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M.Sc. in Civil Engineering

AHMED SHAKIR ALI ALI

REPUBLIC OF TURKEY

GAZİANTEP UNIVERSITY

GRADUATE SCHOOL OF NATURAL & APPLIED SCIENCES

**ARTIFICIAL NEURAL NETWORK FOR PREDICTION OF
LOCAL SCOUR DEPTH AROUND BRIDGE PIERS USING
MATLAB**

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CIVIL ENGINEERING

BY

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**M.Sc. Thesis
in
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Gaziantep University**

**Supervisor
Prof. Dr. Mustafa GÜNAL**

**By
Ahmed Shakir Ali ALI**

March 2021



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Ahmed Shakir Ali ALI

ABSTRACT

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ALI, Ahmed Shakir Ali
M.Sc. in Civil Engineering
Supervisor: Prof. Dr. Mustafa GÜNAL
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Scour is the consequence of the moving of bed material through the waterway, besides, scour undermines the stability of bridges, leading to a huge loss in the economic and human lives. In this study, several feed-forward artificial neural network (ANN) models with backpropagation algorithms have been established using deep learning toolbox in MATLAB software, besides, trial and error processes have been used to determine the number of nodes in the hidden layer. Moreover, 400 laboratories dataset from different resources have been used in this study, which included pier width, flow velocity, flow depth, sediment critical mean velocity, particle size distribution as input parameters, and equilibrium scour depth as a target parameter. The regression and mean squared error values have been employed for the evaluation of models. The results showed that the Levenberg-Marquardt training algorithm gives the best performance of prediction compared to other algorithms, moreover, sensitivity analysis showed that the elimination of pier width from input parameters decreases the efficiency of prediction more than other parameters. Also, ANN models with dimensional parameters provide better results than non-dimensional parameters. It has been found that ANN could be used as a reliable technique for prediction of equilibrium scour depth.

Keywords: Bridge Pier, Local Scour, Artificial Neural Network, MATLAB.

ÖZET

MATLAB KULLANARAK KÖPRÜ AYAKLARI ETRAFINDAKİ YEREL OYULMANIN YAPAY SİNİR AĞLARI KULLANARAK TAHMİNİ

ALI, Ahmed Shakir Ali
Yüksek Lisans Tezi, İnşaat Mühendisliği
Danışman: Prof. Dr. Mustafa GÜNAL
Mart 2021
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Oyulma, yatak malzemesinin su yolu boyunca taşınmasının bir sonucudur, ayrıca oyulma köprülerin dengesini bozarak ekonomik ve insan hayatında büyük bir kayba yol açar. Bu çalışmada, MATLAB yazılımında ki, derin öğrenme araç kutusu kullanılarak geri yayılım algoritmalarına sahip birkaç ileri beslemeli yapay sinir ağı (ANN) modeli oluşturulmuş, ayrıca gizli katmandaki düğüm sayısını belirlemek için deneme yanılma süreçleri kullanılmıştır. Ayrıca, giriş parametreleri olarak perde genişliği, akış hızı, akış derinliği, tane kritik ortalama hızı, tane boyutu dağılımı ve hedef parametre olarak maksimum oyulma derinliği içeren farklı kaynaklardan 400 laboratuvar veri seti kullanılmıştır. Modellerin değerlendirilmesinde regresyon ve ortalama kare hata değerleri kullanılmıştır. Sonuçlar, Levenberg-Marquardt eğitim algoritmasının diğer algoritmalarla kıyasla en iyi tahmin performansını verdiğini, ayrıca duyarlılık analizinin, giriş parametrelerinden köprü ayakları arası genişliğinin çıkarılmasının tahmin verimliliğini diğer parametrelere göre daha fazla azalttığını gösterdi. Ayrıca, boyutsal parametrelere sahip ANN modelleri, boyutsuz parametrelere göre daha iyi sonuçlar vermektedir. ANN'nın denge oyulma derinliğinin tahmini için güvenilir bir yöntem olarak kullanılabileceği bulunmuştur.

Anahtar Kelimeler: Köprü Ayağı, Yerel Oyulma, Yapay Sinir Ağı (ANN), MATLAB

To
My Family

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LIST OF SYMBOLS

b	Pier diameter (m)
d_s	Scour depth (m)
d_{se}	Equilibrium scour depth (m)
d_{50}	mean particle size (mm)
d	Particle diameter (mm)
Fr	Froude number
Fr_{crit}	Critical Froude number
g	Gravitational acceleration
h	Water depth (m)
K_{Shape}	Correction factor for pier nose shape
K_{angle}	Correction factor including the angle of flow impact on the pier
K_{size}	Correction factor is for sediment size effects
K_{bed}	Correction factor for bed form
$K_{armoring}$	Correction factor for armoring effects
net_{pj}	Sum of the inputs
O_{pj}	Outcome of the node j for pattern p
R	Regression value
Re_{pier}	Pier Reynolds number
U	Depth-averaged flow velocity
U_{crit}	Critical depth-averaged flow velocity
X_{norm}	Normalized value of a parameter

X_{min}	Minimum value of the whole dataset.
X_{max}	Maximum value of the whole dataset.
y	Flow depth (m)
μ	Dynamic viscosity of water (m^2/s)
ρ	Fluid density (kg/m^3)
ρ_s	Sediment particle density (kg/m^3)
σ_g	Standard deviation of particle size
β	Correction factor for flow angle of attack
α	Correction factor for pier shape
γ	Correction factor for bed form

