" training. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings [29].

3.6 TYPES OF ARTIFICIAL NEURAL NETWORK

Basically, neural networks can be classified according to their connection geometries. One of the simplest architectures is the layered feed-forward network [31].

3.6.1 Single-Layer Feed forward Networks

In a layered neural network the neurons are organized in the form of layers. In the simplest form of a layered network, we have an input layer of source nodes that projects into an output layer of neurons (computation nodes), but not vice versa. In other words, this network is strictly a feed forward or cyclic type. It is illustrated in Fig. 3.3 for the case of nodes in both the input and output layers. Such a network is called a single-layer network, with the designation "single-layer" referring to the output layer of computation nodes (neurons). We do not count the input layer of source nodes because no computation is performed there [18].

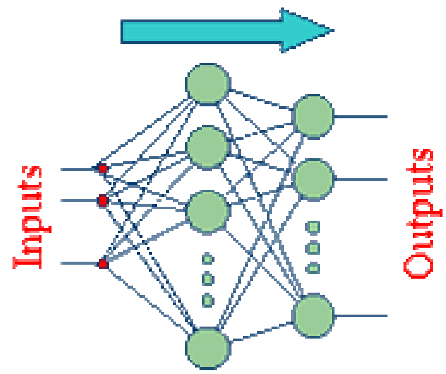


Figure 3-3: Feed forward or acyclic network with a single layer of neurons [48].

3.6.2 Multilayer Feed forward Networks

The second class of a feed forward neural network distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons or hidden units. The function of hidden neurons is to intervene between the external input and the network output in some useful manner Fig 3.4.

The architecture graph in Fig 3.4 illustrates the layout of a multilayer feed forward neural network for the case of a single hidden layer. For brevity the neural network in Fig 3.4 is referred to as a 6-4-2 network because it has 6 source neurons, 4 hidden neurons, and 2 output neurons. As another example, a feed forward network with m source nodes, h1 neurons in the first hidden layer, h2 neurons in the second hidden layer, and q neurons in the output layer is referred as an m-h1-h2-q [18].
The neural network in Fig 3.4 is said to be fully connected in the sense that every node in each layer of the network is connected to every other node in the adjacent forward layer. If, however, some of the communication links (synaptic connections) are missing from the network, we say that the network is partially connected [18].

3.6.3 Recurrent Networks

A recurrent neural network distinguishes itself from a feed forward neural network in that it has at least one feedback loop. Recurrent neural networks (RNN) have a closed loop in the network topology. They are developed to deal with the time varying or time-lagged patterns and are usable for the problems where the dynamics of the considered process is complex and the measured data is noisy).

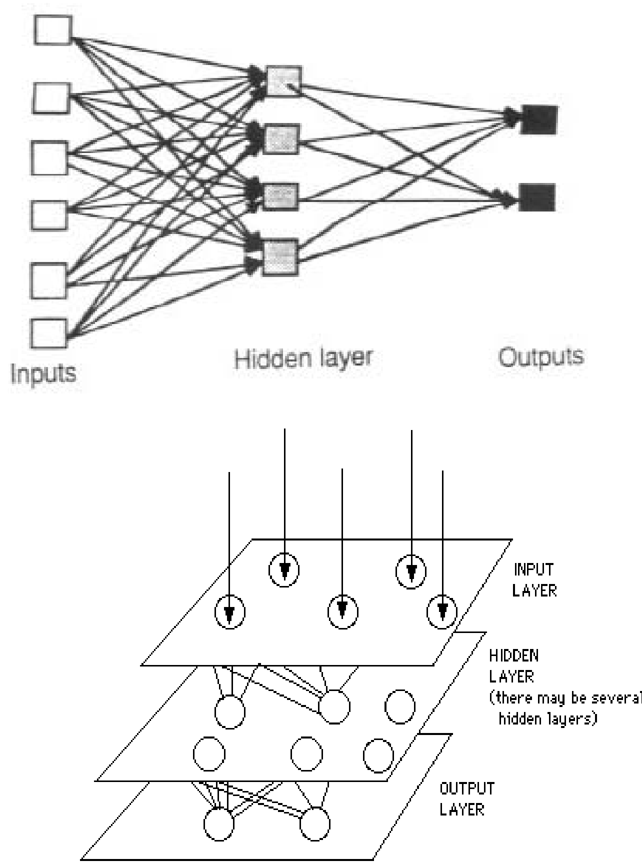


Figure 3-4: Fully connected feed forward network[18,67].

The RNN can be either fully or partially connected. In a fully connected RNN all the hidden units are connected recurrently, whereas in a partially connected RNN the recurrent connections are omitted partially. For example, a recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons, as illustrated in the architectural graph in Fig 3. 5 [18,67].

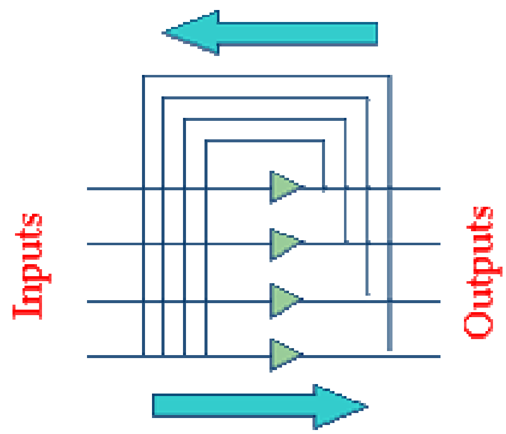


Figure 3-5: Recurrent network with no self-feedback loops and no hidden neurons [48].

3.7 <u>FUNCTIONS USED IN DEVELOPING ANN</u>

There are many types of functions used by ANN among which training and transfer functions are listed below:

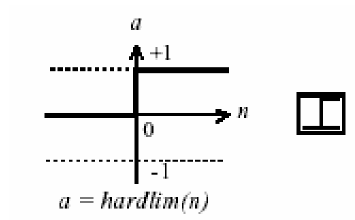
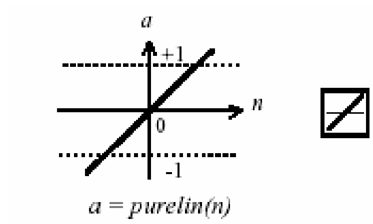
3.7.1 Training Functions

The MATLAB toolbox now has four training algorithms that apply weight and bias learning rules, namely: Batch training function "***trainb***", Cyclical order incremental training function ***"trainc***", Random order incremental training function ***"trainr***", and Sequential order incremental training function ***"trains"***.

All four functions present the whole training set in each epoch (pass through the entire input set) [21].

3.7.2 Transfer (activation) Functions

In neural networks, an activation function is the function that describes the output behavior of a neuron .They can be linear or nonlinear [21].
Three of the most commonly used functions are shown below in Fig 3.6.

<table>
<tr><td>Hard-Limit Transfer Function</td><td>
</td></tr>
<tr><td>Linear Transfer Function</td><td>
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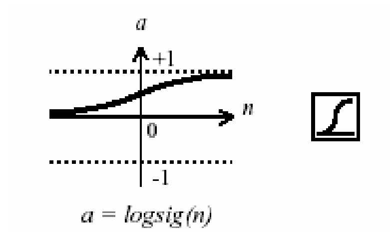
<tr><td>Log-Sigmoid Transfer Function</td><td>
</td></tr>
<tr><td colspan="2">Figure 3-6: Three of the most commonly used transfer functions[21]</td></tr>
</table>

-The hard-limit transfer function shown Fig. 3.6 limits the output of the neuron to either 0, if the net input argument n is less than 0; or 1, if n is greater than or equal to 0.

-Neurons of Linear Transfer Function shown Fig. 3.6 are used as linear approximations in “Linear Filters”.

- The sigmoid transfer function shown in Fig. 3.6 takes the input, which may have any value between plus and minus infinity, and squashes the output into the range 0 to 1. This transfer function is commonly used in back propagation networks, in part because it is differentiable [21].

3.8 ALGORITHMS USED FOR TRAINING ARTIFICIAL NEURAL NETWORK

There are several types of neural networks according to the algorithms used in the training process. The following paragraphs presents some of these training algorithms:

3.8.1 Back-propagation Neural Networks

The most popular type of neural networks is the back propagation neural network (BP). Back-Propagation is a mathematical procedure that starts with the error at the output of a neural network and propagates this error backwards through the network to yield output error values for all neurons in the network. BP is a feed forward network that uses supervised learning to adjust the connection weights. In a feed forward network, the results of each layer are fed to each successive layer. A conventional BP uses three layers of nodes, but it can use more middle layers. The first layer, the input nodes, receives the input data (also called the middle layer or the hidden layer). The results of the first layer are passed to the next layer. This process is repeated for each layer until an output is generated. The difference between the generated output and a training set output is calculated. This difference is fed back to the network where it is used for connection weight readjustment by iteratively attempting to minimize the difference to within a predefined tolerance. The BP can learn many different output patterns simultaneously with dramatic accuracy [32,64].

3.8.2 Radial Basis Neural Networks

Radial Basis Functions are powerful techniques for interpolation in multidimensional space. A Radial Basis Function (RBF) is another type of feed-forward ANN Fig 3.7. Typically in a RBF network, there are three layers: one input, one hidden and one output layer. Unlike the back-propagation networks, the number of hidden layer can not be more than one. The hidden layer uses Gaussian transfer function instead of the sigmoid function. In RBF networks, one major advantage is that if the number of input variables is not too high, then learning is much faster than other type of networks. However, the required number of the hidden units increases geometrically with the number of the input variables. It becomes practically impossible to use this network for a large number of input variables.

The hidden layer in RBF network consists of an array of neurons that contains a parameter vector called a ‘radial center’ vector. The hidden layer performs a fixed non-linear transformation with non-adjustable parameters.

The approximation of the input-output relation is derived by obtaining a suitable number of neurons in the hidden layer and by positioning them in the input space where the data is mostly clustered. At every iteration, the position of the radial centers, its width (variation) and the linear weights to each output neuron are modified. The learning is completed when each radial center is brought up as close as possible to each discrete cluster centers formed from the input space and the error of the network’s output is within the desired limit [32,34,67,68].

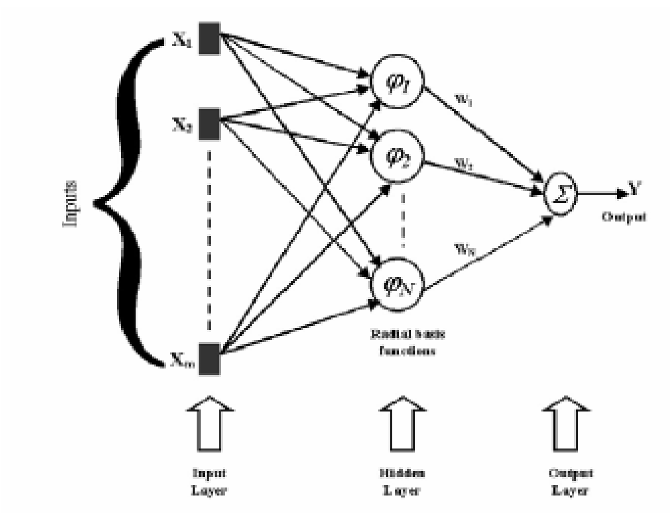


Figure 3-7: Architecture of radial basis function neural network.[68]

3.8.3 Hopfield Neural Networks

Hopfield networks are the recurrent neural networks with no hidden units. The idea of this type of network is to get a convergence of weights to find the minimum value for energy function, just like a ball going down to the hill and stops when energy is converted to other form due to friction and other forces. Also it can be compared to the vortices in a river. Every neuron of the Hopfield net is connected to all other neuron but not to itself, so that the flow is not in a single direction. Even a node can be connected to itself in a way of receiving the information back through other neurons [47,66,67].

3.9 APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS IN CIVIL ENGINEERING

Over the last few years, the use of artificial neural networks (ANN) has increased in many areas of engineering. Many researches in structural and geotechnical engineering have been carried to use ANN in various topics, among them were W.P. Dias and S.P. Pooliyadda [24]; Lai and Serra [46]; Lee and Sterling [46]; W.M. Jenkins [25]; I.C. Yeh [27].

The following explains some of these researches:

3.9.1 ANN Applications in Structural Engineering

Andres et al predicted the confined compressive strength and corresponding strain of circular concrete columns, the artificial neural networks (ANN) was found to be acceptable in predicting the confined compressive strength and corresponding strain of circular concrete columns. Also, the ANN model was compared to analytical models and was found to perform well [38].

Chao-Wei et al predicted the confinement efficiency of concentrically loaded reinforced concrete (RC) columns with rectilinear transverse steel, ANN approach provided better results compared with parametric models [39].

Mansour et al predicted the ultimate shear strength of reinforced concrete (RC) beams with transverse reinforcements, the results show that ANN have strong potential as a feasible tool for predicting this model, also the ANN model was used to show that it could perform a parametric study to evaluate the effects of some of the parameters on the chosen output [40].

Ashour and Alqedra used a feed forward neural network model for evaluating the concrete breakout strength of single cast-in and post-installed mechanical anchors in tension. The relationship between the concrete breakout strength of anchors and different influencing parameters obtained from the trained neural networks were in general agreement with these of the ACI 318-02 for cast-in and post-installed mechanical anchors [41].

Cladera and Mari developed an artificial neural network part I to predict the shear strength of reinforced beams, based on its results. A parametric study was carried out to determine the influence of each parameter affecting the failure shear strength of beams without web reinforcement [43].

Cladera and Mari developed an artificial neural network part II to predict the shear strength of reinforced beams failing on diagonal tension failure, based on its results, a parametric study was carried out to study the influence of each parameter affecting the shear strength of beams with web reinforcement. Finally new design expressions were proposed for both normal and high strength concrete beams [44].

Oreta developed an artificial neural network ANN model using past experimental data on shear failure of slender (RC) beams without web reinforcements, the ANN model performed well when compared with existing empirical, theoretical and design code equations [45].

Hadi presented and discussed the applications of neural networks in concrete structures especially applications in structural design. Based on the applications, it is found that neural networks are comparatively effective for a number or reasons, their ease of use and implementation, provide more flexibility when users and developers deal with different kinds of problems [36].

3.9.2 ANN Applications in Geotechnical Engineering

Artificial neural networks (ANN) have also been applied to many geotechnical engineering tests and have demonstrated degrees of success. A review of the literature reveals that ANN have been used successfully in pile capacity prediction, modeling soil behavior, site characterization, earth retaining structures, settlement of structures, slope stability, design of tunnels and underground openings, liquefaction, soil permeability and hydraulic conductivity, soil compaction, soil swelling and classification of soils[26].

Mohammed A. Shahin et al predicted settlement of shallow foundations using neural networks. They used a large data base of actual measured settlements to develop and verify the artificial neural network model. The predicted settlements found by utilizing ANN are compared with the values predicted by three of the most commonly used traditional methods. The results indicate that ANN are a useful technique for predicting the settlement of shallow foundations on cohesion less soils [22].

Kurup et al evaluated the feasibility of using artificial neural network (ANN) models for estimating the overconsilidation ratios (OCR) of clays from piezocone penetration tests (PCPT), several models were used, comparing their predictions with reference to OCR values obtained from odometer tests ANN models give very good estimates of OCR [37].

4. MODELING OF DEEP BEAMS USING ARTIFICIAL NEURAL NETWORK

4.1 INTRODUCTION

This chapter deals with modeling of deep beams using artificial neural networks. The reliability of the previous experimental test results used in this research is studied. The preprocessing which applied on the collected experimental test results is explained.

This chapter also presents the adopted training process to develop a trained neural network model; the training process includes defining the topology of the required neural network and identifying all neural network parameters. At the end of this chapter, a comparison between predicted results from the trained model, the experimental results, and results obtained using ACI 318-02 equations is presented.

4.2 DETAILS OF PREVIUOS EXPERIMENTAL TESTS

The development of neural network models needs as many reliable training data as possible. The training data consists of those input parameters affecting the system and the corresponding output parameters. These data can be experiment test data, reliable empirical data or theoretical results. The current research utilized experimental test results obtained from previous studies.

A comprehensive study was carried out on the obtained experimental test data in order to ensure the adequacy of these data as a training data.

It should be mentioned that all previous experiments used in this study have identical test setup. The test setup of the previous experiments which performed to predict the ultimate strength of deep beams is explained below.

Setup of Experimental Tests

A number of one hundred sixty one experiments carried out to predict the ultimate shear strength of normal compressive strength of reinforced concrete deep beams. These experiments were obtained from previous studies carried out by De Paiva and Siess [79], Kong et al.[84], Kong et al.[85], Manuel et al.[83], Ramakrishnan and Ananthanarayana [80], Rogowesky et al.[87], Smith and Vantsiotis [81], Subedi et al.[82], Tan and Lu [54].

These experiments had concrete compressive strengths $f_c^{'}$ in the range of $16.07 N/mm^2 \leq f_c^{'} \leq 45 N/mm^2$, shear span *a* varies from 190 to 1760mm, beam width *b* varies from 20 to 50mm, overall height of the beam *h* varies from 177.8 to 1750mm, the shear span to depth ratio *a/h* varies from 0.28 to 2, the yield stress of the vertical web shear reinforcement f_{yv} varies from 0 to 520 N/mm^2,and the yield stress of the horizontal web shear reinforcement f_{yh} varies from 286.83 to 520 N/mm^2, see Table 4.1.

The study of the pervious experimental results indicated that the tested beams showed different types of failures. In this study, those beams failed under shear are kept for further processing. The tested beams failed under other types of failures were excluded from this study.

The tested beams were subjected to two-point loading. This case provides a larger amount of data than other cases do, which is essential for better training of a network [7].

The geometrical dimensions and reinforcement of a typical RC deep beam tested under two point loads is shown in Fig 4.1.

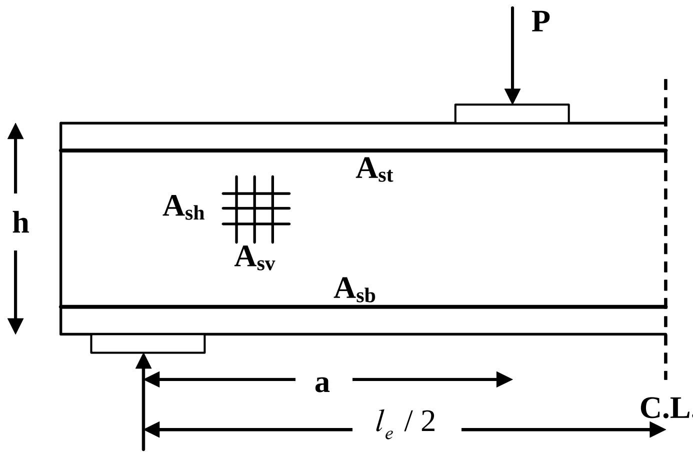


Figure 4.1: Geometrical dimensions of a RC deep beam[8].

The parameters of the tested beams are the width of the beam (b), shear span (a), shear span to depth ratio (a/h), depth of the beam (h), concrete compressive strength ($f_c^{'}$), yield stress of horizontal web reinforcement (f_{yh}), and yield stress of vertical web reinforcement (f_{yv}).

Forty two high strength reinforced concrete deep beams were tested by Oh and Shin [60], with concrete compressive strength in the range of $49.10MPa \le f_c^{'} \le 73.6MPa$ to determine their ultimate shear capacities symmetrically under two-point loading. The effective span-depth ratio l_e / d was varied from 3.0 to 5.0, and the shear span-effective depth ratio a/d from 0.5 to 2.0. All the beams were singly reinforced with longitudinal steel reinforcement ratio ρ_t of 0.0129, 0.0156 and vertical shear reinforcement ratio ρ_v from 0 to 0.0034, and horizontal shear reinforcement ratio ρ_h, from 0 to 0.0094, respectively, see Table 4.2.

All beams had a rectangular cross section of either 120x 560mm or 130 x 560mm. Longitudinal steel reinforcement consisted of a straight bar with a 90 degree hook to provide adequate anchorage. Vertical shear reinforcement has closed stirrups with 6mm bars, while the horizontal shear reinforcement consisted of straight 6mm bars.

In beams with l_e/d of 3.0, 4.0, and 5.0, the effective span of specimen was planed as 1500, 2000, and 2500mm, respectively, and the a/d was varied within the effective span length. For the restraining of local failure, in the top compressive face and support of tested beams, steel plates with widths of 180 and 130mm, respectively, were used.

The parameters of the tested beams are the beam width *b*, shear span –effective depth ratio *a/d*, effective span- depth ratio l_e/d, concrete compressive strength $f_c^{'}$,vertical shear reinforcement ratio ρ_v, horizontal shear reinforcement ratio ρ_h, and longitudinal steel reinforcement ratio ρ_t.

4.3 SELECTION CRITERIA OF EXPERIMENTAL RESULTS AND PRE-PROCESSING OF DATA

The way the data is presented to the neural network affects the learning of the network. Therefore; a certain amount of data processing is required before presenting the training pattern to the network [69].

A comprehensive study was carried out on the collected experimental data results to choose the data which can be used in the training of a neural network model. As the aim of this study is to predict the shear strength of deep beams, the results of the deep beams failed under shear is kept while those results of deep beams which showed other types of failures were excluded.

After applying the above selection criteria a data base of 161 test results was obtained for normal strength deep beams and 42 test results for high strength concrete. These data will go through other selection and preprocessing stages to obtain a reliable training data for neural network.

4.3.1 Statistics of Laboratory Experiments

The collected laboratory data were grouped randomly into three subsets :
a training set, validation set, and the testing set; see Table 4.1 and Table 4.2.

A- Normal Strength Concrete

Table 4-1 shows the statistics of those testes carried on normal compressive strength deep beams.

	b mm	**h mm**	**a mm**	**a/h**	f_c' **N/mm^2**	f_{yv} **N/mm^2**	f_{yh} **N/mm^2**	**V (KN)**
All data								
No. of data	161	161	161	161	161	161	161	161
Mean	97.89	510.66	416.44	0.866	25.31	249.05	383.18	473.80
Standard deviation	29.13	297.11	291.81	0.367	7.32	203.23	76.95	482.37
Minimum	20	177.8	190	0.28	16.07	0	286.83	94.3
Maximum	50	1750	1760	2	49.1	520	520	3272
Testing set								
No. of data	39	39	39	39	39	39	39	39
Mean	98.51	500.66	417.54	0.88	25.18	253.81	381.82	451.94
Standard deviation	30.74	262.94	2.92.85	0.39	7.15	202.12	75.57	416.20

B- High Strength Concrete

Table 4-2: shows the statistics of those testes carried on high compressive strength deep beams.

	b mm	**a/d**	**le/d**	f_c' **MPa**	ρ_v **=rv %**	ρ_h **=rh %**	ρ_t **=rt %**	**V MPa**
All data								
No. of data	42	42	42	42	42	42	42	42
Mean	125.24	0.96	4	55.31	0.16	0.36	1.43	6.79
Standard deviation	5.05	0.45	0.38	10.37	0.09	0.22	0.14	2.32
Minimum	120	0.5	3	49.1	0.12	1.29	3.24	1.73
Maximum	130	2.0	4	73.6	0.24	1.56	10.97	11.47
Testing set								
No. of data	10	10	10	10	10	10	10	10
Mean	125.45	1.04	3.91	51.67	0.13	0.43	1.44	6.18
Standard deviation	5.22	0.46	0.30	13.34	0.03	0.22	0.14	2.29

4.3.2 Frequency of Experimental Data

Shi suggested that an ANN model might perform well over an entire space only when the training data are evenly distributed in the space [86].

The distribution of each parameter across its range in the data base is examined The frequency distribution of all parameters studied across the 161 normal reinforced concrete compressive strength test results and cross the 42 high reinforced concrete compressive strength test results are presented in Fig 4.2 and Fig 4.3 .

A- Normal strength concrete

Frequency distribution of input parameters across the range of 161 experimental results are considered.

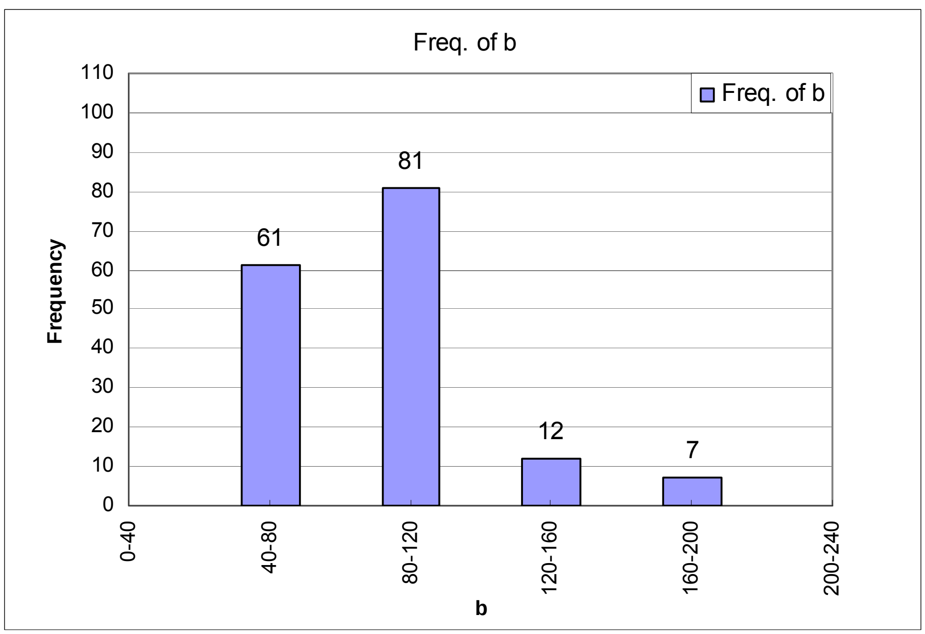


Fig.4.2.a Width of the beam(mm)

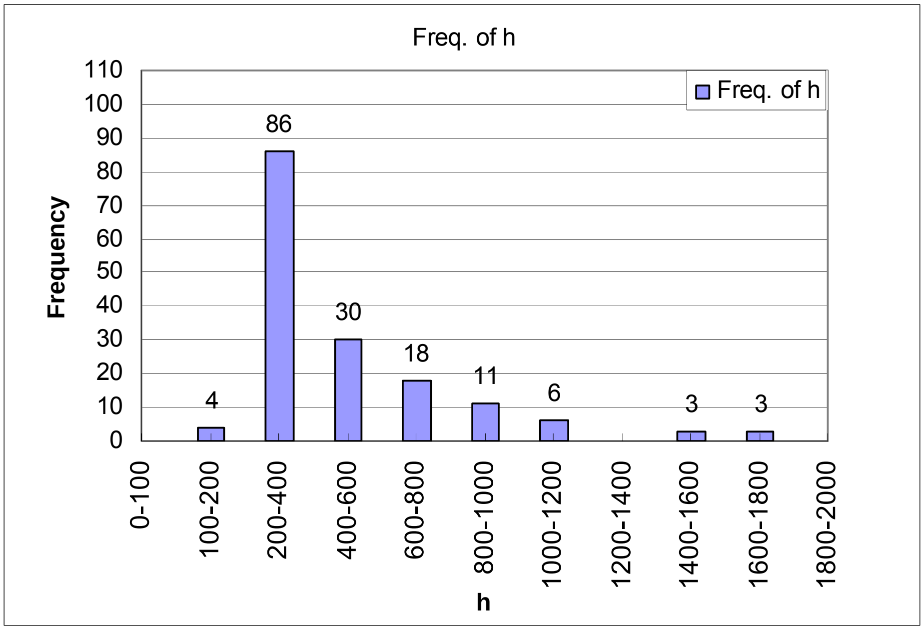


Fig.4.2.b Depth of the beam(mm)

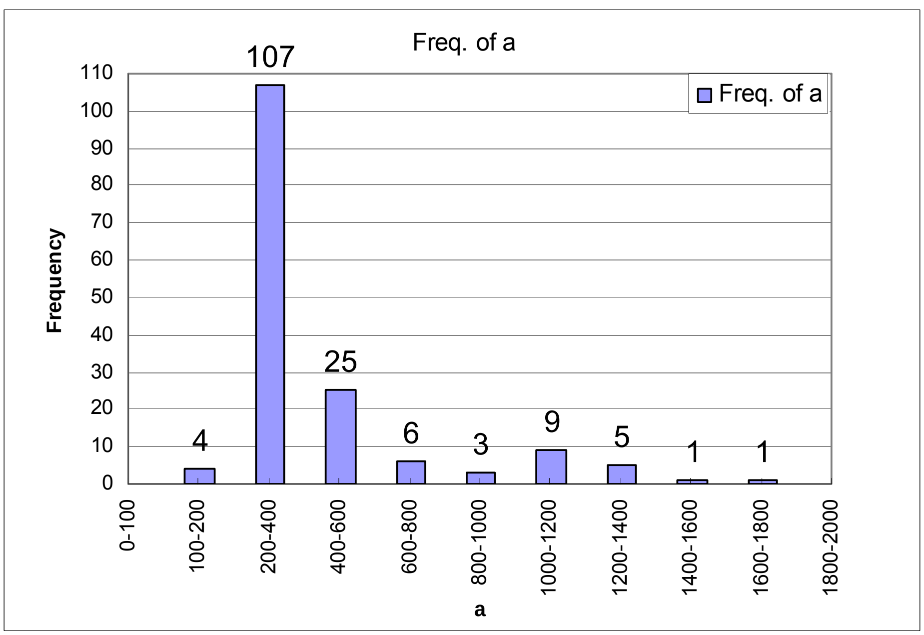


Fig.4.2.c Shear span (mm)

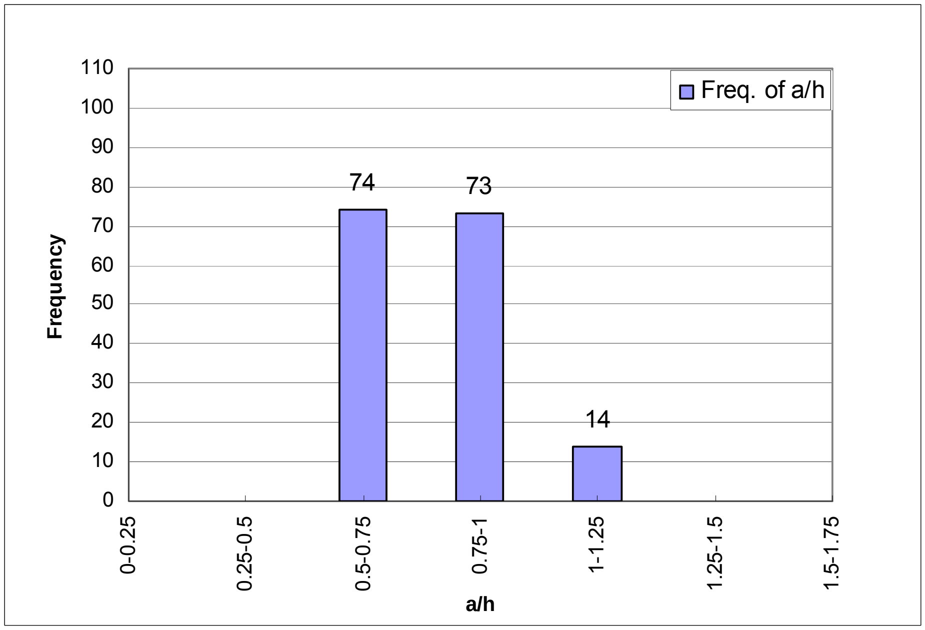


Fig.4.2.d Shear span to depth ratio

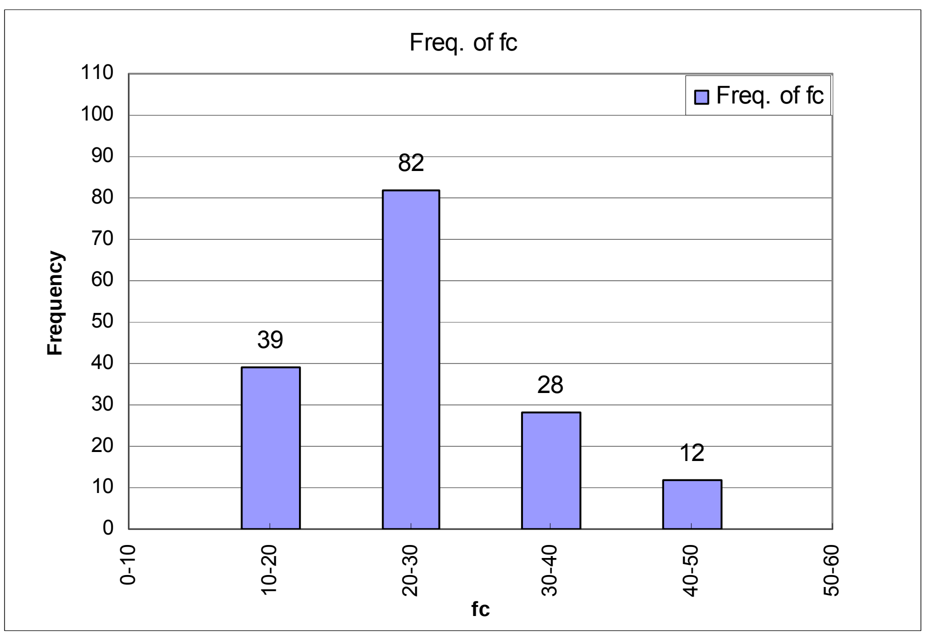


Fig.4.2.e Concrete compressive strength (N/mm2)

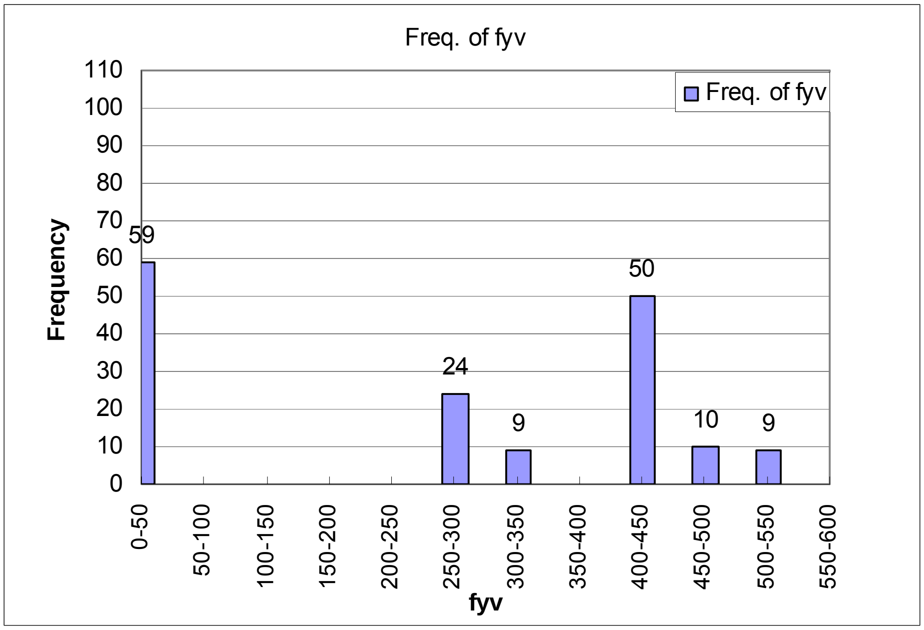


Fig.4.2.f Yield stress of vertical web reinforcement (N/mm2)

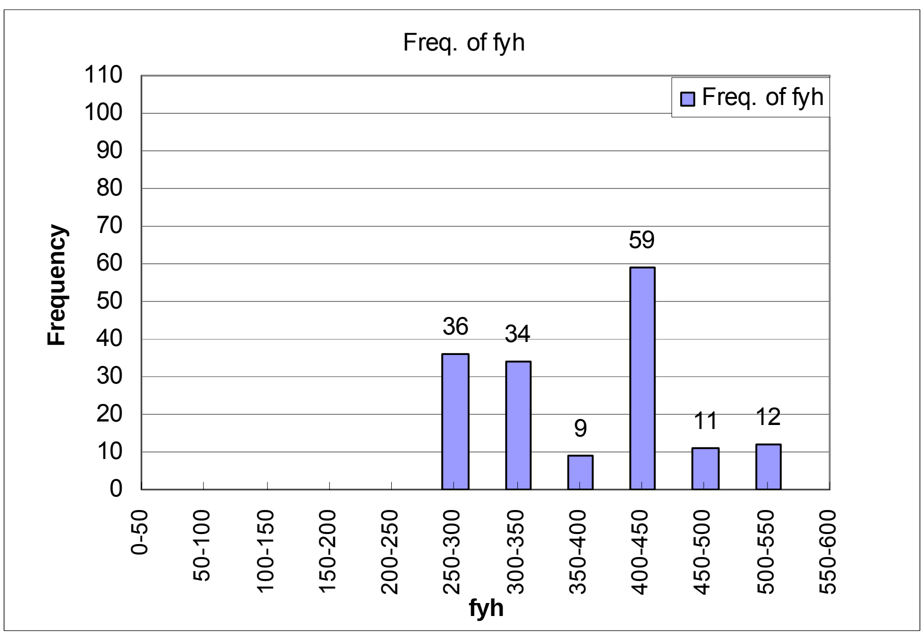


Fig.4.2.g Yield stress of horizontal web reinforcement (N/mm2)

Figure 4-2: Frequency distribution of input parameters across the range of 161 test results.

The frequency distribution shown in Fig 4.2 (a) shows that 37.89% of the beams tested had a width ranging from 40 to 80mm, 50.31% a width from 80 to 120mm, whereas only 11.8% of the beams tested had a width ranging from 120 to 200mm.

Fig 4.2 (b) shows that 53.4% of the beams tested had a depth ranging from 200 to 400mm, others had 46.58%.

Fig 4.2 (c) shows that 66.46% of the beams tested had a shear span ranging from 200 to 400mm, others had 33.54%.

Fig 4.2 (d)shows that 45.96% of the beams tested had a shear span to depth ratio ranging from 0.50 to 0.75, 45.34% a shear span to depth ratio from 0.75 to 1.0, whereas only 8.7% of the beams tested had a shear span to depth ratio ranging from 1.0 to 1.25.

Fig 4.2 (e)shows that 24.22% of the beams tested had a concrete compressive strength ranging from 10 to 20N/mm^2, 50.9% a concrete compressive strength from 20 to 30 N/mm^2, whereas only 24.22% of the beams tested had a concrete compressive strength ranging from 30 to 50 N/mm^2.

Fig 4.2 (f)shows that 36.64% of the beams tested had a yield stress of vertical web reinforcement ranging from 0 to 50N/mm^2, 31.05% a yield stress of vertical web reinforcement from 400 to 450 N/mm^2, others had 32.3%.

Fig 4.2 (g)shows that 43.48% of the beams tested had a yield stress of horizontal web reinforcement ranging from 250 to 350 N/mm^2, 36.65% a yield stress of horizontal web reinforcement from 400 to 450 N/mm^2, others had 19.87%.

As the shear span to depth ratio and concrete compressive strength the most effective parameters as drawn from the literature review and they are distributed evenly no need for excluding any data.

B- High strength concrete

Frequency distribution of input parameters across the range of 42 experimental results are considered.

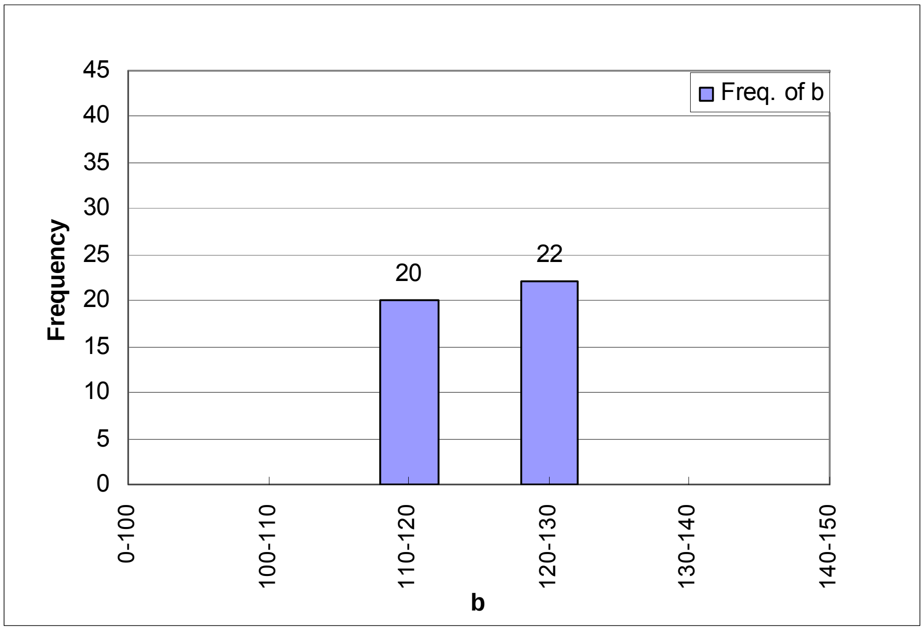


Fig.4.3.a Width of the beam (mm)

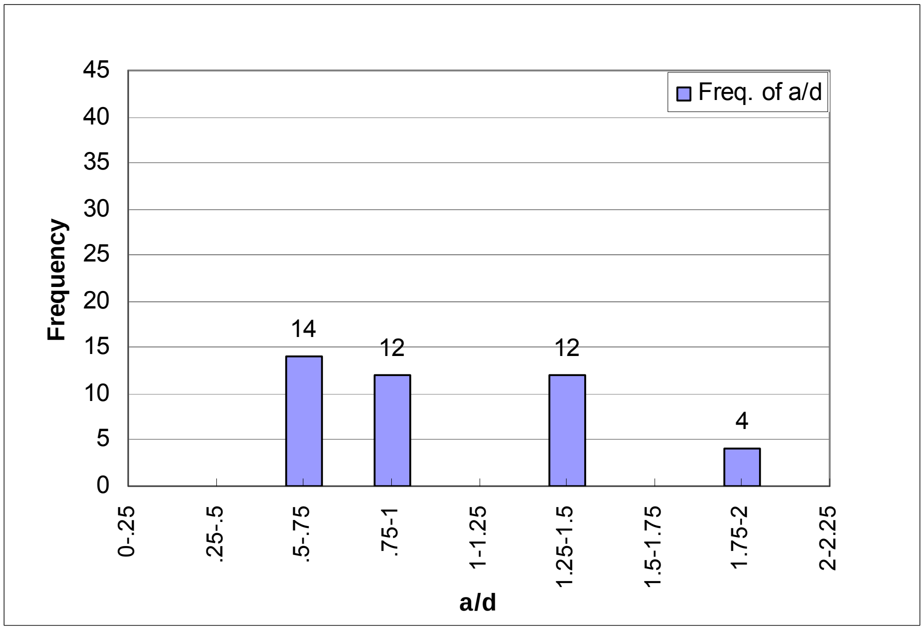


Fig.4.3.b Shear span –effective depth ratio.