LIST OF ABBREVIATIONS

ANN Artificial neural network

MSE Mean squared error



CHAPTER ONE

INTRODUCTION

1.1 Introduction

Scour is a naturalistic event caused by denudation action of the outflow of water on the bottom and banks of silty canals (Khawairakpam and Mazumdar, 2009). Besides, scour happens in the seaboard's territories as a result of the transit of waves. It is the sweep of sediment about or nearby the structures situated in flowing water. It expresses the depreciation of the riverbed level by flow abrasions such that there is an inclination to disclose the base of a bridge as a consequence of the erosive act off decreasing of stream, digging up and transporting far the materials from the bottom and edges of rivers and from near of the pillars and abutments of bridges (Arneson, 2013). A scour at the pier of the bridge, pile-supported framework and abutments could outcome in the fall of structure and forfeit of livelihood and estates, moreover, extreme disturbance to infrastructure networks, public and economical issues, and endangering places of cultural heritage. The building of bridges in alluvial canals gives rise to a shrinkage in the watercourse at the bridge location and hence causes considerable scour at that position. As the scour constantly happening at the location of the building, a likely collapse at the foundations of the construction could occur. Lack of success of various bridges in the different places of nations due to severe scour around piers. An enormous amount of studying has been implemented during the recent decades on the physics and modeling of scour. Structures and infrastructure that have been built by humans are an object of continued development because of their significant role in the community. This challenge observable in all the steps of design, construction, monitoring, rebuilding, and maintenance. Sediments scouring close to bridge foundations is the most well-known threat to the stability of bridges. A little boost to the investigation and workable repair schemes for weak bridges could protect from many costly breaking down which causes heavy consequences and impacts to the infrastructures system. Bed scour around bridge piers is an unpretentious thought but

contains a number of various forms. It could happen due to a naturalistic situation or because of changes to a river by humans, furthermore, it could happen at any time. All scouring is the outcome of the moving of material of bed through the waterway. The lack of stability of the channel is a normal event and is the effect of the corrosion and precipitation of the substance of the bed, which happens progressively under common cases or quite rapidly when deluges occur. Streams that carry on a significant quantity of bed material confront scouring and channel instability. These comprise the gravel bed of rivers and the sand - bed of rivers. The natural variation that taking place, which impacted by a massive amount of different activity, impacts the river streams, these involve the establishing or elimination of unnatural hindering such as dykes or training walls, extraordinary rainfall, and growing of runoff because of clearing a wide area of trees or urbanization. The potential changing of the channel of the river could happen in the longitudinal and plane part. Alterations in the watercourse take place when the substance of the bed is transmitted along the river. The deposition zone shifts to erosion districts, in a natural way or due to the consequence of artificial works, and the bottom of the river's level dropping consequently, impacting the constancy of any build established on that bed. Moreover, channel instability influences a bridge, leading to undermining bases and aim streams towards or behind the structure. Mostly, building pier and abutments of a bridge in the bed of river and banks are alteration in the natural geometry of the river section and, that way, originate an obstacle for the flow of the river that, as it is oncoming the bridge, furthermore, the flow of water obtains a powerful erosive force because of the adjusted flow situation at the crossing of the bridge. As a result, in the case of the subcritical flow that is generally confronted in the river canals, the outcome of the rising velocity of flow and erosive power of the flow creates a situation that puts the foundation of the bridge at risk of collapsing. However, a good screening that includes checking off a bed of river and engineering analysis can figure out signs of evolving scour before the condition turns out tough. The reasons for changing in the longitudinal part of a stream it's as well responsible for modification in the plane part. In overflowed plains, a zigzag of the river occurs due to erosion. Also, the edges of a river on the outside of curves wear out, and alluvium sediments on the inside of detours where the flow of water is indolent. Thus, the path of the prime stream alters over time or, on occasion, massively when floods taking place. Extension of a bridge primarily prepared to be for flood-relief intends only may lastly turn into the prime flow spans, predominantly, the piers engaged builds

at a deepness lower than those of the main river's expansion, as shown in Figure 1.1 (Maddison, 2012).

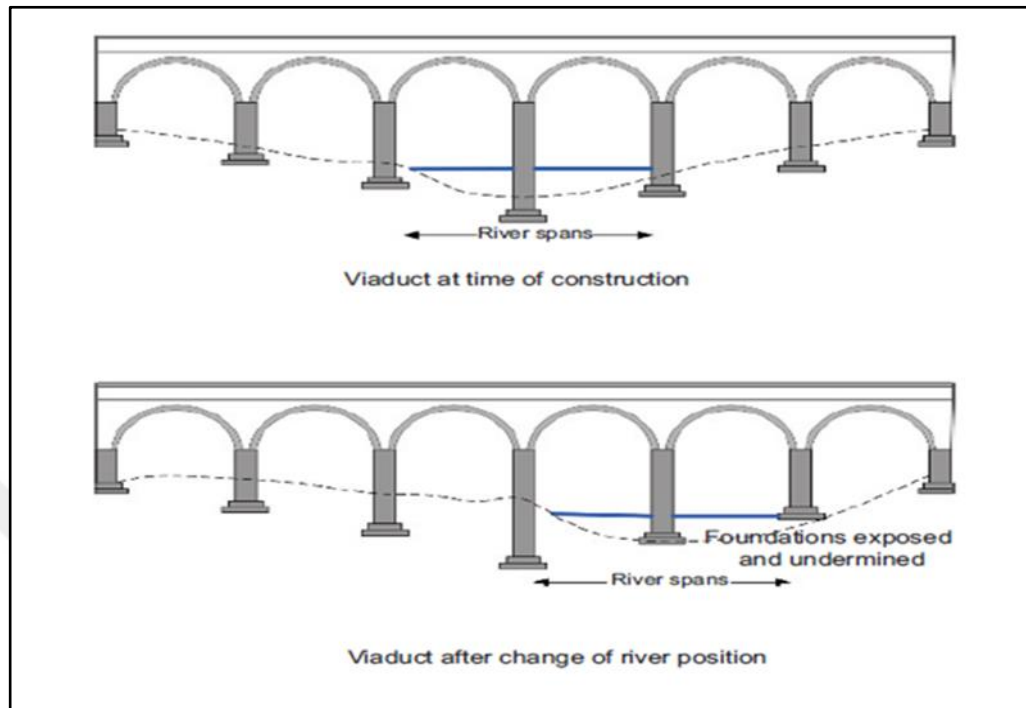


Figure 1.1 Piers at hazard due to changes in the path of river (Maddison, 2012).

In Europe, compensations of the infrastructure of road and bridges have reached €577 million because of a flood that happened in 2002 in Germany (Schulz 2011), Meanwhile, flooding has cost ÖBB, the Austrian Federal Railways operator, approximately €100 million due to flooding (Kellermann et al., 2016). In the United Kingdom, in 2009, flood occurrences have damaged parts, or entirely 20 road bridges (Wedawatta et al. 2013), and financial forfeit has estimated to approximately £2 million in a week. In addition, in Europe, it has been estimated that the scouring hazard alleviation could reach €541 million in a year for the duration of 2040-2070 (Nemry and Demirel, 2012). Furthermore, in the United States, the costs of collapsing bridges and highways due to overflow in 1964 and 1972 reached about one hundred million dollars for each flood incident (Brice, 1978). In New Zealand, damages due to scour were estimated at approximately 36 million NZ dollars per year (Macky,1990). While, in South Africa, the yearly estimation of the worth of damage because of scouring reaches 22 million ZAR (South African Rands) (Armitage et al., 2007). Moreover, in 2007, the damaging of a flood has reached 34 percent of the transport infrastructure of the total costs of infrastructures in Bangladesh, which cost 363 million US dollars, meanwhile, in Indonesia, it was 25 percent, which cost 35 million US dollars (Regmi

and Hanaoka, 2011). Pier and abutment undermining due to scouring and erosion of the bed of the river were recognized as being the essential reason for the collapse of the bridge (Melville and Coleman, 2000; Richardson and Davis, 2001). The Federal Highway Administration has predicted that sixty percent of falling of bridges in the United States because of scouring (Parola et al., 1997), and, approximately between 50 to 60 bridges collapse each year in the United States (Shirole and Holt, 1991). According to an inclusive collection of bridge collapse information from different nations assembled, the natural hazard is the leading reason for the bridge falling (Imhof, 2004), besides, flooding, or scour is in charge of approximately 60% of the falling of bridges worldwide, Figure 1.2 shows the percentage of bridges collapsing due to natural hazards.

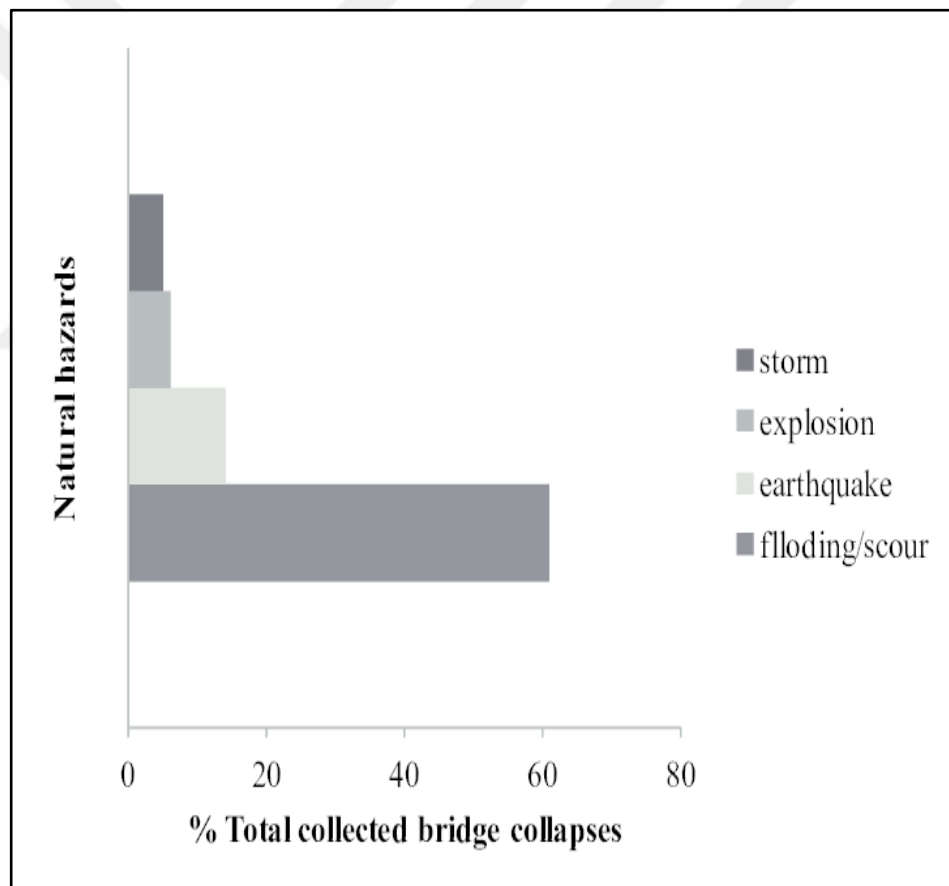


Figure 1.2 Collapsing of bridges due to various natural risk (Imhof, 2004).

From 1989 to 2000, a study of 500 of collapsed bridge structures in the U.S.A showed that the most frequent reasons for failures of bridges were because of scouring, floods, and impacts. Moreover, for these 500 bridges that have been examined, their mean ages were 52.5 years (Wardhana and Hadipriono, 2003).

1.2 Types of Scour

The procedure of scouring mechanizations is well established, also, it is not a simple mission to quantify the volume of scour at a bridge crossing, because of complication of the cyclic nature of the event, and also to the truth that geometry of bridge, morphology, the canal of the river and the hydrologic process are various in each bridge. Scour at bridge crossings is generally the outcome of the linked influences of three varied scour procedures (local, contraction, and general scour at abutments and piers) that could happen either at the same moment or independently, whose various source proposes a various prediction of contribution of each individual scour. In addition, total scour includes a long period of erosion of material and declining in the river bed because of scarce in the suppling of sediment that coming from upstream, local scour at the abutments and piers of the bridge, and general scour at the bridge. Variation in the altitude of riverbed could be because of artificial or naturalistic reasons, such as barrages and Dams, urbanization, or natural decline of the riverain system. Figure 1.3 indicates types of scour (Cheremisinoff et al., 1987).