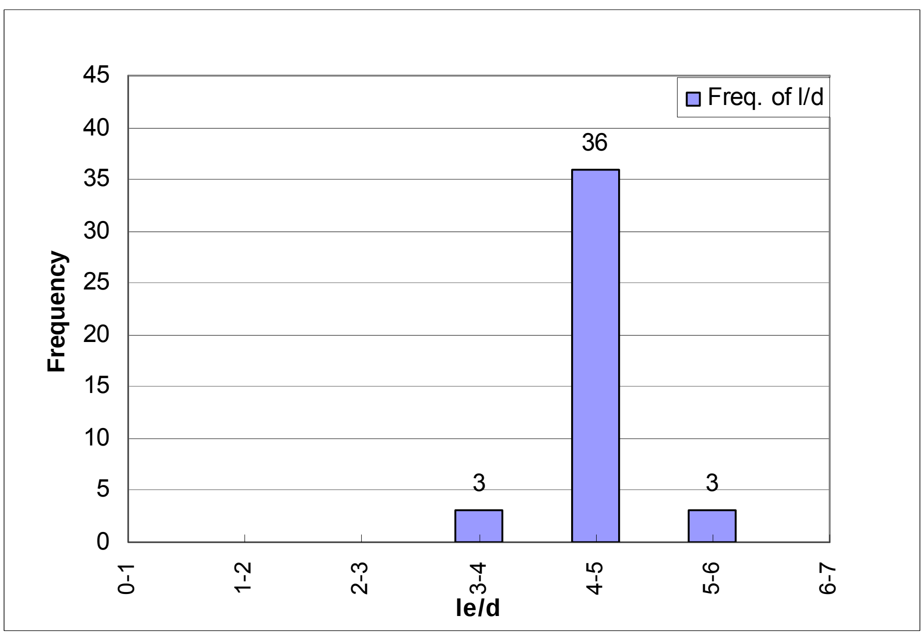


Fig.4.3.c Effective span- depth ratio.

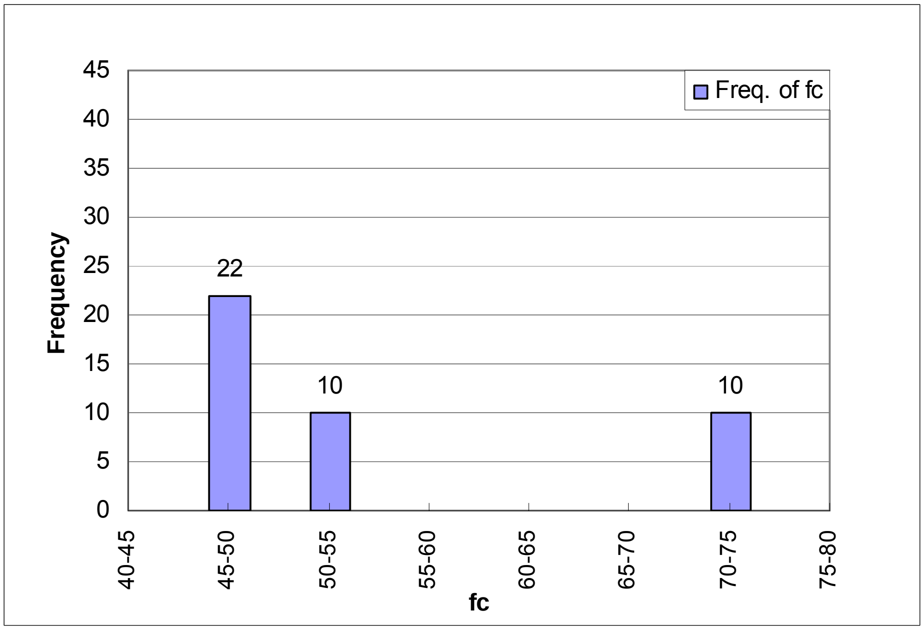


Fig.4.3.d Concrete compressive strength (MPa)

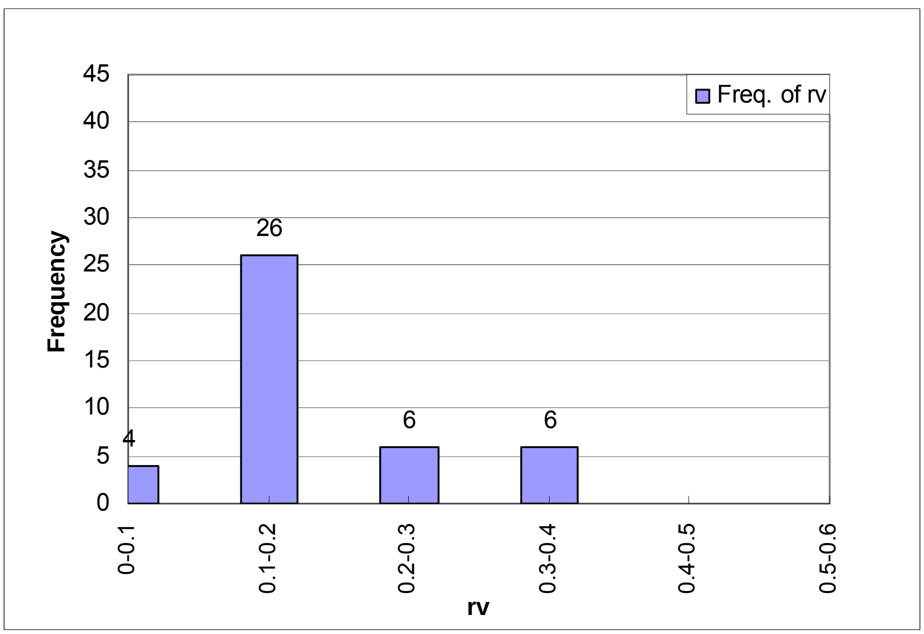


Fig.4.3.e Vertical shear reinforcement ratio (%)

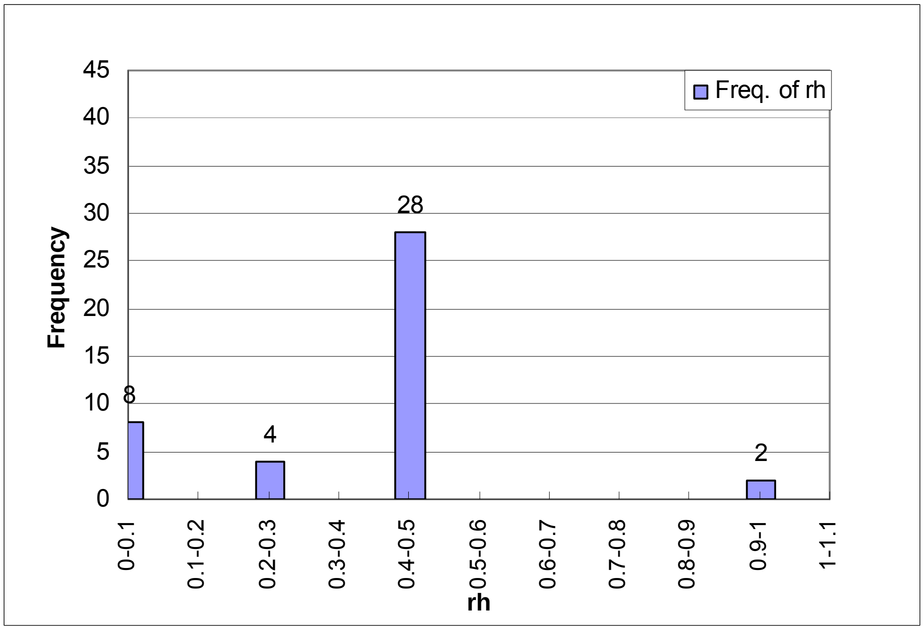


Fig.4.3.f Horizontal shear reinforcement ratio (%)

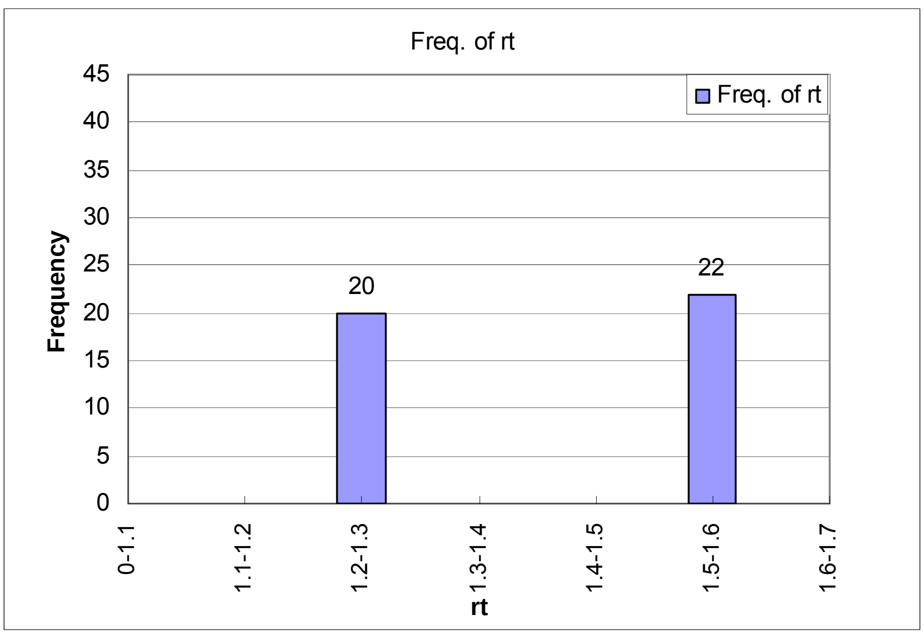


Fig.4.3.g Longitudinal steel reinforcement ratio (%)

Figure 4-3: Frequency distribution of input parameters across the range of 42 test results.

The frequency distribution shown in Fig 4.3 (a) shows that 47.62% of the beams tested had a width ranging from 110 to 120mm, whereas 52.38% of the beams tested had a width ranging from 120 to 130mm.

Fig 4.3 (b) shows that 33.33% of the beams tested had a shear span to effective depth ranging from 0.5 to 0.75, 28.6% had a shear span to effective depth ranging from 0.75 to 1.0, 28.6% had a shear span to effective depth ranging from 1.25 to 1.5, and 9.5% had a shear span to effective depth ranging from 1.75 to 2.0.

Fig 4.3 (c)shows that 85.7% of the beams tested had a effective span- depth ratio ranging from 3 to 4, and 7.1% had effective span- depth ratio ranging from 4 to 5, 7.1% had a effective span- depth ratio ranging from 5 to 6.

Fig 4.3 (d) shows that 52.38% of the beams tested had a concrete compressive strength ranging from 45 to 50MPa, 23.81% had concrete compressive strength from 50 to 55 MPa, whereas 23.81% of the beams tested had a concrete compressive strength ranging from 70 to 75 MPa.

Fig 4.3 (e) shows that 61.9% of the beams tested had a vertical shear reinforcement ratio ranging from 0.1 to 0.2%, others had 38.1%.

Fig 4.3 (f) shows that 66.69% of the beams tested had a horizontal shear reinforcement ratio ranging from 0.4 to 0.5%, others had 33.33%.

Fig 4.3 (g) shows that 47.62% of the beams tested had a longitudinal steel reinforcement ratio ranging from 1.2 to 1.3%, 52.38% had longitudinal steel reinforcement ratio from 1.5 to 1.6%.

As the shear span to effective depth ratio, concrete compressive strength, and longitudinal steel reinforcement ratio the most effective parameters as drawn from the literature review and they are distributed evenly no need for excluding any data.

4.4 MATLAB NEURAL NETWORK TOOLBOX

The neural network toolbox available in MATLAB Version 6.5 was used to build the current neural network model. Neural network algorithms in MATLAB Version 6.5 can be quickly implemented, and large-scale problems can be tested conveniently. The ANN toolbox enables modeling the problem using back propagation ANN, radial ANN and recurrent ANN with a wide range of transfer functions, learning techniques, network architectures, performance optimization and performance functions [41,70].

4.5 CONSTRUCTION OF ANN MODEL

By applying the mentioned selection and preprocessing criteria, it was thought that a reliable training set of data was obtained. The following sections explain the details of the training process which was followed in this research. The validation of the developed neural network model is discussed.

4.5.1 Training Strategy of the ANN Model

It was decided to use a feed forward back propagation neural network after pre-processing the data has been completed. Back propagation is the most successful and widely used in civil engineering applications [40,41].

Data Scaling

The first step in training is the data scaling.

Data scaling is an essential step for network training. One of the reason for pre-processing the output data is that a sigmoid transfer function is usually used within the network. Upper and lower limits of output from a sigmoid transfer function are generally 1 and 0, respectively. Scaling of the inputs to the range [-1, +1] greatly improves the learning speed, as these values fall in the region of the sigmoid transfer function where the output is most sensitive to variations of the input value. It is therefore recommended to normalize the input and output data before presenting them to the network. Scaling data can be linear or non-linear, depending on the distribution of the data. Most common functions are linear and logarithmic functions [69].

A simple linear normalization function within the values of zero to one is:

$$S = {(P - P_{\min})}\big/{(P_{\max} - P_{\min})}$$

Where S is the normalized value of the variable P, $P_{\min}$ and $P_{\max}$ are variable minimum and maximum values, respectively.

The function premnmx can be used to scale inputs and targets so that they fall in the range [-1, 1]. The following code illustrates the use of this function.

```
[pn,minp,maxp,tn,mint,maxt] = premnmx(p,t);
net=train(net,pn,tn)
```

The original network inputs and targets are given in the matrices p and t, respectively. The

normalized inputs and targets, pn and tn, that are returned will all fall in the interval [-1,1]. The vectors minp and maxp contain the minimum and maximum values of the original inputs, and the vectors mint and maxt contain the minimum and maximum values of the original targets. After the network has been trained, these vectors should be used to transform any future inputs that are applied to the network. They effectively become a part of the network, just like the network weights and biases [21].

The second step in training a feed forward network is to create the network object. The function newff creates a feed forward network.

It requires four inputs and returns the network object. The first input is an R by 2 matrix of minimum and maximum values for each of the R elements of the input vector. The second input is an array containing the sizes of each layer. The third input is a cell array containing the names of the transfer functions to be used in each layer. The final input contains the name of the training function to be used.

The third step is setting the training parameters :

a- The number of 'epochs'(number of times that the whole set of patterns is presented to the network) affects the performance of the network. This number depends on many factors, of which the following are most important :

Number of training data,

Number of hidden layers,

Number of neurons in hidden layers,

Number of dependent output parameters[69].

b-Maximum permissible error.

c- The number of iterations for which the error becomes constant.

d-The training status is displayed for every show iteration of the algorithm.

Back propagation algorithm in MATLAB Version 6.5 recommends dividing the data set into three sets: training, validation and testing sets.

The training set is used to gradually reduce the ANN error. The error on the validation set is monitored during the training process. The validation set error will normally decrease during the initial phase of training, as does the training set error [41,21].

However, when the network begins to over-fit the data, the error on the validation set will typically begin to rise. When the validation set error increases for a specified number of epochs, the training is stopped. The test set is used as a further check for the generalization of the ANN, but do not have any effect on the training.

In the present study, training data set comprises a half of all data entries, and the remaining data entries are equally divided between the validation and testing sets [41].

The final step is plotting the training progress and the correlation coefficient "r"

Fig 4.4 presents a flow chart showing the training process of artificial neural networks.

Flow chart showing the training process

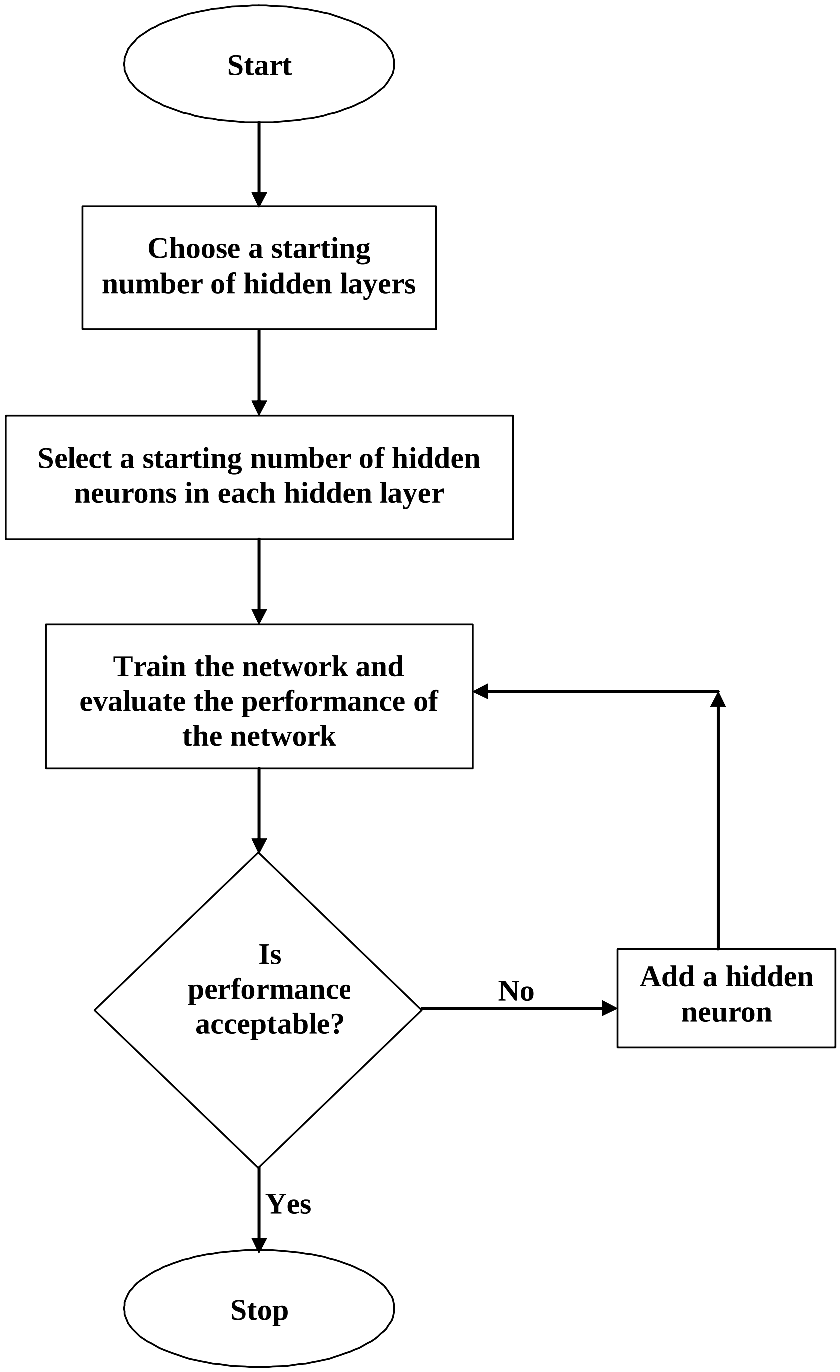


Figure 4-4: Flow chart showing the training process of ANN [77]

In Fig. 4.4. if the number of neurons in the first hidden layer is large or there is no change in performance, add a new (second) hidden layer.

4.6 TOPOLOGY OF THE DEVELOPED ANN

Two separate ANN models were trained: one for the normal strength concrete deep beams, and the second for high strength concrete deep beams.

4.6.1 Normal Strength Concrete ANN Model.

There were seven input parameters; namely the width of the beam (b), shear span (a), shear span to depth ratio (a/h), depth of the beam (h), concrete compressive strength ($f_c^{'}$), yield stress of horizontal web reinforcement (f_{yh}), and yield stress of vertical web reinforcement (f_{yv}). The output parameter is the shear strength V (N/mm^2).

After several trials and iterations using MATLAB tools the following topology can be obtained for the normal concrete compressive strength deep beams.

The topology of the network is:

- Type of architecture : Multi-layer feed forward
- Number of layers (hidden + output): 3

Note :We do not count the input layer of source nodes because no computation is performed there.

Table 4-3: Number of Used Neurons and Transfer Functions for Normal Strength Concrete .

Layer Name	Number of Neurons	Transfer Function
First hidden layer	5	logsig
Second hidden layer	5	logsig
Output layer	1	purlin

- Training algorithm used: Back probation algorithm
- Number of epochs required for training: 5000
- Goal (Sum Squared Error SSE): 0.9

The architecture of ANN model for normal strength concrete deep beams is shown in Fig 4.5.

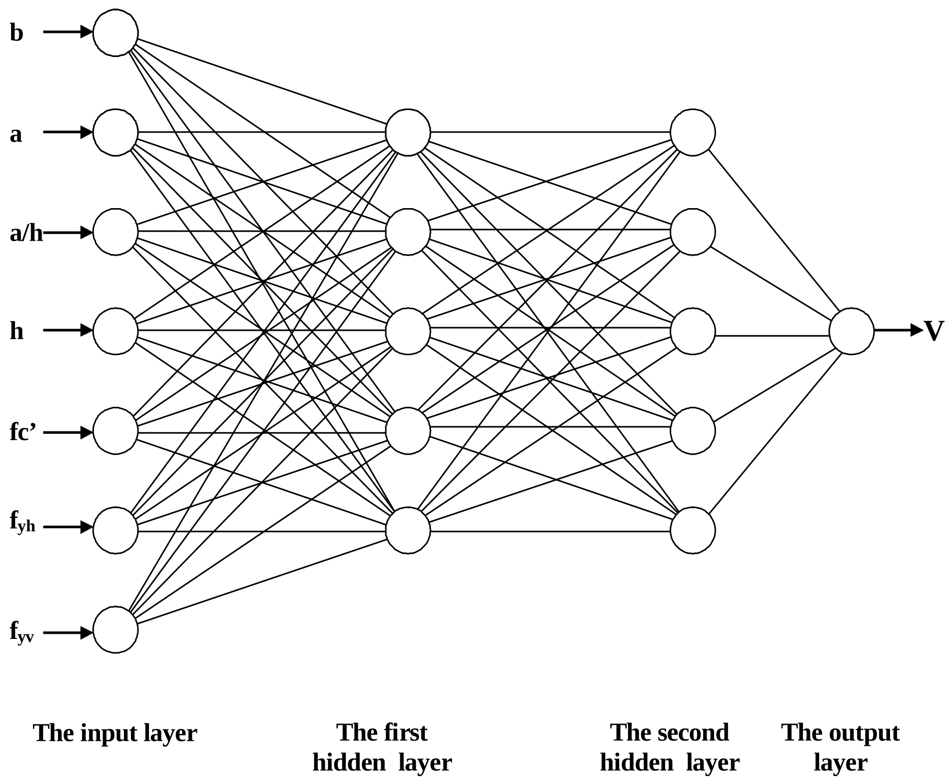


Figure 4.5: The architecture of ANN model for normal strength concrete deep beams.

4.6.2 High Strength Concrete ANN Model.

There were seven input parameters; namely the width of the beam (b), shear span –effective depth ratio (a/d), effective span- depth ratio (l_e/d), concrete compressive strength (f_c'), vertical shear reinforcement ratio(ρ_v), horizontal shear reinforcement ratio(ρ_h), and longitudinal steel reinforcement ratio(ρ_t). The output parameter is the shear strength V (MPa).

After several trials and iterations using MATLAB tools the following topology can be obtained for the high concrete compressive strength deep beams.

The topology of the network is:

- Type of architecture : Multi-layer feed forward
- Number of layers (hidden + output):3

Table 4-4: Number of Used Neurons and Transfer Functions for High Strength Concrete .

Layer Name	Number of Neurons	Transfer Function
First hidden layer	5	logsig
Second hidden layer	5	logsig
Output layer	1	purlin

- Training algorithm used: Back probation algorithm
- Number of epochs required for training: 5000
- Goal (Sum Squared Error SSE): 0.9

The architecture of ANN model for high strength concrete deep beams is shown in Fig 4.6.

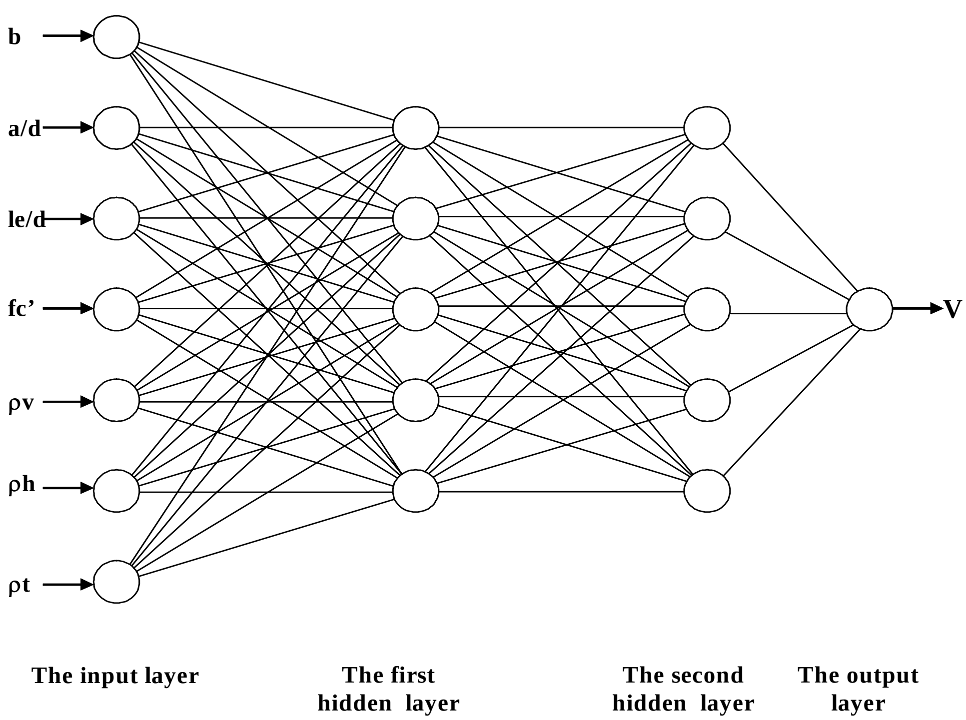


Figure 4.6: The architecture of ANN model for high strength concrete deep beams.

4.7 PERFORMANCE OF ANN

The performance of the trained neural networks was monitored during the training process as the sum squared error (SSE) over all the training data. The training process stops when any of the following criteria is satisfied:

- the maximum number of iterations (epochs) is reached;
- the performance has been minimized to the required target;
- the average training error level has reached a predetermined target value;
- the performance gradient falls below a minimum value; the validation set error starts to rise for a specified number of epochs [21,69,41].

4.7.1 Normal Strength Concrete

A statistical comparison between the ANN, the test result, and ACI code is presented in Table 4.5. These statistical parameters show that the predicted shear strength using the trained ANN method is in good agreement with the experimental results.

Table 4-5: Comparisons between the ANN, the test result, and ACI for Normal Strength Concrete.

	Mean	**Standard deviation**
V_{Test} **(N/mm²)**	496.82	560.598
V_{ANN} **(N/mm2)**	479.58	537.61
V_{ACI} **(N/mm2)**	703.46	474.37
V_{Test}/V_{ANN}	1.04	0.278
V_{Test}/V_{ACI}	2.78	9.05

The progress of the training was examined by plotting the training, validation and test sum squared errors, SSE, versus the performed number of iterations, as presented in Fig. 4.7.

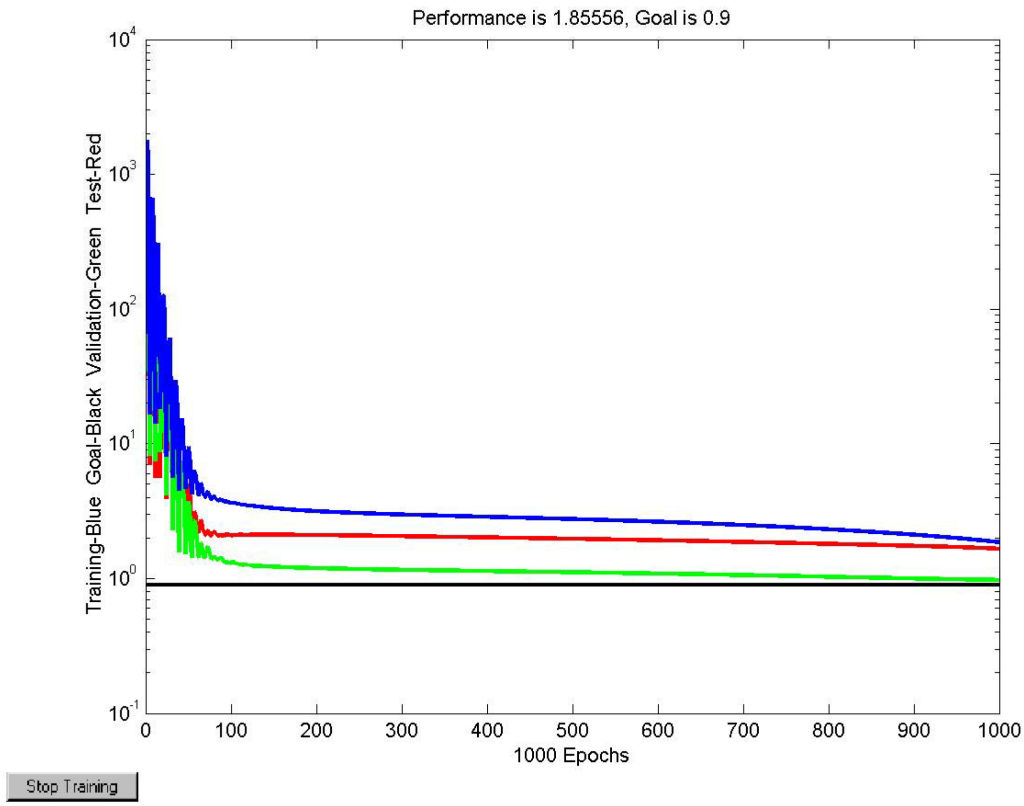


Figure 4-7: Training progress of ANN

The results shown in Fig. 4.7 are fairly reasonable, since the test set error and the validation set error have very similar characteristics and no significant over-fitting has occurred.

To insure the adequacy of the trained neural network model the testing data which has been taken randomly from the whole data is taken and trained separately, these testing data were 39 deep beams for normal concrete compressive strength.

Fig. 4.8 gives comparisons of the shear strength from experiments and those obtained from the trained neural network (a) for 161 training data set and (b) for 39 testing data set only.

These comparisons show that the predicted shear strength using the trained ANN is in good agreement with the experimental results. Overall, it could be concluded that the trained neural networks were successful in learning the relationship between the input and output data.

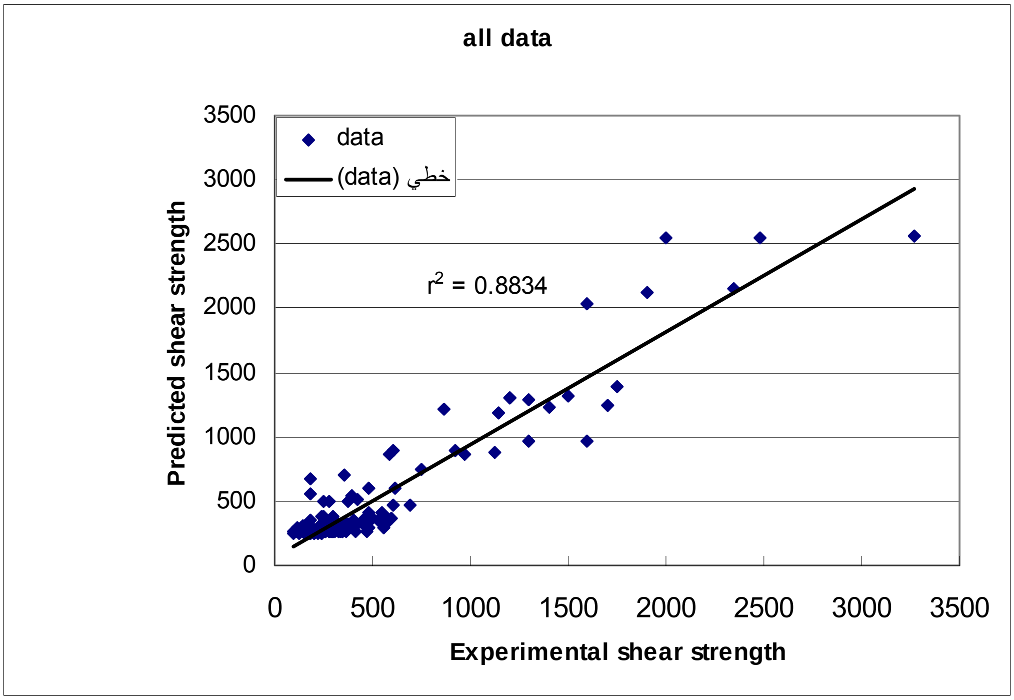


Fig.4.8. a

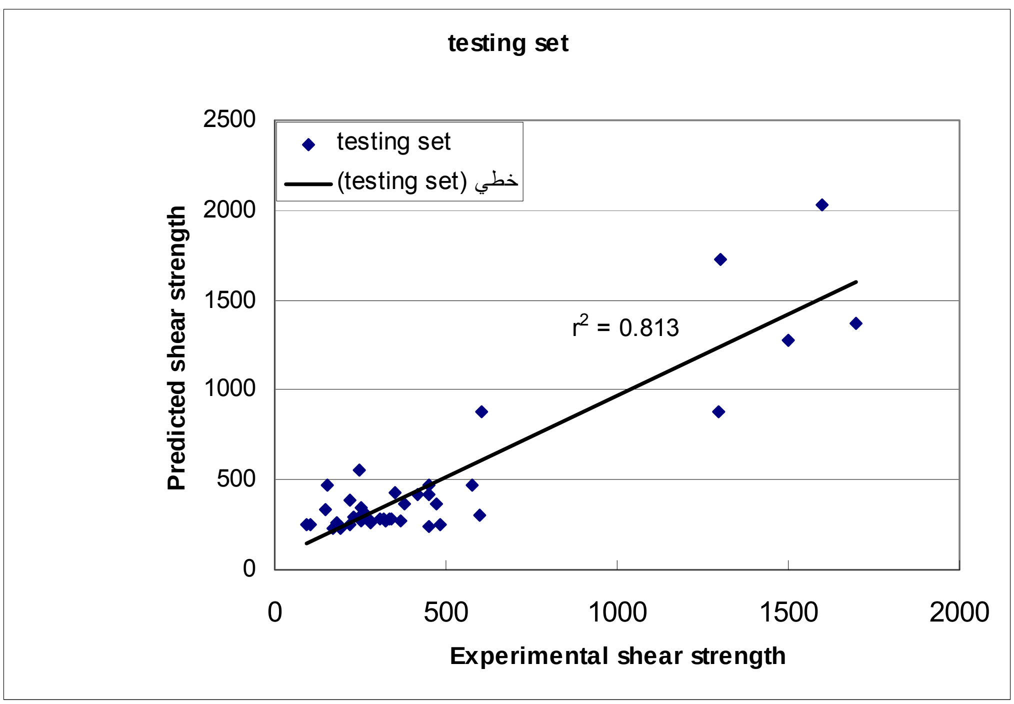


Fig.4.8. b

Figure 4-8: Neural network shear strength (N/mm^2) predictions (a)training data, (b)testing set.

4.7.2 High Strength Concrete

A statistical comparison between the ANN, the test result, and ACI code is presented in Table 4.6. These statistical parameters show that the predicted shear strength using the trained ANN method is in good agreement with the experimental results.

Table 4-6: Comparisons between the ANN, the test result, and ACI for High Strength Concrete.

	Mean	**Standard deviation**
V_{Test} **(MPa)**	6.445	2.34
V_{ANN} **(MPa)**	6.449	2.184
V_{ACI} **(MPa)**	7.00	2.308
V_{Test} / V_{ANN}	1.002	0.169
V_{Test} / V_{ACI}	1.228	0.192

To insure the adequacy of the trained neural network model, the testing data which has been taken randomly from the whole data is taken and trained separately, these testing data were 10 deep beams for high concrete compressive strength.

Fig. 4.9 gives comparisons of the shear strength from experiments and those obtained from the trained neural network (a) for 42 training data set and (b) for 10 testing data set only.

These comparisons show that the predicted shear strength using the trained ANN is in good agreement with the experimental results. Overall, it could be concluded that the trained neural networks were successful in learning the relationship between the input and output data.

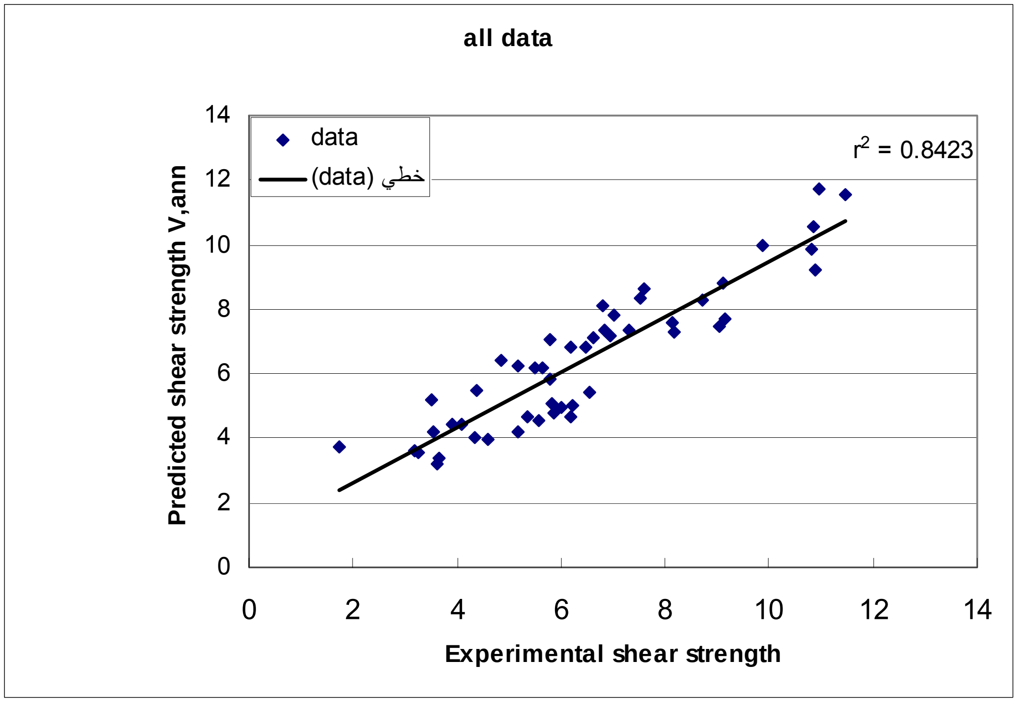


Fig.4.9. a

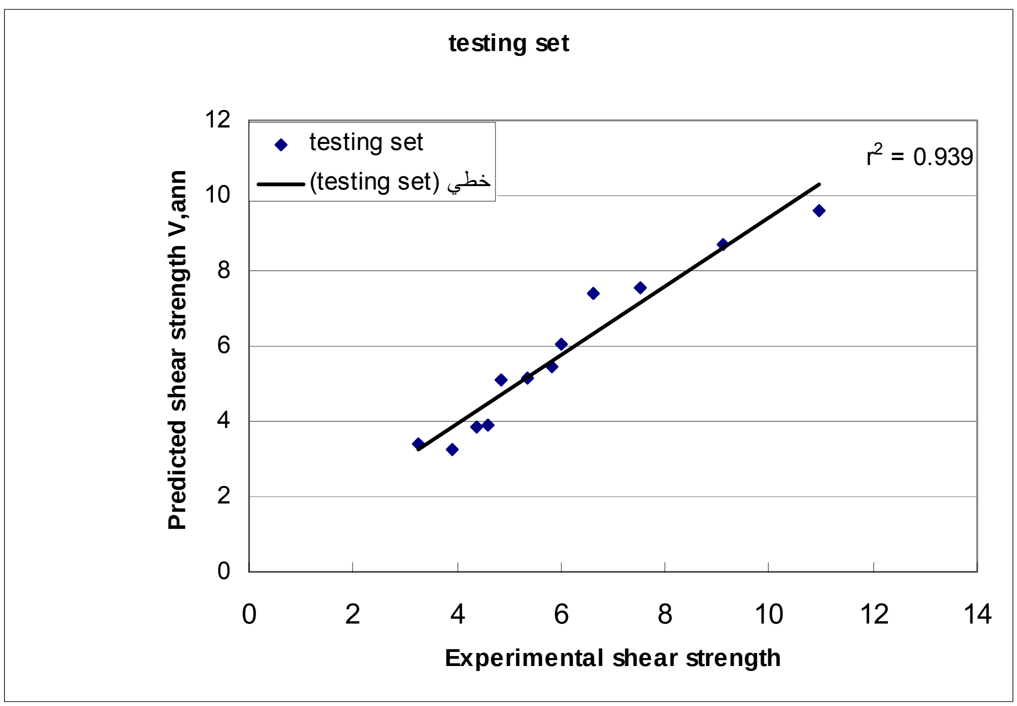


Fig.4.9. b

Figure 4-9: Neural network shear strength (MPa) predictions (a)training data, (b)testing set.

5. PARAMETRIC STUDY

The advantage of trained neural network models is that parametric studies can be easily done by simply varying one input parameter and all remaining input parameters are set to constant values [45].

Using neural networks technique, it will be possible to study the effect of all parameters on the ultimate shear strength of deep beams using all test results available in the literature at the same time; this may eliminate the inconsistency and conflicting conclusions drawn by different researches [8].

The ultimate shear strength in deep beams is controlled by many parameters specially, the width of the beam (b),shear span (a), shear span to depth ratio (a/h), overall depth of the beam (h), concrete compressive strength ($f_c^{'}$), yield stress of horizontal web reinforcement (f_{yh}), yield stress of vertical web reinforcement (f_{yv}), effective span-depth ratio (l_e/d), vertical shear reinforcement ratio(ρ_v), horizontal shear reinforcement ratio(ρ_h), and longitudinal steel reinforcement ratio(ρ_t).