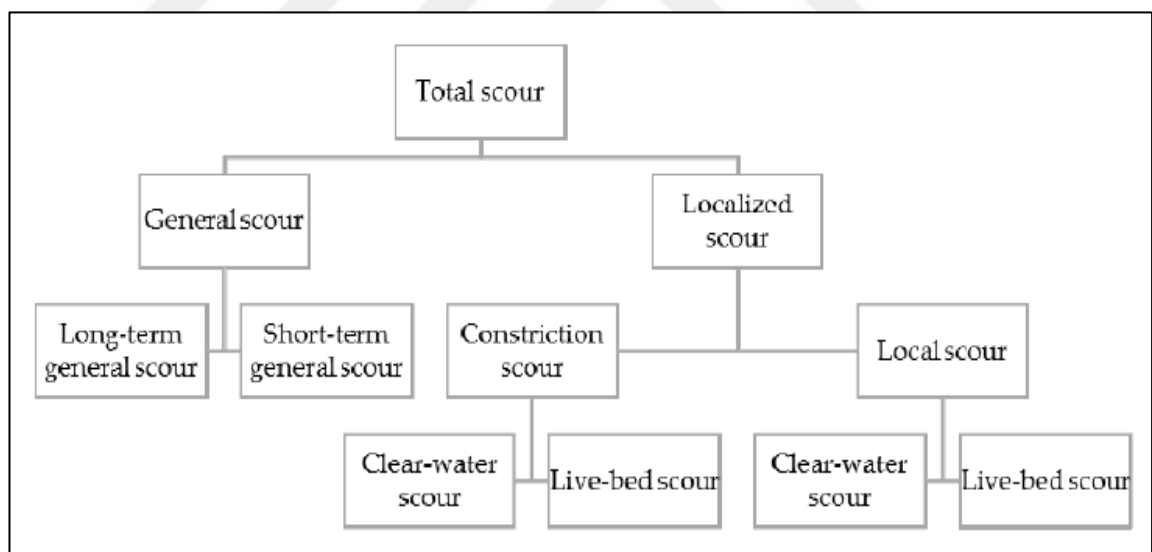


Figure 1.3 Scour classification (Cheremisinoff et al., 1987).

1.2.1 General Scour

General scour is known as a noticed lowering in the river bed due to the rising of water flow. The happening of this procedure is clarified by a huge amount of sediment transported because of flood condition, which is created by high streamflow density, explained as the bed shear stress (which is in charge of the initial transportation of bed

particles) and the average flow velocity (which sustain the movement of grains) (Farias et al., 2003). It should be recognized that the evolution of this process taking place within a short time scale, concerned with a flood, and thence its volume is a symbol of the watershed hydrologic features, especially the time and size of concentration. Thus, the time scale differs from the short time within hours for small-sized watersheds to several weeks for enormous basins. Furthermore, general scour takes place in a river in its natural situation, even without structures presences. Degradation refers to lowering in the bed of a river, which happens through a long scale of time, for instance, erosion of a river bed under the dam, as a result of trapping of sediment in the reservoir. However, it's important to calculate general scour for the initial phase of analyzing of bridge scour, in which way, the deformation of a channel is computed for the layout stage before putting in the bridge.

1.2.2 Localized Scour

Localized scour happens in the part of a river structure (Dey 2014), commonly, comprise of scouring around piers of a bridge, embankments, spurs, and abutment. Contraction scour is a type of localized scour, taking place at a location where the space of the opening for a bridge is least than the upstream streamflow space, which may contain the flood plains and major channel. A lowering in the area of flow leads to a rise in the median promptness for the same influx, also, a boosting in the shear stresses onto the riverbed. The growth of erosive powers causes the removal of bed materials at the contracted part more than which carried from upstream. As a consequence, the riverbed is decreased through the width of the channel. However, the reduction of the riverbed could not be steady through the width of the channel because of the various velocities in a channel section. In addition, contraction scour happens when a bridge is situated on an obviously tight expansion of a river. The edge of a river could be subjected to damage due to the influence of abutment scour and contraction scour when the abutment is retreating a short range from the edge, lower than of 3 to 5 times the mean deepness of streamflow across the viaduct. In that event, the edge and bed of a river under a viaduct in the flooding zone have to be kept by rock riprap. Contraction scour can happen in the overbank regions and the main channel. The occurrence of clear-water scour and live-bed scour are potential, relying on whether the streamflow upstream of a viaduct is carrying bed substance (clear-water scour) or

is not (live-bed scour), this could be specified by utilizing the notion of a crucial speed above which substances of the bed will be worn away (Akan, 2006).

Local scour is another type of localized scours that occurs at piers due to horseshoe vortices that shape at the grounds of the pier. Moreover, the stagnancy line originating at the front of the pillar because of the flux obstruction by piers. Both downflow and detaching of the boundary layer create the horseshoe vortex twisted around the pier base. This system of vortices eliminates the material of the bed from around the pier base and leads to producing a local scour hole.

1.3 Objective of Study

1. Clarifying types and general concepts about scour.
2. Utilizing Artificial Neural Networks for predicting equilibrium local scour depth.
3. Examine the most important factors that affect the prediction.
4. Performance of modeling with dimensional and non – dimensional variables.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter shows the mechanism of local scour around the pier, and factors that influence local scour. Moreover, presents a brief review of empirical equations that have applied to estimate scour depth at a pier, which was found by different researchers, then introduces summarized details regarding the artificial neural network, also focuses on recent attempts to predict the scour depth using artificial neural network.

2.2 Mechanism of Local Scour

The essential mechanism leading to local scour around viaduct piers is the down-flow at the upstream confronts the pillar and creates a whirlpool at the bottom. The flux becomes faster when it near the pier coming to comfort at the countenance of the pillar. The approach flux velocity is decreased to about zero at the upstream portion of the pier, as an outcome, the pressure rises at the pier countenance. The linked compressions reach the extremest at near to the uppermost of flow, where the dragging is greater and reduces toward down (Melville and Raudkivi, 1977). The pressure on the countenance of the pier weakens because the speed is lowering from the top to the base, as results, creating a gradually downward compression. The gradual pressure hence imposes the flux at the lower of the countenance of the pier. The outcoming downflow hits over the stream of the river and originates a puncture around the bottom of the pier. The down-flow that hitting on the streambed is the major scouring factor. Figure 2.1 presents the flux manner around a cylindrical pier in the case of movement of water. As shown in Figure 2.1 (Melville and Coleman, 2000), the sturdy vortex motion due to the presence of the pier drags sediments of the bottom within the nearness of the foundation of the pier (Lauchlan and Melville, 2001).