The ACI 318-02 formulas takes into consideration the effect of some of these parameters as shown in the following equations :

The normal shear resisting force V_c of the of the plain concrete can be taken as

$$V_c = (3.5 - 2.5\frac{M_u}{V_u d})(1.9\sqrt{f_c^{\backslash}} + 25000\rho w\frac{V_u d}{M_u})b_w d \leq 6\sqrt{f_c^{\backslash}}b_w d \qquad (5\text{-}1)$$

The force resisted by the shear reinforcement V_s :

$$V_s = \left[\frac{A_v}{s_v}\left(\frac{1+{l_n}/{d}}{12}\right) + \frac{A_{vh}}{s_h}\left(\frac{11-{l_n}/{d}}{12}\right)\right]f_y d \qquad (5\text{-}2)$$

provided such that $V = \phi(V_c + V_s)$

In this chapter, the influence of these parameters on shear strength of deep beams for both normal and high compressive strength concrete will be discussed using the trained neural network, after that a relationship between the ultimate shear strength predicted from the neural networks model versus the parameter under consideration will be discussed.

5.1 PARAMETRIC STUDY FOR NORMAL STRENGTH CONCRETE DEEP BEAMS

Three cases will be studied to show the effect of each parameter on the chosen output which is the shear strength, these cases are the lower, the average, and the upper case.

Case 1 :The lower case

b = 70mm; h = 350mm; a = 300mm; a/h = 0.50;

$f_c^{'}$ = 20 N/mm^2 ; f_{yv} = 150 N/mm^2; and f_{yh} = 330 N/mm^2.

Case 2 :The average case

b = 98mm; h = 510mm; a = 415mm; a/h = 0.86;

$f_c^{'}$ = 25 N/mm^2 ; f_{yv} = 250 N/mm^2; and f_{yh} = 380 N/mm^2.

Case 3 :The upper case

b = 126mm; h = 670mm; a = 515mm; a/h = 1.22;

$f_c^{'}$ = 30 N/mm^2 ; f_{yv} = 350 N/mm^2; and f_{yh} = 430 N/mm^2.

Table 5.1 shows the variations of the input parameters which used in the ANN model for normal strength concrete.

Table 5-1: Variations for normal strength concrete.

Parameter	Variations						
b (mm)	50	75	100	125	150	175	200
h (mm)	250	500	750	1000	1250	1500	1740
a(mm)	200	400	600	800	1000	1200	1400
a/h	0.25	0.5	0.75	1	1.25	1.5	1.75
$f_c^{'}$ N/mm^2	15	20	25	30	35	40	45
f_{yv} N/mm^2	300	330	360	390	420	450	480
f_{yh} N/mm^2	250	275	300	325	350	375	400

5.1.1 The Shear span-Depth ratio.

It can be noted from Fig. 5.1 that the ultimate shear strength increases with decreasing the shear span-depth ratio while other parameters constant.

In other words, it is clear that the shear strength is inversely proportional to the shear span-depth ratio and has the most significant effect on the shear strength of deep beams This result is in a good agreement with findings of other researchers such as Smith, Goh, and Ashour [8,42,81].

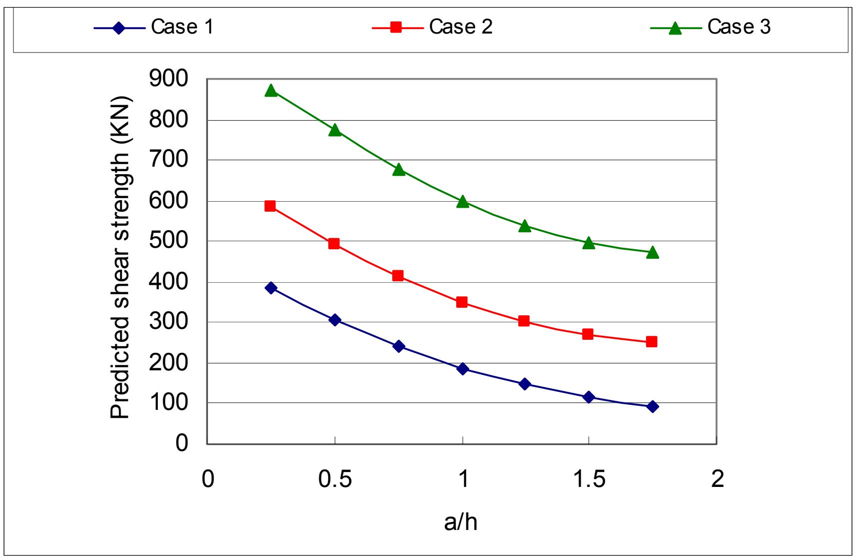


Figure 5-1:Effect of shear span to depth ratio on shear strength.

Equation (5.3) shows the relationship between the predicted shear strength and the shear span to depth ratio, it can be noted from equation (5.3) that a parabolic relationship between the shear span- depth ratio and the predicted ultimate shear strength, while in the ACI code this relationship does not exist.

$$V = a_2\left(a/h\right)^2 - a_1\, a/h + a_0 \qquad (5\text{-}3)$$

Where : a_2, a_1 and a_0 are coefficients have the following values:

a_2= 119.7, a_1=462.27,and a_0=693.1

r^2=0.9999

Fig 5.2 shows the relationship between shear span to depth ratio and the predicted shear strength for three levels of concrete compressive strength, while keeping all other input parameter constant as follows:

b = 98mm; h = 510mm; a = 415mm; f_{yv} = 250 N/mm^2; and f_{yh} = 380 N/mm^2.

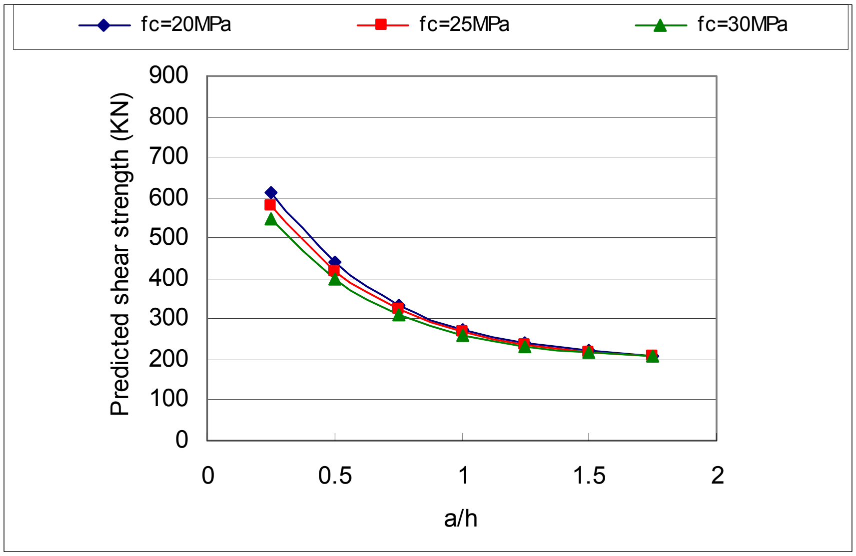


Figure 5-2: Effect of shear span to depth ratio on shear strength.

The concrete compressive strength has no effect on the ultimate shear strength when a/d > 1. and have a small effect when a/d < 1.

5.1.2 The Concrete Compressive Strength.

It can be noted from Fig. 5.3 that the ultimate shear strength increases with increasing the compressive strength of concrete while other parameters constant. This is consistent with Smith and Goh [42,81]. Fig 5.3 shows also that the increasing rate in the predicted shear strength is larger in case 3 than in the other cases, which means that the other parameters are significantly effective on the predicted value of shear strength.

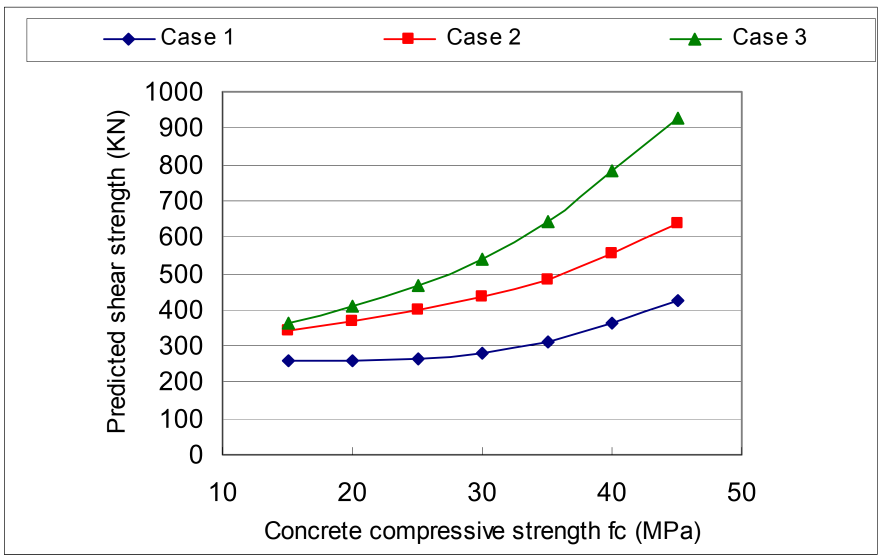


Figure 5-3:Effect of concrete compressive strength on shear strength .

Equation (5.4) shows the relationship between the predicted shear strength and the concrete compressive strength.

$$V = a_0 \left(f_c'\right)^n \tag{5-4}$$

a_0=73.327 and n=0.5436

r^2=0.9119

Equation 5.4 means that the predicted strength is directly proportional with approximately the square root of the concrete compressive strength.

$$V \;\; \alpha \;\; \sqrt{f_c'}$$

Fig 5.4 shows the relationship between concrete compressive strength and the predicted shear strength for three levels of shear span to depth ratio, while keeping all other input parameter constant as follows:

b = 98mm; h = 510mm; a = 415mm; f_{yv} = 250 N/mm^2; and f_{yh} = 380 N/mm^2.

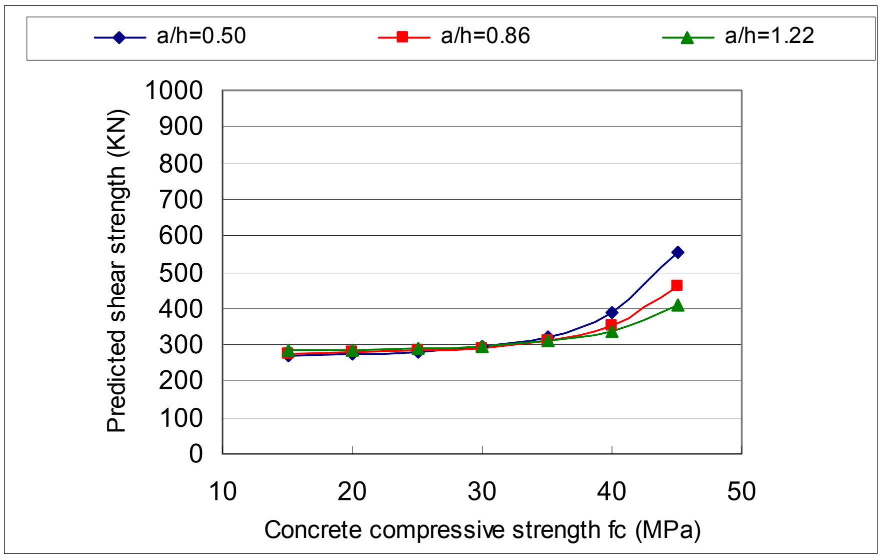


Figure 5-4:Effect of concrete compressive strength on shear strength .

It is clear that the shear span to depth ratio has no effect on the predicted shear strength when the concrete compressive strength is smaller than 35 MPa and when the concrete compressive strength is larger than 35MPa the shear strength increases with decreasing the shear span-depth ratio.

5.1.3 The Yield Stress of Vertical Web Reinforcement.

It can be noted from Fig. 5.5 that the ultimate shear strength is slightly affected by the yield stress of vertical web reinforcement .

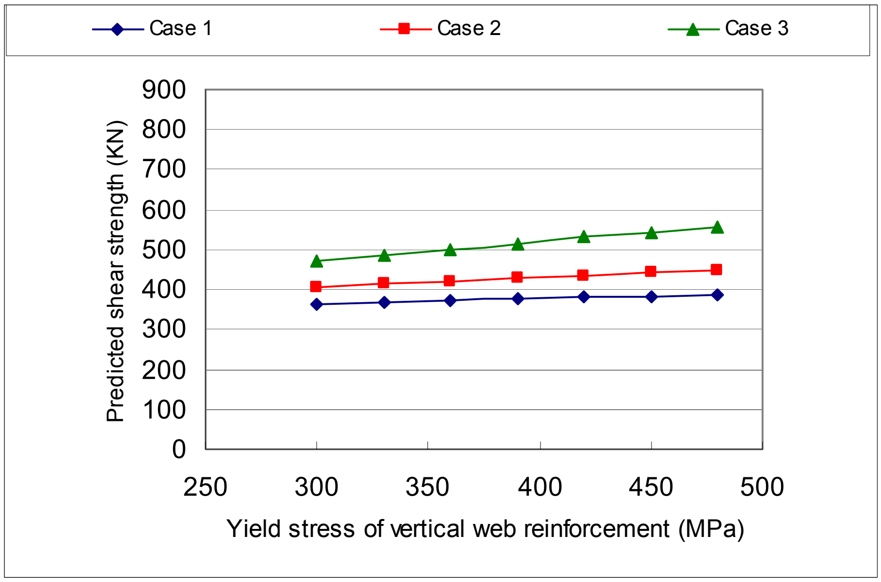


Figure 5-5: Effect of yield stress of vertical web reinforcement on shear strength .

Equation (5.5) shows a linear relationship between the predicted shear strength and yield stress of vertical web reinforcement.

$$V = a_1 f_{yv} + a_0 \qquad (5\text{-}5)$$

a_1=0.2321 and a_0=336.8

r^2=0.9919

Equation 5.5 shows that the predicted shear strength is directly proportional with the yield stress of vertical web reinforcement and the relationship between them is linear.

$$\mathrm{V} \;\alpha\; f_{yv}$$

5.1.4 The Yield Stress of Horizontal Web Reinforcement.

It can be noted from Fig. 5.6 that the ultimate shear strength is slightly affected by the yield stress of horizontal web reinforcement .

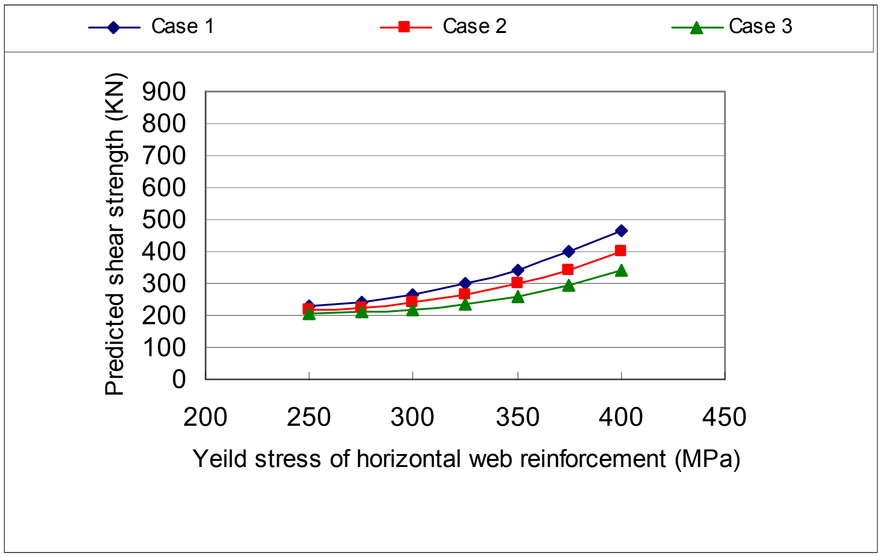


Figure 5-6: Effect of yield stress of horizontal web reinforcement on shear strength.

Equation (5.6) shows the relationship between the predicted shear strength and yield stress of horizontal web reinforcement.

$$V = a_0 \left(f_{yh}\right)^n \qquad (5\text{-}6)$$

a_0=0.1473 and n=1.3067

$r^2=0.9314$

5.1.5 The Width of The Beam.

It can be noted from Fig. 5.7 that the ultimate shear strength increases with increasing the width of the beam.

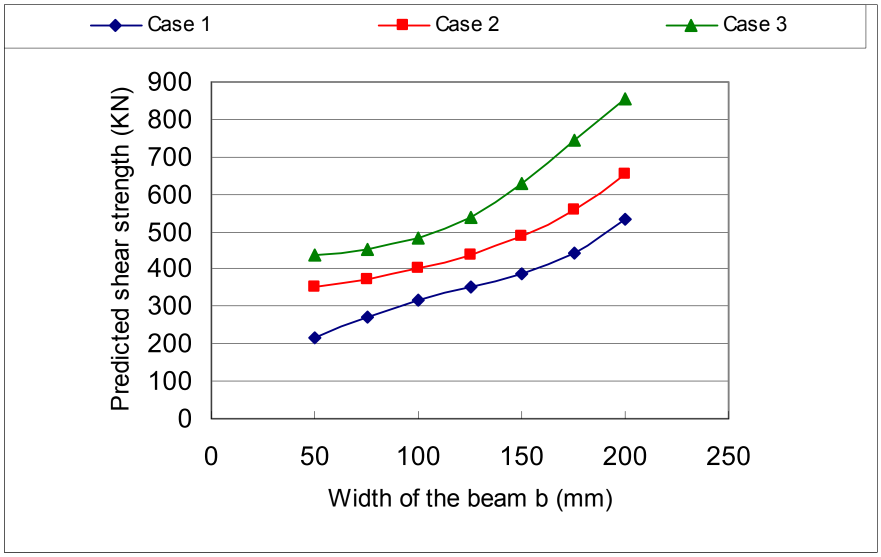


Figure 5-7: Effect of the beam width on shear strength.

Equation (5.7) shows the relationship between the predicted shear strength and the beam width.

$$V = a_2 b^2 - a_1 b + a_0 \tag{5-7}$$

$a_2=0.0117,\ a_1=0.9792, and\ a_0=375.99$

$r^2=0.9974$

Equation 5.7 shows that the predicted shear strength is directly proportional with the width of the beam.

5.1.6 The Shear Span.

It can be noted from Fig. 5.8 that the ultimate shear strength increases with increasing the shear span of the beam. Fig 5.8 shows also that the increasing rate is larger in case 3 than in the other cases, which means that the other parameters are effective on the predicted value of shear strength.

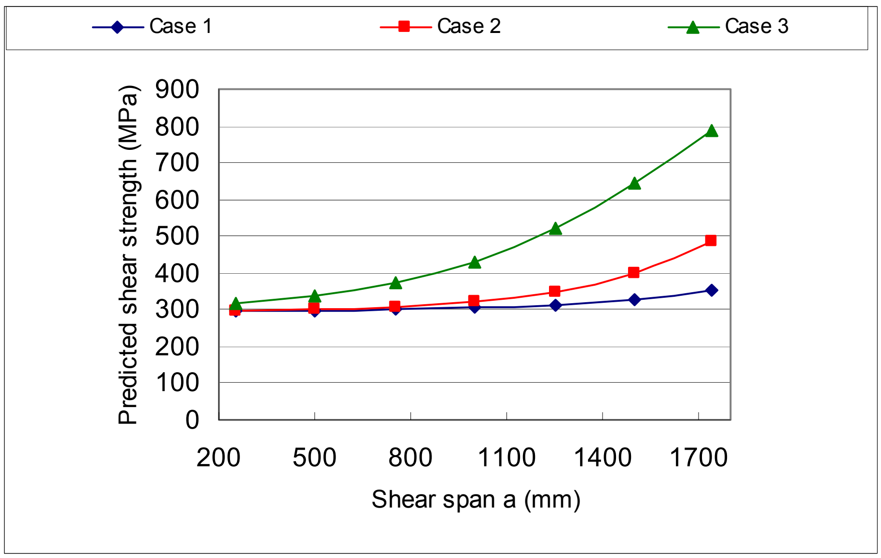


Figure 5-8: Effect of shear span on shear strength.

Equation (5.8) shows the relationship between the predicted shear strength and the shear span.

$$V = a_2 a^2 - a_1 a + a_0 \tag{5-8}$$

a_2=0.0001, a_1=0.1349,and a_0=330.47

r^2=0.9822

Equation 5.8 shows that the predicted shear strength is directly proportional with shear span.

5.1.7 The Height of The Beam.

It can be noted from Fig. 5.9 that the ultimate shear strength increases with increasing the height of the beam.

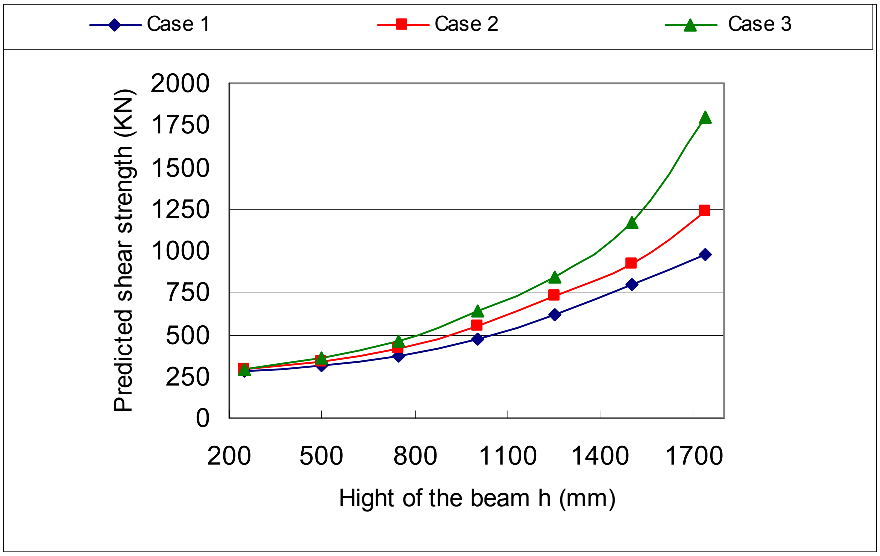


Figure 5-9: Effect of height of the beam on shear strength.

Equation (5.9) shows the relationship between the predicted shear strength and the height of the beam.

$$V = a_2 h^2 - a_1 h + a_0 \qquad (5\text{-}9)$$

$a_2 = 0.0004$, $a_1 = 0.1789$, and $a_0 = 320.83$

$r^2 = 0.9979$

5.2 PARAMETRIC STUDY FOR HIGH STRENGTH CONCRETE DEEP BEAMS

Three cases will be also studied to show the effect of each parameter on the chosen output which is the shear strength, these cases are the lower, the average, and the upper case .

Case 1 :The lower case

b = 124mm; a/d = 0.8; l_e/d = 3.5; $f_c^{'}$ = 45 MPa ;

ρ_v = 0.12 %; ρ_h = 0.2 %; and ρ_t = 1.35 %.

Case 2 :The average case

b = 126mm; a/d = 0.97; l_e/d = 4; $f_c^{'}$ = 50 MPa ;

ρ_v = 0.16 %; ρ_h = 0.36 %; and ρ_t = 1.45 %.

Case 3 :The upper case

b = 128mm; a/d = 1.14; l_e/d = 4.5; $f_c^{'}$ = 55 MPa ;

ρ_v = 0.2 %; ρ_h = 0.52 %; and ρ_t = 1.55 %.

Table 5.2 shows the variations of the input parameters which used in the ANN Model for normal strength concrete.

Table 5-2: Variations for high strength concrete.

Parameter	Variations						
b (mm)	121	122	123	124	125	126	127
a/d	0.5	0.6	0.7	0.8	0.9	1	1.1
l_e/d	3.5	3.7	3.9	4.1	4.3	4.5	4.7
$f_c^{'}$ MPa	40	45	50	55	60	65	70
ρ_v = rv	0.1	0.15	0.18	0.22	0.26	0.3	0.34
ρ_h = rh	0.2	0.3	0.4	0.5	0.6	0.7	0.8
ρ_t = rt	1.3	1.34	1.38	1.42	1.46	1.5	1.54

5.2.1 The Shear span-depth ratio.

It can be noted from Fig. 5.10 that the ultimate shear strength increases with decreasing the shear span-depth ratio while other parameters held constant, as well as the ultimate shear strength is affected predominantly by a/d, this agrees with Tan and Oh [54,60].

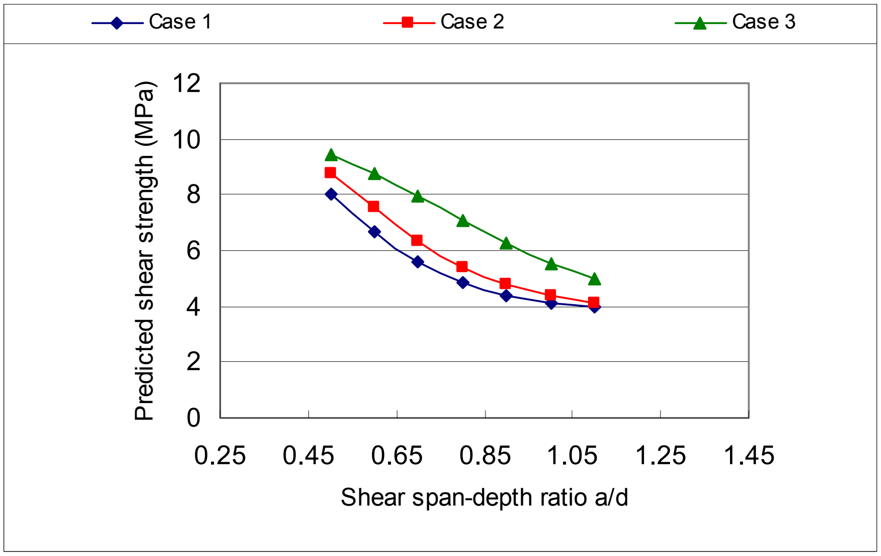


Figure 5-10: Effect of shear span-depth ratio on shear strength.

Equation (5.10) shows the relationship between the predicted shear strength and the shear span to effective depth ratio, it can be noted from equation (5.10) that a parabolic relationship between the shear span- effective depth ratio and the predicted ultimate shear strength. While in the ACI code this relationship does not exist .

$$V = a_2 \left(a/d \right)^2 - a_1\, a/d + a_0 \qquad (5\text{-}10)$$

Where : a_2, a_1 and a_0 are coefficients and

a_2= 11.377, a_1=26.057,and a_0=19.025

r^2=0.9994

Fig 5.11 shows the relationship between shear span to effective depth ratio and the predicted shear strength for three levels of concrete compressive strength, while keeping all other input parameter constant as follows:

b = 126mm; $l_e / d = 4$; $\rho_v = 0.16$ %; $\rho_h = 0.36$ %; and $\rho_t = 1.45$ %.

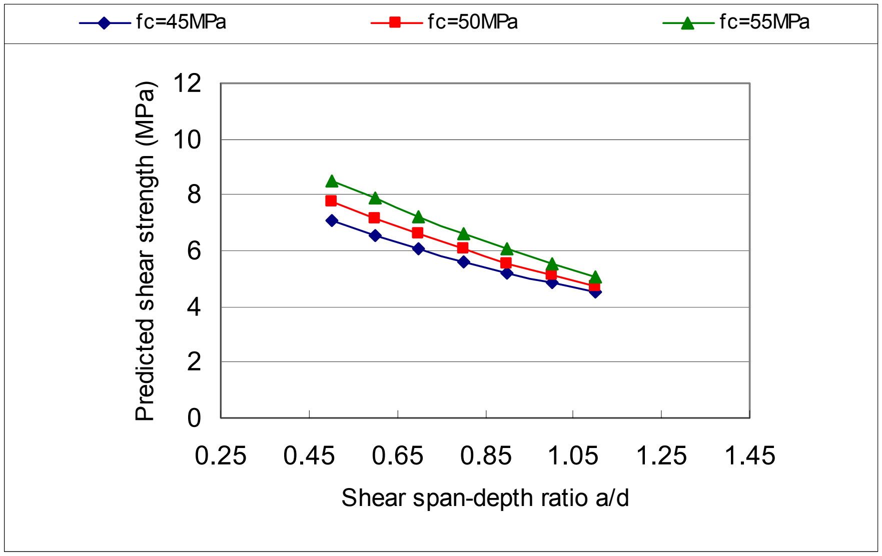


Figure 5-11: Effect of shear span to effective depth ratio on shear strength.

From Fig 5.11 it is clear that the concrete compressive strength has almost a constant effect on the predicted shear strength that the three cases are approximately parallel to each other .

5.2.2 Concrete Compressive Strength.

It can be noted from Fig. 5.12 that the ultimate shear strength increases with increasing the compressive strength of concrete while other parameters held constant, this agrees with Oh [60].

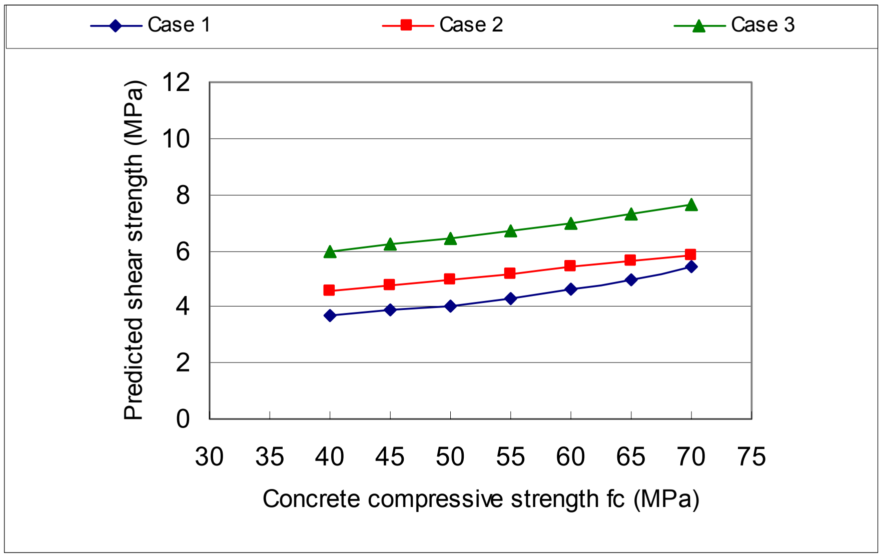


Figure 5-12: Effect of concrete compressive strength on shear strength.

Equation (5.11) shows the relationship between the predicted shear strength and the concrete compressive strength, it can be noted from equation (5.11) that concrete compressive strength has a slight change on the shear strength in the case of high concrete compressive strength, and a linear relationship is found between concrete compressive strength and shear strength.

$$V = a_1 f_c^{'} + a_0 \qquad (5\text{-}11)$$

a_1=0.0374, and a_0=2.9706

r^2=0.9998

$$V \quad \alpha \quad f_c^{'}$$

Fig 5.13shows the relationship between concrete compressive strength and the predicted shear strength for three levels of shear span to effective depth ratio, while keeping all other input parameter constant as follows:

b = 126mm; l_e / d = 4; ρ_v = 0.16 %; ρ_h = 0.36 %; and ρ_t = 1.45 %.

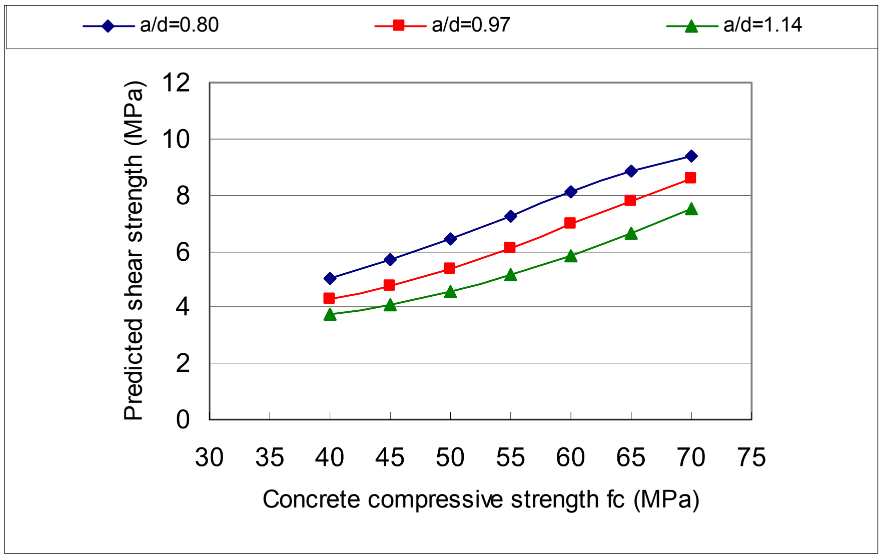


Figure 5-13: Effect of concrete compressive strength on shear strength.

From Fig 5.13 it is clear that the shear span to effective depth ratio has constant effect on the predicted shear strength, and the three cases are almost constant.

It can be noted that in normal strength deep beams the ultimate shear strength is directly proportional to the square root of the concrete compressive strength as in the ACI code, while in high strength deep beams the ultimate shear strength is directly proportional to the concrete compressive strength.

5.2.3 The Effective span-depth ratio.

It can be noted from Fig. 5.14 that the ultimate shear strength increases with decreasing the effective span-depth while other parameters held constant, also the ultimate shear strength was slightly affected by l/d this agrees with Oh [60].

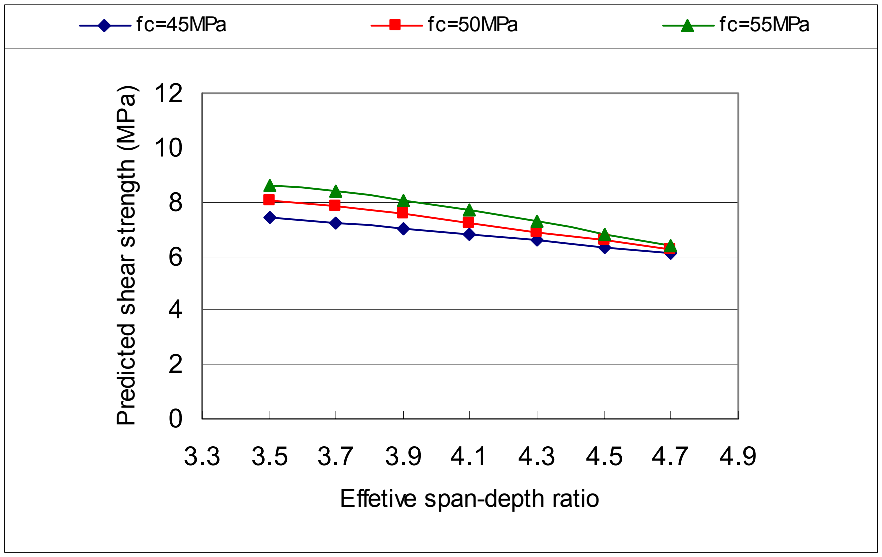


Figure 5-14 Effect of effective span-depth ratio on shear strength.

Equation (5.12) shows a linear relationship between the predicted shear strength and the effective span to depth ratio.

$$V = a_1\left(\frac{l_e}{d}\right) + a_0 \qquad (5\text{-}12)$$

Where :

a_1=-1.5309and a_0=13.46

r^2=0.9971

5.2.4 The Width of The Beam.

It can be noted from Fig. 5.15 that the ultimate shear strength increases with increasing the width of the beam while other parameters held constant.

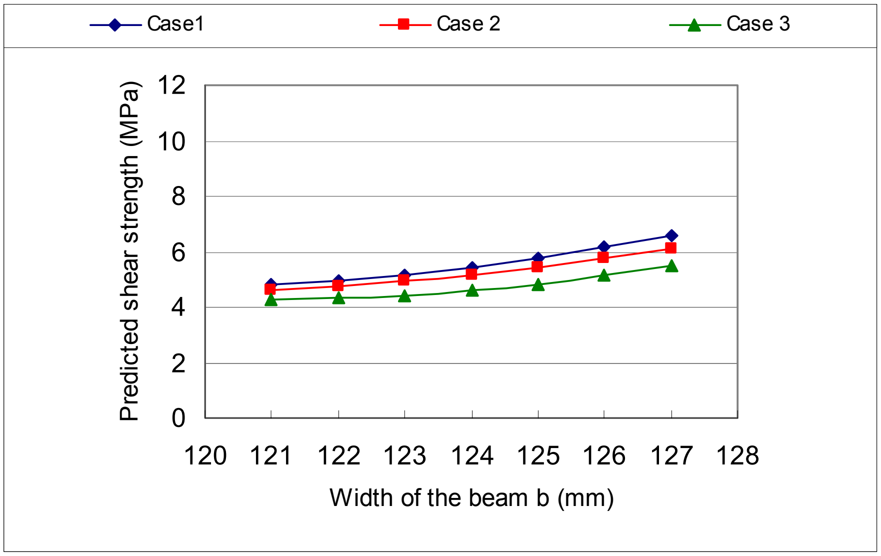


Figure 5-15: Effect of width of the beam on shear strength.

Equation (5.13) shows a linear relationship between the predicted shear strength and the width of the beam.

$$V = a_1 b + a_0 \qquad (5\text{-}13)$$

Where :

a_1=-0.2501and a_0=-25.762

r^2=0.9725

5.2.5 The Vertical Shear Reinforcement Ratio.

It can be noted from Fig. 5.16 that the ultimate shear strength increases slightly with increasing the web vertical shear reinforcement ratio while other parameters held constant, this agrees with Oh [60].

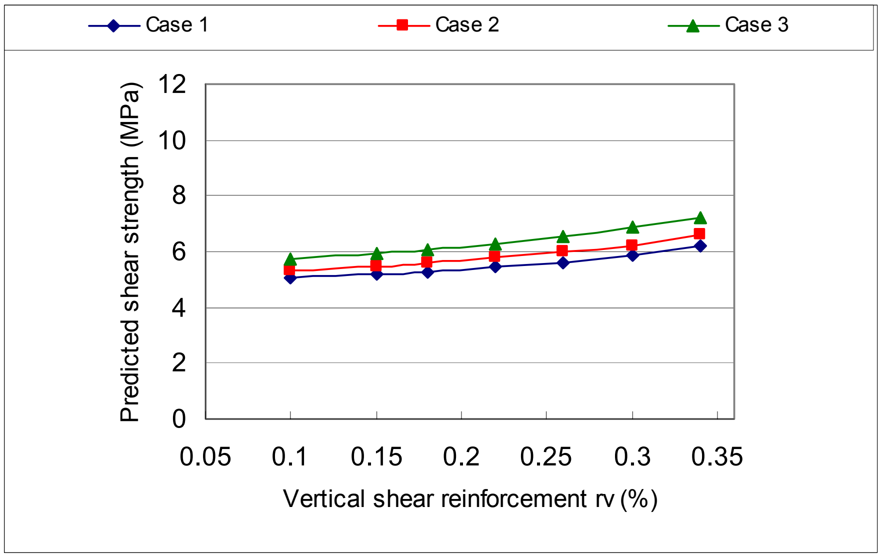


Figure 5-16:Effect of vertical shear reinforcement ratio on shear strength.

Equation (5.14) shows a linear relationship between the predicted shear strength and the vertical shear reinforcement ratio.

$$V = a_1 \rho_v + a_0 \qquad (5\text{-}14)$$

Where :

a_1=5.1278 and a_0=4.7218

r^2=0.9636

5.2.6 The Horizontal Shear Reinforcement Ratio.

It can be noted from Fig. 5.17 that the ultimate shear strength increases slightly with increasing the web horizontal shear reinforcement ratio while other parameters held constant, this agrees with Oh [60].

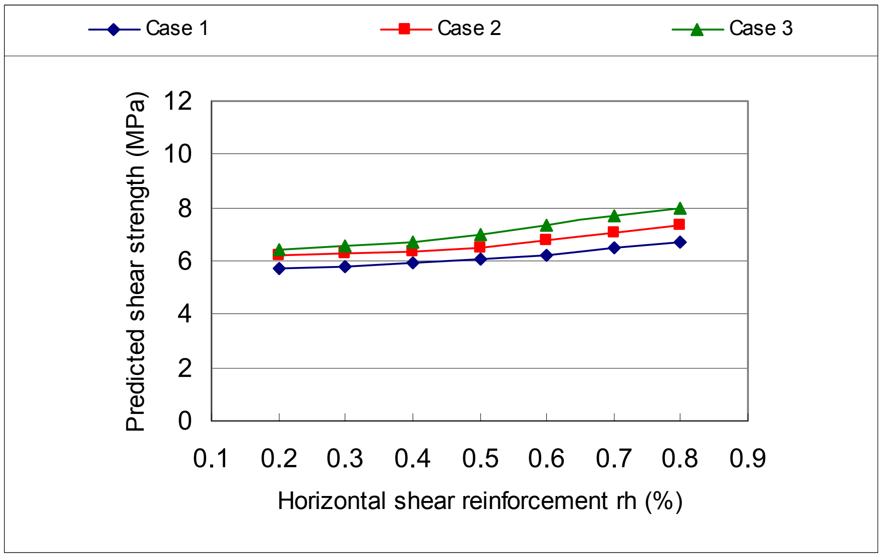


Figure 5-17:Effect of horizontal shear reinforcement ratio on shear strength.

Equation (5.15) shows a linear relationship between the predicted shear strength and the horizontal shear reinforcement ratio.

$$V = a_1 \rho_h + a_0 \qquad (5\text{-}15)$$

Where :

a_1=1.9343 and a_0=5.6682

r^2=0.9416

5.2.7 The Longitudinal Steel Reinforcement ratio .

It can be noted from Fig. 5.18 that the ultimate shear strength increases with increasing the longitudinal steel reinforcement ratio, longitudinal steel reinforcement ratio has higher effect on ultimate shear strength than predicted vales using ACI code equations in deep beams with high strength concrete [88].