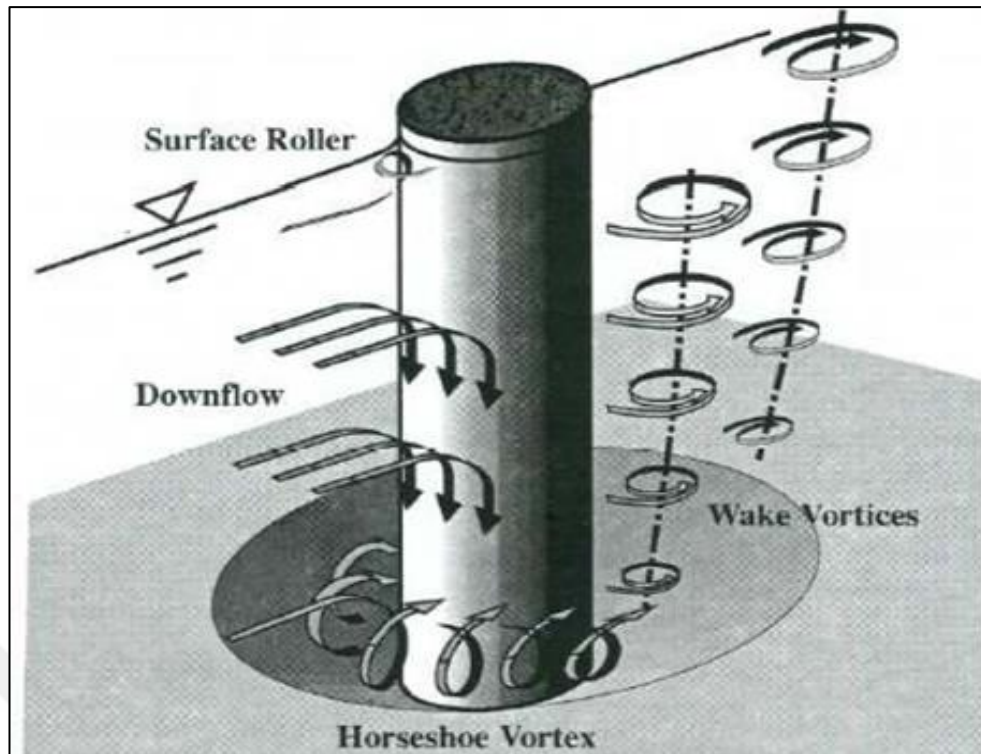


Figure 2.1 Pattern of flux around a pier (Melville and Coleman, 2000).

The down-flow rolls, and it's ongoing to originate a puncture, thus, during reacting with the approaching flux, it evolves into a complicated swirl system. The vortex then stretches in the direction in which a river flows alongside the laterals of the pillar. This eddy is oftentimes mentioned as a horseshoe eddy due to its considerable resemblance to the shoe of a horse (Breusers et al., 1977). The horseshoe swirl is much efficient in moving the forced-out particles long-distance from the pier. As the scour profoundness raises, the horseshoe vortex force decreases, which subsequently results in a lowering in the sediment sweep away ratio from the bottom of the pier (Lagasse and Richardson, 2001). Alongside the horseshoe swirl in the surrounding of the bottom of a pier, there are as well the perpendicular eddies downstream of the pier indicated to as wake eddies. The segregation of flux near the pier generates the so-called wake whirlpools (Dargahi, 1990). These wake swirls are not steady, and it is eliminated off and on from a single aspect of the pier and then from the else side. However, both the wake and horseshoe eddies sweep substances from the bottom zone of the pier. The strength of the wake swirls is dramatically decreased with extent after downstream, such that particles precipitated directly toward the downstream of the pier. Besides, the scour mechanism under waves is dependent on the vortex shedding (Khwairakpam and Mazumdar, 2009).

2.3 Parameters Influencing Scouring

The local scour depth is the role of a number of variables, numerous of which are related to one another. The parameters affecting local scour can be separated into which characterizing the fluid, which exemplifies the flow, which indicates the features of the sediment, and which explains the pier features.

2.3.1 Effect of Approach Flow Velocity

As the approach velocity (V) rises to an appointed part (0.5 for cylindric piers) of the decisive velocity (V_C), the scour will start near to the pier (Nicollet, 1971). Then, the scour profoundness rising nearly straight line with velocity until the approach velocity is on a par with crucial velocity. When the approach velocity overrides critical velocity, bed-load motion is inserted and the issue is converted to the live-bed scour trouble. At the moment in which the bed motion is founded wholly, the deepness of scouring is decreased slightly at a level lower than the scour deepness at critical velocity. Any equilibrium scour depth is disappeared, but the value of the deepness of scouring wobbles around a median value. The latest researches have presented that as speed surpasses the threshold velocity, the depth of local scouring decreases foremost and then rises once more. Also, the differentiation between clear water and live bed regimes depends on whether the flux concentration (V/V_C) is below or above 1 (Akhlaghi et. al, 2020).

2.3.2 Effect of Flow Depth

The effect of flow deepness on the scouring depth has been examined by various scientists. The presence of a pier in the orientation of flow leads to a horseshoe vortex at the bed level and causes a surface roller at the upstream. These vortices motions that are evolving at the superficies and the bottom, move-in an adverse way. Also, depending the local scour on the approach flow deepness is related to the collision of the vortex locomotions. As a common rule, if two rollers do not react with each other, the flux deepness doesn't influence the local scour depth. In other meaning, when the flux depth is enormous sufficient, the interference between the vortices misses out on its strength (Breusers and Raudkivi, 1991). The effectiveness of the uppermost roller turns out extra impact and drives the swirls of the base to erode the bottom of the footing lesser with lowering the deepness of flow. Clark et al. (1982) has figure out

that the restricting provision for the deepness to a diameter of the pile ratio is $h/D > 2$. In the condition of minimal values, the mechanics of scouring and the modality of flow at the pile is irritated. Melville and Sutherland (1988) disregard the influence of the deepness of flux for assured d_o/D values for coarse and fine aggregates, for fine aggregates, $d_o/D \geq 3.0$, for coarse aggregates, $d_o/D \leq 6.0$, above of these boundaries, the influence of approach flux deepness on creating local scour is trivial. Raudkivi (1991) has indicated that Neill (1964) deduced a formula presenting that local scour depth is the role of flux deepness by employing the information by Laursen and Toch (1956) for steady flux:

$$\frac{d_s}{d_o} = \left(\frac{D}{d_o}\right)^{0.7} \quad (2.1)$$

where d_s : scour depth, d_o : flow depth, D : pier diameter. Figure 2.2 presents the varied of depth local scour with the deepness of flux that is indicated in the literature by different researchers (Yanmaz, 2002).