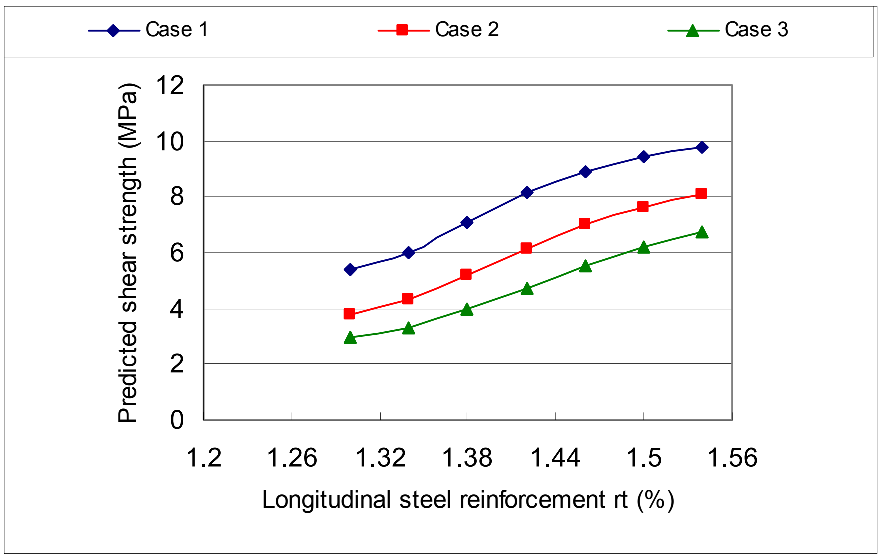


Figure 5-18: Effect of longitudinal steel reinforcement ratio on shear strength.

Equation (5.16) shows the relationship between the predicted shear strength and the vertical shear reinforcement ratio.

$$V = -a_2\rho_t^{\ 2} + a_1\rho_t - a_0 \qquad (5\text{-}16)$$

Where :

a_2=10.923, a_1=50.117,and a_0=43.051

r^2=0.9922

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

The application of Artificial Neural Networks (ANN) to predict the ultimate shear strengths of deep reinforced concrete (RC) beams with normal and high compressive strength has been investigated in this thesis. An ANN model is built, trained and tested using the available test data of 161 normal strength RC deep beams and 42 high strength RC deep beams collected from the technical literature.

The ANN model was used to perform parametric studies in order to evaluate the effects of the variables of the deep beams on the ultimate shear strength which is the chosen output parameter.

6.2 GENERAL CONCLUSIONS ON THE USE OF ANN

On the basis of results obtained in this study, important conclusions would be summarized as follows:

1. The study has added another success for artificial neural networks to predict the ultimate shear strength of deep beams for both normal and high concrete compressive strength, as previous researchers showed. The neural networks are powerful tools and have strong potential in learning the relationship between the input and output parameters and thus predicting outputs from new inputs.

2. The ANN is capable of modeling nonlinear relationship between different parameters such as the relation of deep beams, where the critical factors include the strength of the concrete, the beam geometry, and the steel reinforcement in the beam.

6.3 CONCLUSIONS ON THE USE OF ANN IN PREDICTNG SHEAR STRENGTH OF DEEP BEAMS

The topology of the network for both normal and high strength concrete deep beams has the following features:

1- The type of architecture used was the Multi-layer feed forward, four layers where used the input layer containing 7 neurons, the first and second hidden layers each contains 5 neurons while in the output layer there was 1 neuron. The training algorithm used was back probation algorithm .

2- The average ratio of the experimental shear strength to the predicted shear strength using ANN $(V_u)_{experimental}/(V_u)_{ANN}$ is 1.04 for normal strength concrete, whereas the average ratio of the experimental shear strength to predicted shear strength from ACI 318-02 $(V_u)_{experimental}/(V_u)_{ACI}$ is 2.78.

3- The average ratio of the experimental shear strength to the predicted shear strength using ANN $(V_u)_{experimental}/(V_u)_{ANN}$ is 1.002 for high strength concrete, whereas the average ratio of the experimental shear strength to predicted shear strength from ACI 318-02 $(V_u)_{experimental}/(V_u)_{ACI}$ is 1.228.

4- The conclusions 2 and 3 proved that the developed neural network was much successful in predicting the ultimate shear strength in deep beams than the ACI 318-02 equations within the ranges of the training data.

6.4 CONCLUSIONS OF THE PERFORMED PARAMETRIC STUDY

Using the current technique(ANN), it was possible to study the effect of each of the influencing parameters on the ultimate shear strength of deep beams using all test results available in the literature at the same time; this may eliminate the inconsistency and conflicting conclusions drawn by different researches.

The parametric study was conducted using the trained artificial neural networks, the following conclusions may be drawn:

6.4.1 Normal Strength Concrete Deep Beams

- The ultimate shear strength increases with decreasing the shear span to depth ratio, and has the most significant effect on the shear strength of deep beams .
- The concrete compressive strength has a slight effect on the ultimate shear strength when $a/d > 1$, and have a small effect when $a/d < 1$.
- The ultimate shear strength is directly proportional to the compressive strength of concrete. The predicted shear strength is larger in case 3 than in the other cases, which means that the other parameters have a significant effect on the predicted value of shear strength .
- The shear span to depth ratio has no effect on the predicted shear strength when the concrete compressive strength is smaller than 35 MPa and when the concrete compressive strength is larger than 35MPa the shear strength increases with decreasing the shear span-depth ratio.
- The ultimate shear strength is slightly affected by the yield stress of vertical and horizontal web reinforcement .
- The ultimate shear strength increases with increasing the width, the shear span, and the height of the beam.

6.4.2 High Strength Concrete Deep Beams

- The ultimate shear strength increases with decreasing the shear span-depth ratio, the ultimate shear strength is affected predominantly by a/d.
- The ultimate shear strength increases with increasing the compressive strength of concrete.
- In normal strength deep beams the ultimate shear strength is directly proportional to the square root of the concrete compressive strength as in the ACI code, while in high strength deep beams the ultimate shear strength is directly proportional to the concrete compressive strength.
- The ultimate shear strength was slightly affected by l/d.
- The ultimate shear strength increases with increasing the width of the beam .
- The ultimate shear strength increases slightly with increasing the web vertical and horizontal shear reinforcement ratio.
- The ultimate shear strength increases with increasing the longitudinal steel reinforcement ratio, the longitudinal steel reinforcement ratio has higher effect on ultimate shear strength than predicted vales using ACI code equations in deep beams with high strength concrete .

6.5 RECOMMENATIONS FOR FUTURE STUDIES

The current study showed very promising results in predicting the ultimate strength of deep beams. However, the following points would be recommended for future studies to support the findings of this study:

1- It is recommended to carry out neural network modeling using different ANN types such as recurrent networks with various training algorithms such as radial bases can be used.

2- It is recommended to utilize other artificial intelligence techniques such as fuzzy logic or genetic programming.

3- Compare the results of the developed ANN with other codes of practice and techniques (Strut-and –Tie model).

4- Compare the results of the developed ANN with other results obtained from nonlinear material model using Finite Element packages.

5- Obtain more training data from newly tested deep beams and add them to the training data. This will improve the training process of the problem.

REFERENCES

[1] Strut-and-Tie Model

http://www.cee.uiuc.edu/kuchma/strut_and_tie/STM/.htm [Jan.21,2004]

[2] MacGregor, J.G.(1997) 3rd ed. *Reinforced Concrete Mechanics and Design*. Prentice –Hall :New Jersey

[3] Waked, K.I.(1997) 3rd ed. *Design of Reinforced Concrete Beams According to New Egyptian Code Concept*. Al-Handasa for Publishing and Distribution: Cairo.

[4] Nilson, A. H. and Winter, G. (1991) eleventh ed. *Design of Concrete Structures* .McGraw –Hill, Inc.: Singapore.

[5] Department of Civil Engineering ;Monash University .Lecture notes for Advanced Structural Design. CIV4235

http://cleo.eng.monash.edu.au/teaching/subjects/civ4235/.pdf [Jan .21,204]

[6] ACI 318-02. Building code requirements for structural concrete (ACI318-02). MI, USA: ACI International; 2002.

[7] Sanad,A. and Saka, M.P. (2001) “Prediction of Ultimate Shear Strength of Reinforced Concrete Deep Beams Using Neural Networks". Journal of Structural Engineering .July/818-828

[8] Ashour, A.F. and et al. (2003) “Empirical modeling of Shear Strength of RC Deep Beams by Genetic programming ". School of Engineering, Design and Technology, University of Bradford, West Yorkshire .November.

[9] Eurocode1992

[10] ACI Committee 318. Building code requirements for structural concrete (ACI 318-99) and commentary (ACI 318R-99) .Detroit: American Concrete Institute; 1999.

[11] CEB-FIP. Model Code 1990 for Concrete Structures. Thomas Telford Services, Ltd, London, Comite Euro-International du Beton, Lausanne, 1993. p. 437.

[12] CIRIA Guide 2. The design of deep beams in reinforced concrete. London: Over Arup and Partners, and Construction Industry Research and Information Association; 1977. p. 131. Reprinted 1984.

[13] CSA Technical Committee on Reinforced Concrete Design, A23.3-94. Design of concrete structures. Ontario, Canada: Canadian Standards Association; 1994. p. 199.

[14] Dr. C. C. Fu, Ph.D., P.E. (Aug, 2001). *The Strut-and-Tie Model of Concrete Structures*. http://www.cee.umd.edu/best/Reports/stm.pdf [Jan.21,2004]

[15] Kong FK .In: Kong FK, editor .Reinforced concrete deep beams. New York: Blackie; 1990.

[16] Tan KH, Weng LW, Teng S. A strut-and-tie model for deep beams subjected to combined top-and-bottom loading. Struct Eng J (Lond) 1997; 75(13):215–25.

[17] Teng S, Kong FK, Poh SP. Shear strength of reinforced and pre-stressed concrete deep beams. Part I: current design methods and a proposed equation. Proc Inst Civil Eng Struct Buildings 1998; 128:112–23.

[18] Haykin, S.(1999) 2nd ed. *Neural Networks A comprehensive Fundamentals*. Prentice-Hall ,Inc: New Jersey.

[19] Neural network history

http://www-cse.stanford.edu/classes/sophomore-college/projects-00/neural-networks/History/history1.html [Mar.5,2004]

[20] Neural networks

http://opim.wharton.upenn.edu/~opim101/fall98/lectures/f98neuralnets/tsld003.htm [Mar.5,2004]

[21] MathWorks Inc. MatLab the language of technical computing. Natick, MA, USA: MathWorks Inc; 1999. Version 6.5.

[22] Shahin, M.A. and et al. (2002) “Predicting Settlement of Shallow Foundations Using Neural Networks". *Journal of Geotechnical and Geoenvironmental Engineering* .September/785-793.

[23] Hong-Guang, N and Ji-Zong, W. (2000) “Prediction of Compressive Strength of Concrete by Neural Networks ". *Cement and Concrete Research*. Elsevier Science Ltd.June.

[24] Dias, W and Pooliyadda, S. (2000) “Neural Networks for Properties of Concretes with Admixtures ". *Construction and Building Materials*. Elsevier Science Ltd .December

[25] Jenkins, W. (1998) “A Neural Networks for Structural Re-analysis ". *Computers and Structures*. Elsevier Science Ltd .November

[26] Shahin, M.A. and et.al. (2001) “Artificial Neural Network Applications in Geotechnical Engineering ". *Australian Geomechanics* .March/49-62.

[27] Yeh, I.C. (1998) “Modeling of Strength of High-Performance Concrete Using Artificial Neural Networks ". *Cement and Concrete Research* .September/1797-1808

[28] Kirkegaard, P. H. and A. Rytter. “Use of Neural Networks for Damage Detection and Location in a Steel Member ". Proc. of the 3rd International Conference on the Application of Artificial Intelligence to Civil and Structural Engineering. CIVIL-COMP93, Edinburgh, August 17-19,1993

[29] O'Brien, E.J. and Dixon, A.S. (1995) *Reinforced and Prestressed Concrete Design the Complete Process*. Longman Group: London.

[30] Neural networks

http://www.cse.unsw.edu.au/~billw/mldict.html[March.17, 2004].

[31] Neural networks

http://scom.hud.ac.uk/scomtlm/book/node358.html[March.27, 2004]

[32] Neural networks

http://pubs.acs.org/hotartcl/tcaw/99/nov/simon.html[March.27, 2004]

[33] Neural networks

http://hem.hj.se/~de96klda/NeuralNetworks.htm[March.27, 2004]

[34] Neural networks

[March.27, 2004]

http://www.ncl.ac.uk/cpact/neural_networks.html

[35] Neural networks

http://campus.umr.edu/smartengineering/EducationalResources/Neural_Networks_Lab.pdf [June.20,2004]

[36] Hadi, M.N. (2003) "Neural Networks Applications in Concrete Structures". *Computers and Structures-Elsevier* .

www.elsevier.com/locate/compstruc

[37] Kurup, P.U. and et al. (2002) "Neural Networks for Profiling Stress History of Clays from PCPT Data". *Journal of Geotechnical and Geoenvironmental Engineering* .July/569-579.

[38] Oreta, W.C. and et al. (2003) "Neural Network Modeling of Confined Compressive Strength and Strain of Circular Concrete Columns ". *Journal of Structural Engineering* .April/554-561.

[39] Tang, C. and et al. (2003) "Modeling of Confinement Efficiency of Reinforced Concrete Columns with Rectilinear Transverse Steel Using Artificial Neural Network ". *Journal of Structural Engineering* .June/775-783.

[40] Mansour, M.Y. (2004) "Predicting the Shear Strength of Reinforced Concrete Beams Using artificial Neural Networks ". *Engineering Structures-Elsevier* .

www.elsevier.com/locate/engstruc

[41] Ashour, A.F and Alqedra,M.A. (2004) "Concrete Breakout Strenght of Single Anchors in Tension using Neural Networks ". *Engineering Software-Elsevier* .

www.elsevier.com/locate/advengsoft

[42] Goh, A.T. (1995) "Prediction of Ultimate Shear Strength of Deep Beams Using Neural Networks".*ACI Structural Journal*.January-February/28-32.

[43] Cladera, A and Mari,A.R. (2004) "Shear Design Procedure for Reinforced Normal and High-Strength Concrete Beams Using artificial Neural Networks. Part I: Beams without Stirrups ". *Engineering Structures-Elsevier* .

www.elsevier.com/locate/engstruc

[44] Cladera, A and Mari,A.R. (2004) “Shear Design Procedure for Reinforced Normal and High-Strength Concrete Beams Using artificial Neural Networks. Part I-Beam without Stirrups ". *Engineering Structures-Elsevier* .

www.elsevier.com/locate/engstruc

[45] Oreta,A.W. (2004) “Simulating size Effect on Shear Strength of RC Beams without Stirrups Using artificial Neural Networks. ". *Engineering Structures-Elsevier* .

www.elsevier.com/locate/engstruc

[46] Lai, S. and Serra,M. (1997) “Concrete Strength Prediction by Means of Neural Network ". *Construction and Building Material* .March/93-98.

[47] Applications of Neural networks

http://documents.wolfram.com/applications/neuralnetworks/ NeuralNetwork Theory/2.7.0.html[January.11,2005].

[48] Hopfield Neural networks

http://people.uncw.edu/tagliarinig/Courses/415/Lectures/Hopfield%20Neural %20Networks_files/frame.htm[January.11,2005].

[49] Teng, S. and et al (1998)”Shear Strength of Reinforced and Pre-stressed Concrete Deep Beams. Part I: Current Design Methods and A proposed Equation”. Proc Inst Civil Eng Struct Buildings; 128:112–23.

[50] Nawy, E.G.(2003) 5th ed. *Reinforced Concrete Fundamental Approach*. Pearson Education ,Inc :New Jersey.

[51] Siao, W.B. (1995) “Deep Beams Revisited". ACI Structural Journal. January-February /95-102.

[52] Tan, K.H. and et al. (1995) “High-Strength Concrete Deep Beams with Effective Span and Shear Span Variations". ACI Structural Journal. July-August/395-405.

[53] Foster, S.J. and Gilbert, R. I. (1998) “Experimental Studies on High-Strength Concrete Deep Beams". ACI Structural Journal. July-August/382-390.

[54] Tan, K.H. and Lu, H. Y. (1999) “Shear Behavior of Large Reinforced Concrete Deep Beams and Code Comparisons". ACI Structural Journal. September-October /836-845.

[55] Ashour, A.F. and Rishi, G. (2000) “Test of Reinforced Concrete Continuous Deep Beams with Web Opening". ACI Structural Journal. May - June/418-426.

[56] Hwang, S.J. and et al. (2000) “Shear Strength Prediction for Deep Beams". ACI Structural Journal. May – June /367-376.

[57] Teng, S. and et al. (2000) “Shear Strength of Concrete Deep Beams under Fatigue Loading". ACI Structural Journal. July-August/572-580.

[58] Zararis, P.D. (2003) “Shear Compression Failure in Reinforced Concrete Deep Beams". ACI Structural Journal. April /544-553.

[59] Aguilar, G. and et al. (2002) “Experimental Evaluation of Design Procedure for Shear Strength of Deep Reinforced Concrete Beams". ACI Structural Journal. July-August /539-548.

[60] Oh, J.K and Shin, S.W (2001) “Shear Strength of Reinforced High Strength Concrete Deep Beams ". *ACI Structural Journal* .March-April/164-173.

[61] Neural networks

http://www.dacs.dtic.mil/techs/neural/neural4.html[February.20,2005].

[62] Neural networks

http://www.ukcalling.pwp.blueyonder.co.uk/uni/t8_ANN.htm[February.21,2005].

[63] Neural networks

http://www.tfhrc.gov/safety/98133/ch02/body_ch02_05.html[February.21,2005].

[64] Neural networks

http://www.colinfahey.com/2003apr20_neuron/2003apr20_neuron.htm

[February.21,2005].

[65] Kohonen Neural networks

http://page.mi.fu-berlin.de/~prechelt/statbook/stneunet.html#kohonen

[February.21,2005].

[66] Neural networks

http://www.jeffheaton.com/ [February.21,2005].

[67] Neural networks

http://www.stowa-nn.ihe.nl/ANN.htm#Basic[February.21,2005].

[68] Neural networks

www.dice.ucl.ac.be/~lee/work/publications/chapter01.pdf [February.21,2005].

[69] Rafiq, M.Y. and Bugmann, G.(2001) "Easterbrook DJ. Neural network design for engineering application". Comput Struct ;79(17):1541–52.

[70] Hagan, M.T. and et al.(1996) *Neural network design*. PWS Publishing C: Boston.

[71] Shear notes

http://www.engr.usask.ca/classes/CE/418/notes/shear.pdf [July.29, 2003].

[72] Kartam, N. and et al.(1997) "Artificial neural networks for civil engineers: fundamentals and applications". New York: ASCE.

[73] Waszczyszyn, Z.(1996) "Some recent and current problems of neuro computing in civil and structural engineering. In: Topping BHV, editor". Advances in computational structures technology. Edinburgh: Civil-Comp Press. p. 43–58.

[74] Bi-axial members

http://www.cv.titech.ac.jp/~niwa-lab/member/pasonal/mon/research/bi-axial/bi-axial.htm [July.29, 2003].

[75] Concrete products

http://www.keepmedia.com/pubs/ConcreteProducts/1999/10/01/142086?extID=10032 &oliID=213[February.24,2005].

[76] Flood, I. and Kartam, N.(1994) "Neural network in civil engineering I: principles and understandings". J Comput Civil Eng, ASCE ;8(2):131–48.

[77] High performance concrete

http://www.jeffheaton.com/ai/javaneural/ch5.shtml[January.11,2005].

[78] High strength concrete

www.gorgerock.com/pdf/CIP33p.pdf[February.5,2005].

[79] De Paiva, H.A. and Siess, C.P.(1965) “Strength and behaviour of deepbeams in shear”. J Struct Div, ASCE ;ST5:19–41.

[80] Ramakrishnan, V. and Ananthanarayana, Y.(1968)” Ultimate strength of deep beams in shear”. ACI J ;65:87–98.

[81] Smith, K.N. and Vantsiotis, A.S.(1982)” Shear strength of deep beams”. ACI Struct J ;79:201–13.

[82] Subedi, N .K .and et al.(1986) “Reinforced Concrete Deep Beams—Some Test Results”. Mag Concr Res ; 38(137):206–19

[83] Manuel, R.F. and et al.(1971)” Deep beam behavior affected by length and shear span variations”. ACI J ;68:954–8.

[84] Kong, F.K. and et al .(1970) “Web reinforcement effects on deep beams”. ACI J ;67:1010–7.

[85] Kong, F.K. and et al.(1972)” Short DR. Deep beams with inclined web reinforcement”. ACI J ;69:172–6.

[86] Shi, J.J.(2002)” Clustering technique for evaluating and validating neural network performance”. J Comput Civil Eng, ASCE ;16(2):152–5.

[87] Tan, K.H and et al.(1997)"A Strut-and-Tie Model for Deep Beams Subjected to Combined Top-and-Bottom Loading". Struct Eng J ; 75(13):215–25.

[88] Rogowesky, D.M and et al. (1968) “Test of Reinforced Concrete Deep Beams". *ACI Structural Journal* .83/614-623.