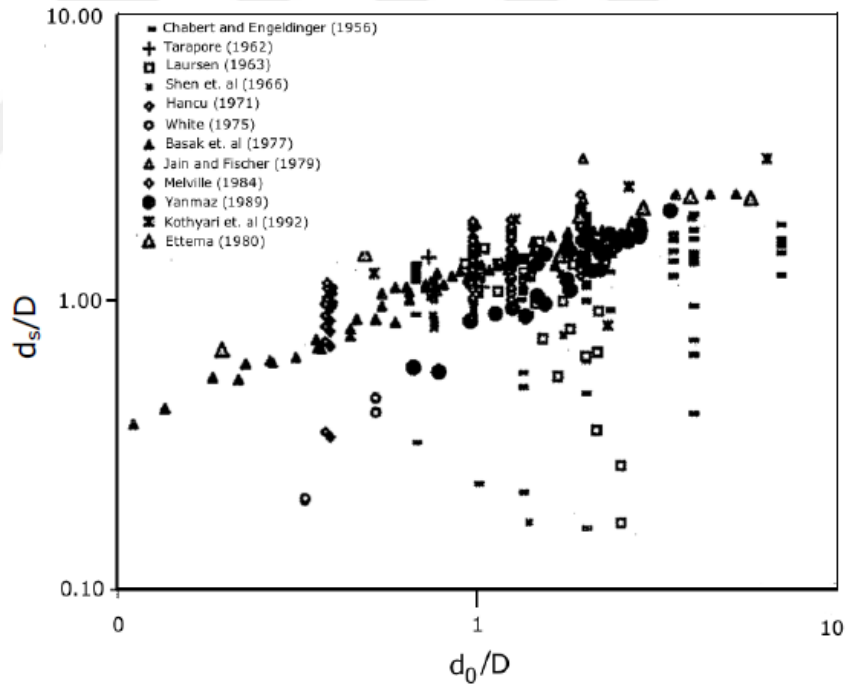


Figure 2.2 Relative scour depth with relative depth of flux (Yanmaz, 2002).

Melville (1997) stated that the scouring deepness is out of control of the depth of flow when $y_o/b > 1.43$, moreover, this value is various from the generally reasonable value of $y_o/b > 3 - 4$ (Breusers et. al. 1977; Raudkivi 1986; Ettema 1980). The shallowness of flux b/y_o (where y_o and b are flow depth and pier width) could be utilized to distinguish the effect of flux deepness concerning the pier width (Melville

and Coleman 2000). Table 2.1 presents a rating of local scour producers at the bottom of the bridge pier.

Table 2.1 Sorting of local scour at bridge piers (Melville and Coleman, 2000).

Class	D/d_o	Local Scour Dependence
Narrow	$D/d_o < 0.7$	$d_s \propto D$
Intermediate width	$0.7 < D/d_o < 5$	$d_s \propto (Dd_o)^{0.5}$
Wide	$D/d_o > 5$	$d_s \propto d_o$

2.3.3 Effect of Sediment Size

Pioneer experimenter researches of local scour presented that the influence of the magnitude of sediment to be comparatively petty. Moreover, the latest findings have demonstrated that the magnitude of sediment has an assured bearing on the scour mechanics (Nicollet, 1971; Ettema, 1980). Breusers et al. (1977) disputed that the effect of volume of grain (d) is restricted for single-particle magnitude sediment. Breusers and Raudkivi (1991) stated on the researches of Raudkivi and Ettema (1977). It was realized that size of the sediment of $d_{50} \leq 0.7$ mm creates a figuration of streams, while a sediment size of $d_{50} \geq 0.7$ mm does not lead to undulations. Raudkivi and Ettema indicated that in the case of non-undulations- figuration sediments ($d_{50} \geq 0.7$ mm), tests can hold efficaciously with a flux stipulation, V_o/V_{oc} , without the disturbed of upstream bed by the approach flux, while with smoother sands ($d_{50} \geq 0.7$ mm) a flatbed cannot be sustained for a similar case of flux. Breusers and Raudkivi (1991) deduced that streams commonly evolve at shear velocity (V_o), above $0.6V_{oc}$, for the size of sediment, $d_{50} \geq 0.7$ mm.

2.3.4 Effect of Grain Size Distribution

Nicollet and Ramette (1971) were pioneers' researchers in the inspection of the effectiveness of the distribution of sediment grain magnitude on the depth of the local scour at cylindric pier shapes. An experiment collection with regular particle (sand) as well as an admixture of sediment has proceeded within similar hydraulic stipulations and the shape of the pier. The substance of bed was a blend of thirty-three percent of the already employed regular sands, giving a sort of upright graduating curve of amidst 0.8 mm and 3.2 mm. Also, they were detected that the superior scour of the mixing

happens in the near of the crucial flux velocity of the midst magnitude of grain and that the deepness is approximately twenty-five percent lower than those possessed with regular substance. In addition, the deepness of scouring for the test with sediment nurture is lesser than the scour depth clear-water. The impact of sediment graduating on pier scour for clear-water situations has been examined by different scientists (Dey and Raikar, 2007). The principal noticing is that there is a big decrease of scouring deepness with raising non-symmetry (σ) because of the creation of an armour sheet. Another figuring out was that in the vicinity of $\sigma = 1.5$, the scour action for streams-creating sediments varies from non-streams-creating sediments.

2.3.5 Effect of Pier Size

It is an actuality that the horseshoe whirlpool mechanics in which dimension is a representing of the diameter of a pier (Kothyari et. al, 1992). Shen et. al. (1969) noticed that the horseshoe eddy size is proportionate to the pier Reynolds number, which indicates the pier diameter. Under clear-water situations, pier magnitude affects the duration taken to accomplish the eventual scour deepness but not its prorated volume, y_s/b , if the influence of prorated deepness, y/b , and coarseness b/d_{50} on the local scour depth are eliminated. In addition, they deduced that the size of the local scour bore created around the middle of the uppermost half of the circumference of the pier is proportionate to the cube of the pier diameter. The influence of pier size on the scour local depth is of main attention when lab datums are explicated for field utilization. The views which have given on the linkage inter equilibrium scour and depth are completely branched. Almost these standpoints can be summed up like all other factors being preserved stabilized, the scour depth alters as D^β where D is the pier width and $0.5 \leq \beta \leq 1$. For example, Laursen (1958) design curve corresponds to $\beta = 0.7$, Larras (1963) suggests $\beta = 0.7$ and Shen et. al. (1969) found out $\beta = 0.619$, Breusers (1972) offers $\beta = 1$, Melville (1997) referred that d_s is out of control of b when $b/y_o > 5$.