APPENDIX A: DATABASE USED FOR THIS STUDY

Database used for normal strength reinforced concrete deep beams

	Ref.	Beam	b	h	a*	f'c	V	fyv	fyh
			mm	mm	mm	N/mm2	KN	N/mm2	N/mm2
1	De-Paiva	G23S-11	50.8	330.2	203.2	24.55	179.70	0	315.1015
2	De-Paiva	G23S-21	50.8	330.2	203.2	23.58	106.75	0	354.403
3	De-Paiva	G24S-11	50.8	330.2	203.2	38.61	181.48	0	315.1015
4	De-Paiva	G24S-21	50.8	330.2	203.2	36.13	100.52	0	354.403
5	De-Paiva	G33S-11	76.2	228.6	203.2	23.31	170.80	0	326.1335
6	De-Paiva	G33S-12	76.2	228.6	203.2	19.93	169.02	220.64	326.1335
7	De-Paiva	G33S-21	76.2	228.6	203.2	21.03	108.97	0	311.654
8	De-Paiva	G33S-31	76.2	228.6	203.2	19.93	213.95	0	311.654
9	De-Paiva	G33S-32	76.2	228.6	203.2	20.06	202.83	220.64	304.759
10	De-Paiva	G34S-11	76.2	228.6	203.2	35.16	219.73	0	325.444
11	De-Paiva	G34S-21	76.2	228.6	203.2	34.2	112.09	0	324.065
12	De-Paiva	G43S-11	101.6	177.8	203.2	24.2	153.90	0	304.0695
13	De-Paiva	G44S-11	101.6	177.8	203.2	36.96	167.24	0	330.2705
14	De-Paiva	F2S1	50.8	330.2	203.2	33.92	192.60	220.64	317.17
15	De-Paiva	F2S2	50.8	330.2	203.2	31.72	245.10	220.64	308.896
16	De-Paiva	F3S2	76.2	228.6	203.2	24.34	122.80	220.64	326.823
17	De-Paiva	F3S3	76.2	228.6	203.2	34.34	242.86	220.64	326.823
18	De-Paiva	F4S1	101.6	177.8	203.2	34.27	94.30	220.64	321.9965
19	De-Paiva	F4S22	101.6	177.8	203.2	34.68	182.37	220.64	335.097
20	Kong(1970)	1-30.	76.2	762	254	22.13	477.72	280	286.83
21	Kong(1970)	1-25.	76.2	635	254	24.55	448.36	280	286.83
22	Kong(1970)	1-20.	76.2	508	254	21.24	378.97	280	286.83
23	Kong(1970)	1-15.	76.2	381	254	21.24	328.26	280	286.83
24	Kong(1970)	1-10.	76.2	254	254	21.65	178.81	280	286.83
25	Kong(1970)	2-30.	76.2	762	254	19.20	498.18	303	286.83
26	Kong(1970)	2-25.	76.2	635	254	18.62	448.36	303	286.83
27	Kong(1970)	2-15.	76.2	381	254	22.75	279.33	303	286.83

28	Kong(1970)	2-10.	76.2	254	254	20.13	199.27	303	286.83
29	Kong(1970)	3-30.	76.2	762	254	22.55	552.44	0	286.83
30	Kong(1970)	3-25.	76.2	635	254	20.96	451.03	0	286.83
31	Kong(1970)	3-20.	76.2	508	254	19.24	415.44	0	286.83
32	Kong(1970)	3-15.	76.2	381	254	21.93	318.48	0	286.83
33	Kong(1970)	3-10.	76.2	254	254	22.62	172.58	0	286.83
34	Kong(1970)	4-30.	76.2	762	254	22.00	483.94	0	286.83
35	Kong(1970)	4-25.	76.2	635	254	20.96	402.10	0	286.83
36	Kong(1970)	4-20.	76.2	508	254	20.13	361.18	0	286.83
37	Kong(1970)	4-15.	76.2	381	254	21.99	218.84	0	286.83
38	Kong(1970)	4-10.	76.2	254	254	22.61	191.26	0	286.83
39	Kong(1970)	5-30.	76.2	762	254	18.55	478.60	280	286.83
40	Kong(1970)	5-25.	76.2	635	254	19.24	416.33	280	286.83
41	Kong(1970)	5-20.	76.2	508	254	20.14	345.16	280	286.83
42	Kong(1970)	5-15.	76.2	381	254	21.93	254.43	280	286.83
43	Kong(1970)	5-10.	76.2	254	254	22.55	155.68	280	286.83
44	Kong(1970)	6-15.	76.2	381	254	26.08	345.16	0	286.83
45	Kong(1970)	6-10.	76.2	254	254	25.10	196.60	0	286.83
46	Kong(1972)	S-30	76.2	762	254	22.13	575.57	337.855	286.83
47	Kong(1972)	S-25	76.2	635	254	21.24	562.67	337.855	286.83
48	Kong(1972)	S-20	76.2	508	254	21.79	478.16	337.855	286.83
49	Kong(1972)	S-15	76.2	381	254	27.65	415.89	337.855	286.83
50	Kong(1972)	S-10	76.2	254	254	23.31	220.18	337.855	286.83
51	Kong(1972)	D-30	76.2	762	254	23.17	556.89	296.485	286.83
52	Kong(1972)	D-25	76.2	635	254	23.79	539.10	296.485	286.83
53	Kong(1972)	D-20	76.2	508	254	24.75	555.56	296.485	286.83
54	Kong(1972)	D-15	76.2	381	254	27.65	473.27	296.485	286.83
55	Kong(1972)	D-10	76.2	254	254	24.20	237.08	296.485	286.83
56	Manueletal	Beam5	101.6	460	266.5	34.26815	569.344	0	409.563
57	Manueletal	Beam6	101.6	460	266.5	37.43985	538.208	0	409.563
58	Manueletal	Beam7	101.6	460	266.5	31.9928	600.48	0	409.563
59	Manueletal	Beam8	101.6	460	266.5	38.8878	560.448	0	409.563
60	Manueletal	Beam9	101.6	460	410	37.6467	378.08	0	409.563

61	Manueletal	Beam10	101.6	460	410	44.8175	329.152	0	409.563
62	Manueletal	Beam11	101.6	460	410	37.16405	342.496	0	391.636
63	Manueletal	Beam12	101.6	460	410	33.71655	342.496	0	409.563
64	Ram	A1	76.2	381	216	0.00	0.00	0	320
65	Ram	B1	76.2	381	216	0.00	0.00	0	320
66	Ram	B2	76.2	508	216	0.00	0.00	0	320
67	Ram	B3	78.7	572	216	0.00	0.00	0	320
68	Ram	B4	78.7	762	216	0.00	0.00	0	320
69	Ram	C1	76.2	381	216	0.00	0.00	0	320
70	Ram	C2	78.7	508	216	0.00	0.00	0	320
71	Ram	C3	76.2	572	216	0.00	0.00	0	320
72	Ram	C4	78.7	762	216	0.00	0.00	0	320
73	Rogowsky	BM1-1	200	1000	1000	26.1	1204	0	381
74	Rogowsky	BM2-1	200	1000	1000	26.8	1500	0	381
75	Rogowsky	BM1A-1	200	1000	1000	26.4	1200	0	368
76	Rogowsky	BM1-15	200	600	1000	42.4	606	0	452
77	Rogowsky	BM2-15	200	600	1000	42.4	696	0	452
78	Rogowsky	BM1-2	200	500	1000	43.2	354	0	452
79	Rogowsky	BM2-2	200	500	1000	43.2	370	0	452
80	Smith&Vantsiotis	0A0-44	101.6	355.6	304.8	20.48	279.07	0	437.4
81	Smith&Vantsiotis	0A0-48	101.6	355.6	304.8	20.93	272.22	0	437.4
82	Smith&Vantsiotis	1A1-10	101.6	355.6	304.8	18.69	322.48	437.4	437.4
83	Smith&Vantsiotis	1A3-11	101.6	355.6	304.8	18.03	296.68	437.4	437.4
84	Smith&Vantsiotis	1A4-12	101.6	355.6	304.8	16.07	282.45	437.4	437.4
85	Smith&Vantsiotis	1A4-51	101.6	355.6	304.8	20.55	341.87	437.4	437.4
86	Smith&Vantsiotis	1A6-37	101.6	355.6	304.8	21.06	368.16	437.4	437.4
87	Smith&Vantsiotis	2A1-38	101.6	355.6	304.8	21.68	348.99	437.4	437.4
88	Smith&Vantsiotis	2A3-39	101.6	355.6	304.8	19.75	341.16	437.4	437.4
89	Smith&Vantsiotis	2A4-40	101.6	355.6	304.8	20.34	343.83	437.4	437.4
90	Smith&Vantsiotis	2A6-41	101.6	355.6	304.8	19.13	323.81	437.4	437.4
91	Smith&Vantsiotis	3A1-42	101.6	355.6	304.8	18.41	322.04	437.4	437.4
92	Smith&Vantsiotis	3A3-43	101.6	355.6	304.8	19.24	345.43	437.4	437.4
93	Smith&Vantsiotis	3A4-45	101.6	355.6	304.8	20.82	357.09	437.4	437.4

94	Smith&Vantsiotis	3A6-46	101.6	355.6	304.8	19.93	336.27	437.4	437.4
95	Smith&Vantsiotis	0B0-49	101.6	355.6	368.3	21.68	298.02	0	437.4
96	Smith&Vantsiotis	1B1-01	101.6	355.6	368.3	22.06	294.90	437.4	437.4
97	Smith&Vantsiotis	1B3-29	101.6	355.6	368.3	20.1	287.12	437.4	437.4
98	Smith&Vantsiotis	1B4-30	101.6	355.6	368.3	20.82	280.67	437.4	437.4
99	Smith&Vantsiotis	1B6-31	101.6	355.6	368.3	19.51	306.69	437.4	437.4
100	Smith&Vantsiotis	2B1-05	101.6	355.6	368.3	19.17	257.98	437.4	437.4
101	Smith&Vantsiotis	2B3-06	101.6	355.6	368.3	19	262.43	437.4	437.4
102	Smith&Vantsiotis	2B4-07	101.6	355.6	368.3	17.48	252.20	437.4	437.4
103	Smith&Vantsiotis	2B4-52	101.6	355.6	368.3	21.79	299.80	437.4	437.4
104	Smith&Vantsiotis	2B6-32	101.6	355.6	368.3	19.75	290.45	437.4	437.4
105	Smith&Vantsiotis	3B1-08	101.6	355.6	368.3	16.24	261.54	437.4	437.4
106	Smith&Vantsiotis	3B1-36	101.6	355.6	368.3	20.41	317.90	437.4	437.4
107	Smith&Vantsiotis	3B3-33	101.6	355.6	368.3	19	316.70	437.4	437.4
108	Smith&Vantsiotis	3B4-34	101.6	355.6	368.3	19.24	310.03	437.4	437.4
109	Smith&Vantsiotis	3B6-35	101.6	355.6	368.3	20.65	332.27	437.4	437.4
110	Smith&Vantsiotis	4B1-09	101.6	355.6	368.3	17.1	306.91	437.4	437.4
111	Smith&Vantsiotis	0C0-50	101.6	355.6	457.2	20.69	231.30	0	437.4
112	Smith&Vantsiotis	1C1-14	101.6	355.6	457.2	19.24	237.97	0	437.4
113	Smith&Vantsiotis	1C3-02	101.6	355.6	457.2	21.89	246.86	0	437.4
114	Smith&Vantsiotis	1C4-15	101.6	355.6	457.2	22.68	261.99	0	437.4
115	Smith&Vantsiotis	1C6-16	101.6	355.6	457.2	21.79	244.64	0	437.4
116	Smith&Vantsiotis	2C1-17	101.6	355.6	457.2	19.86	248.20	437.4	437.4
117	Smith&Vantsiotis	2C3-03	101.6	355.6	457.2	19.24	207.28	437.4	437.4
118	Smith&Vantsiotis	2C3-27	101.6	355.6	457.2	19.31	230.63	437.4	437.4
119	Smith&Vantsiotis	2C4-18	101.6	355.6	457.2	20.44	249.09	437.4	437.4
120	Smith&Vantsiotis	2C6-19	101.6	355.6	457.2	20.75	248.20	437.4	437.4
121	Smith&Vantsiotis	3C1-20	101.6	355.6	457.2	21.03	281.56	437.4	437.4
122	Smith&Vantsiotis	3C3-21	101.6	355.6	457.2	16.55	249.98	437.4	437.4
123	Smith&Vantsiotis	3C4-22	101.6	355.6	457.2	18.27	255.32	437.4	437.4
124	Smith&Vantsiotis	3C6-23	101.6	355.6	457.2	19	274.44	437.4	437.4
125	Smith&Vantsiotis	4C1-24	101.6	355.6	457.2	19.58	293.12	437.4	437.4
126	Smith&Vantsiotis	4C3-04	101.6	355.6	457.2	18.55	257.09	437.4	437.4

127	Smith&Vantsiotis	4C3-28	101.6	355.6	457.2	19.24	304.69	437.4	437.4
128	Smith&Vantsiotis	4C4-25	101.6	355.6	457.2	18.51	305.13	437.4	437.4
129	Smith&Vantsiotis	4C6-26	101.6	355.6	457.2	21.24	318.92	437.4	437.4
130	Smith&Vantsiotis	0D0-47	101.6	355.6	635	19.51	146.78	0	437.4
131	Smith&Vantsiotis	4D1-13	101.6	355.6	635	16.07	174.81	437.4	437.4
132	Subedietal	1A1	100	500	190	26	479	454	382
133	Subedietal	1A2	100	500	190	29.6	750	455	493
134	Subedietal	1B1	100	500	690	24.8	156	456	382
135	Subedietal	1B2	100	500	690	29.6	299	457	493
136	Subedietal	1C1	100	900	390	24.8	585	458	326
137	Subedietal	1C2	100	900	390	28.4	970	459	330
138	Subedietal	1D1	100	900	1290	36	247	460	326
139	Subedietal	1D2	100	900	1290	33.2	422	461	330
140	Subedietal	2A1	100	500	150	26	360	438	378
141	Subedietal	2A2	100	500	190	22.72	615	438	322
142	Subedietal	2C1	100	900	350	27.92	606	438	334
143	Subedietal	2D1	100	900	1290	34.72	180	438	334
144	Subedietal	2D2	100	900	1290	31.52	398	438	303
145	Subedietal	"3E1"	50	500	333.5	41.6	180	211	479
146	Subedietal	4G1	100	900	395	41.6	1296	450	484
147	Subedietal	4G2	100	900	845	43.2	1121	444	484
148	Subedietal	4G3	100	900	395	43.2	1595	444	490
149	Subedietal	4G4	100	900	845	41.6	922	450	490
150	Tan&Lu	1-500-050	140	500	250	49.1	1700	0	520
151	Tan&Lu	1-500-075	140	500	375	42.5	1400	0	520
152	Tan&Lu	1-500-1	140	500	500	37.4	1140	0	520
153	Tan&Lu	2-1000-050	140	1000	500	31.2	1750	520	520
154	Tan&Lu	2-1000-075	140	1000	740	32.7	1300	520	520
155	Tan&Lu	2-1000-1	140	1000	1000	30.8	870	520	520
156	Tan&Lu	3-1400-05	140	1400	705	32.8	2350	520	520
157	Tan&Lu	3-1400-075	140	1400	1050	36.2	1900	520	520
158	Tan&Lu	3-1400-1	140	1400	1420	35.3	1600	520	520
159	Tan&Lu	4-1750-05	140	1750	880	42.6	3272	520	520

160	Tan&Lu	4-1750-075	140	1750	1320	40.4	2480	520	520
161	Tan&Lu	4-1750-1	140	1750	1760	44.8	2000	520	520

Database used for high strength reinforced concrete deep beams

No	fc MPa	b mm	le/d	a/d	rv %	rh %	r t %	Vn,test MPa
1	49.1	130	4	0.5	0	0	1.56	9.88
2	49.1	130	4	0.5	0.12	0.43	1.56	10.97
3	49.1	130	4	0.5	0.22	0.43	1.56	10.86
4	49.1	130	4	0.5	0.34	0.43	1.56	10.9
5	49.1	130	4	0.85	0	0	1.56	6.17
6	49.1	130	4	0.85	0.12	0.43	1.56	7.51
7	49.1	130	4	0.85	0.22	0.43	1.56	7.02
8	49.1	130	4	0.85	0.34	0.43	1.56	6.47
9	49.1	130	4	1.25	0	0	1.56	5.19
10	49.1	130	4	1.25	0.12	0.43	1.56	5.34
11	49.1	130	4	1.25	0.22	0.43	1.56	5.86
12	49.1	130	4	1.25	0.34	0.43	1.56	6.19
13	49.1	130	4	2	0	0	1.56	1.73
14	49.1	130	4	2	0.12	0.43	1.56	3.24
15	49.1	130	4	2	0.22	0.43	1.56	3.65
16	49.1	130	4	2	0.34	0.43	1.56	3.62
17	49.1	130	3	0.5	0.12	0.43	1.56	11.47
18	49.1	130	3	0.85	0.12	0.43	1.56	8.15
19	49.1	130	3	1.25	0.12	0.43	1.56	5.81
20	49.1	130	5	0.5	0.12	0.43	1.56	10.8
21	49.1	130	5	0.85	0.12	0.43	1.56	8.73
22	49.1	130	5	1.25	0.12	0.43	1.56	5.58
23	50.67	120	4	0.5	0.13	0	1.29	5.79
24	50.67	120	4	0.5	0.13	0.23	1.29	6.63
25	50.67	120	4	0.5	0.13	0.47	1.29	8.17
26	50.67	120	4	0.5	0.13	0.94	1.29	7.58
27	50.67	120	4	0.85	0.13	0.47	1.29	6.54

28	50.67	120	4	0.85	0.24	0.47	1.29	6.01
29	50.67	120	4	0.85	0.37	0.47	1.29	6.23
30	50.67	120	4	1.25	0.13	0	1.29	3.56
31	50.67	120	4	1.25	0.13	0.23	1.29	4.34
32	50.67	120	4	1.25	0.13	0.47	1.29	4.61
33	73.6	120	4	0.5	0.13	0	1.29	7.3
34	73.6	120	4	0.5	0.13	0.23	1.29	9.03
35	73.6	120	4	0.5	0.13	0.47	1.29	9.14
36	73.6	120	4	0.5	0.13	0.94	1.29	9.11
37	73.6	120	4	0.85	0.13	0.47	1.29	6.96
38	73.6	120	4	0.85	0.24	0.47	1.29	6.84
39	73.6	120	4	0.85	0.37	0.47	1.29	6.8
40	73.6	120	4	1.25	0.13	0	1.29	4.85
41	73.6	120	4	1.25	0.13	0.23	1.29	5.17
42	73.6	120	4	1.25	0.13	0.47	1.29	5.64

APPENDIX B: MATLAB CODE

MATLAB code used to train the artificial neural networks model in this study.

```
clc
clear all
load data.mat;
%T3=Input matrix
%P3=Output matrix
%RP3=Matrix contains max and min of input parameters
%RT3=Matrix contains max and min of output parameters
[P3n,minP3,maxP3,T3n,minT3,maxT3]=premnmx(P3,T3);
[RP3n,minRP3,maxRP3]=premnmx(RP3);
net=newff(RP3n,[5 5 1],{'logsig','logsig','purelin'},'trainb','learngdm','sse');
net.trainParam.epochs=5000;
net.trainParam.goal=0.9;
net.trainParam.max_fail=200;
net.trainParam.mu_inc=2;
net.trainParam.mu_dec=0.02;
net.trainParam.mu_max=1e30;
net.trainParam.show=500;
[R,Q]=size(P3n);
iitst=2:4:Q;
iival=4:4:Q;
iitr=[1:4:Q 3:4:Q];
val.P=P3n(:,iival); val.T=T3n(:,iival);
test.P=P3n(:,iitst);test.T=T3n(:,iitst);
P3tr=P3n(:,iitr); T3tr=T3n(:,iitr);
[net,tr3,Y3,E3]=train(net,P3tr,T3tr,[],[],val,test);
weights11=net.iw{1,1};
bias1=net.b{1};
```

```
loglog(tr3.epoch,tr3.perf,'-',tr3.epoch,tr3.vperf,'--',tr3.epoch,tr3.tperf,'-.');
legend('Training','Validation','Test',-1);
ylabel('Squared Error MSE');xlabel('Number of Epochs');
[Ninput3]=tramnmx(P3,minP3,maxP3);
[Noutput3]=sim(net,Ninput3);
[output3]=postmnmx(Noutput3,minT3,maxT3);
NuANN3=T3'./output3';

%Parametric study
load para-fcf.mat;
% a/h = 0.25,0.5,0.75,1.0,1.25,1.5,1.75   others constant
[outfc1]=tramnmx(fc1,minP3,maxP3);
[Noutfc1]=sim(net,outfc1);
[Vfc1]=postmnmx(Noutfc1,minT3,maxT3);

subplot(3,2,1)
loglog(tr3.epoch,tr3.perf,'-',tr3.epoch,tr3.vperf,'--',tr3.epoch,tr3.tperf,'-.');
legend('Training','Validation','Test',-1);
ylabel('Squared Error MSE');xlabel('Number of Epochs')

subplot(3,2,2)
plot(fcpa,Vfc1);
xlabel('fc1');
ylabel('Vp');

% fc=15,20,25,30,35,40,45     others constant
[outfc2]=tramnmx(fc2,minP3,maxP3);
[Noutfc2]=sim(net,outfc2);
[Vfc2]=postmnmx(Noutfc2,minT3,maxT3);
```

```
subplot(3,2,3)
plot(fcp,Vfc2);
xlabel('fc2');
ylabel('Vp');

[outfc3]=tramnmx(fc3,minP3,maxP3);
[Noutfc3]=sim(net,outfc3);
[Vfc3]=postmnmx(Noutfc3,minT3,maxT3);

subplot(3,2,5)
plot(fcpa,Vfc3);
xlabel('fc3');
ylabel('Vp');
subplot(3,2,6)
[m3,b3,r3]=postreg(output3,T3);
```