2.3.6 Effect of Pier Shape

The form of the pier has a considerable effect on the scour deepness. Breusers et al. (1977) abstracted different approaches from various studies and deduced that if a round-nosed pier or circular pier is presumed as a reference, a decrease of twenty-five

percent in the depth of scour can be gained by well designing the pier. This workable impact vanishes in event of angles of attack bigger than 10° to 15° . Otherwise, piers that have rectangular form can raise the deepness of scour up to forty percent in comparison with reference pier. Neill (1978) indicated that piers with sharpened rim form resort to capture and collect wreckage, while the bracket current caused by unsharpened piers be inclined to dispose of wrack. Ettema (1980) deduced that the more edgeless the pier, the more deep the depth of local scour. The effectiveness of the end of flow for the pier is of small importance to the superior depth of local scouring. Müller and Wagner (2005) figured out that the form of the pier has a minimum impact on the deepness of scour in the field circumstances in comparison with experimental conditions in the lab. Meyering (2012) indicated that the impact of flow directions, sunken debris, and deepness of diversified pier forms in the field especially lower the impact of the pier geometry on the deepness of scour. Figure 2.3 shows usually used pier shapes (Richardson and Davis, 2001).

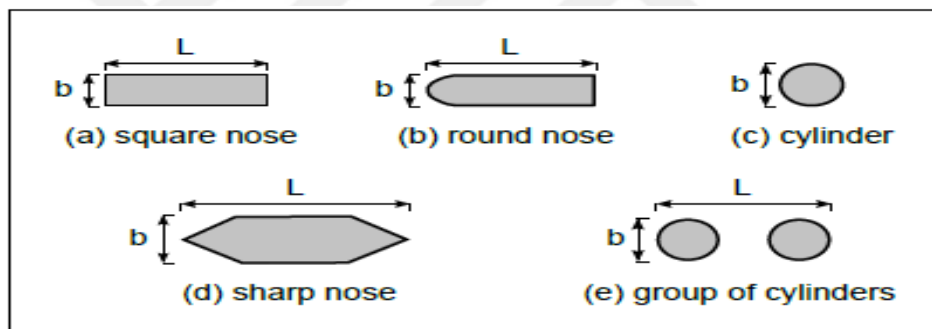


Figure 2.3 Generally used pier shapes (Richardson and Davis, 2001).

2.3.7 Effect of Angle of Attack

The angle of attack of streamflow for piers is the angle inter the major axis of the pier alignment and the flow direction. As the angle of attack rising, the depth of scour raises because of the increase in the efficacious front segment of the pier, and the spot of utmost scour deepness proceeds in a constant way with the uncovered segment of the pier toward the posterior, and the deepness of scour at the posterior begins to be larger than that at the frontal segment of the pier. The impact of the angle of attack has been extremely investigated throughout the period of the ten years ago. By utilizing a solo orbicular pier, this effectiveness has no action on the scour procedures. Thus, a lot of hydraulic scour testing has been executed for solo circuitous piers to decrease the

numeral of affecting factors. Figure 2.4 presents the scheme of multiplying circumstances formed by Laursen and Toch (1956).

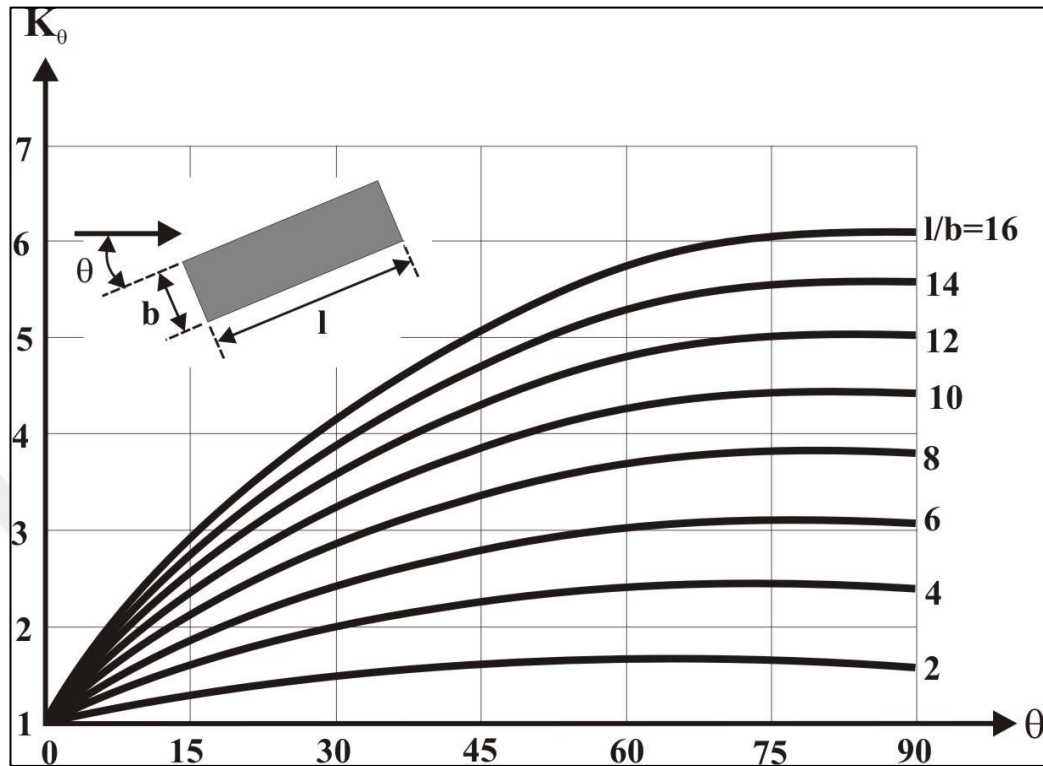


Figure 2.4 Scour depth divergence with pier alignment (Laursen and Toch, 1956).

The K_θ values are gained by normalizing the calculated scour deepness with the value at $\theta =$ zero degrees. The graphic was originated for piers which have rectangle form but can be utilized for further forms of the pier attentively. Figure 2.4 is rationally proportionate with experimentally database by Mostafa (1994), further, shows the noticing that the farthest deepness of scour at leaned piers of feeble ratio (small l/b) happens at oblique angles that little lesser than 90° . This later event emerges due to the projected width b_p ($b_p = l \sin \theta + b \cos \theta$ for rectangular piers) of these piers which θ greater than ninety degrees (Melville, 2008). In addition, Figure 2.4 explains the significance of alignment, that is, the depth of local scour at a rectangle pier $l/b=8$ is approximately becomes three times at an angle of attack of thirty degrees. At viaduct passageways, the angle of attack may alter remarkably in spates events for plaited conduits, and it may shift gradually during overtime for the sinuous canal. The harness of cylindric piers, a straight line of pillars, or different forms in which they have weakly (length-to-width) aspect ratios is useful, where such alteration of flux alignment is potential.

2.4 Empirical Equations

Many attempts and researches offer numerous equations for calculating scour. Most formulas for scour prognostic, such as the equation of the Colorado State University (CSU-Equation), which is actually utilized in the U.S. Federal Highway Administration (FHWA) Hydraulic Engineering Circular Number 18 (HEC-18), also those issued by Melville and Coleman (2000) are experimental and founded on experimentally circumstances. A large number of these formulas produce analogues outcomes for lab-scale cylindric models but vary notably in their prognostic for preliminary scale models (Sheppard and Renna, 2005). Generally, most of these forecasting formulas for the equilibrium scour depth count on to the specific significance for the constancy of the piles' bases. In this chapter, a chosen of the uppermost essential scour equations are fleetingly presented.

Laursen and Toch (1956) examined the effect of the shape of a pier, angle of attack, deepness of water, sediment magnitude, and velocity. The two researchers presented a schemed designing curve, which Neill (1964) explained it for the cylindric pile as shown;

$$d_{se} = 1.35\left(\frac{h}{D}\right)^{0.3}D \quad (2.2)$$

where d_{se} is the equilibrium scour deepness, h is the water deepness, and D is the pier width. Shen et al. (1969) studied a scour formula that relies on the pier Reynolds number. As stated by Breusers et al. (1977), the pier Reynolds number (Re_{pier}) is an inappropriate variable to describe the scour deepness. The presented formula is the just one that contains only the Re_{pier} ;

$$d_{se} = 0.000223Re_{pier}^{0.615} \quad (2.3)$$

while Breusers (1977) worked on elaborated literature analyses and offer the following equation for the forecasting of scouring deepness. For circular piers, K_{shape} and K_{angle} become 1.0.

$$d_{se} = f_1\left(\frac{U}{U_{crit}}\right)\left[2.0 \tanh\left(\frac{h}{D}\right)\right] K_{shape} K_{angle} \quad (2.4)$$

where d_{se} is the equilibrium scour depth, U is the depth-averaged flow velocity, U_{crit} is the critical depth-averaged (incipient-transport) flow velocity, h is the water depth,

D is the pier width, K_{shape} is the correction factor for the pier which has a nose-shape form, and K_{angle} is the correction factor including the angle of flow impact on the pier. Moreover, Jain (1981) investigated the local pier scour for big Froude numbers at the experimental circumstances, and offers the following formula for scouring under clear water stipulations;

$$d_{se} = 1.84 Fr_{crit}^{0.25} \left(\frac{h}{D}\right)^{0.3} D \text{ IF } (Fr - Fr_{crit}) \leq 0.2 \quad (2.5)$$

where h is water depth, D is pier width, and Fr is Froude number. Melville and Sutherland (1988) improved a K-factor based formula. For threshold flux stipulations $U = U_{crit}$, K_{flow} becomes 2.4, K_{depth} becomes 1.0 if $h / D > 2.6$, K_{size} becomes 1.0 if $D / d > 25$ for $D/d < 25$ $K_{size} = 0.57 \log (2.24 D / d)$. The effect of K_{σ} is comprised in $K_{shape} \cdot K_{angle}$ as well as K_{angle} become 1.0 for circular piers;

$$d_{se} = K_{flow} K_{depth} K_{size} K_{\sigma} K_{shape} K_{angle} D \quad (2.6)$$

where K_{size} the correction factor is for sediment size effects, K_{shape} the correction factor for a nose-shaped pile, K_{angle} correction factor composed of the angle of flux influence on the pier, and D is the pier width. In addition, the so-called CSU-Equation (1988) was permanently enhanced throughout the latest ten years and a novel K-factors have been inserted. Furthermore, this adjusted formula has propositioned by the FHWA administration in the US,

$$d_{se} = 2.0 K_{shape} K_{angle} \left(\frac{h}{D}\right)^{0.35} Fr^{0.43} D \quad (2.7)$$

where d_{se} is the equilibrium local scour, h is the water deepness, D is the pier width, K_{shape} the correction factor for nose-shape pile, K_{angle} the correction factor including the angle of flow impact on the pier and Fr is the Froude number. Furthermore, Breusers and Raudkivi (1991) studied the deepness of scouring accompanied by K-factors that can be found by correlated tables and figures. In orderly sediments K_{σ} becomes 1.0, further, K_{depth} becomes 1.0 for fine orderly sediment if $h / D > 2.0$ while K_{depth} for proportional coarse sediment becomes 1.0 if $h / D > 6.0$. K_{size} becomes 1.0 if $D / d_{50} > 50$. K_{shape} and K_{angle} , become 1.0 for circular piers.

$$d_{se} = 2.4 K_{depth} K_{size} K_{\sigma} K_{shape} K_{angle} D \quad (2.8)$$

where d_{se} is the equilibrium local scour, D is the pier width, K_{size} the correction factor is for sediment magnitude actions, Moreover, Johnson (1992) improved a pier scour approach depending on the probability. He adopted that due to the hydraulic parameters such as flow, velocity, and deepness of flow which are mostly randomly determined in the naturalistic, additionally, these variables are essential for the scour procedures, on that account, the deepness of scouring itself is also a random parameter.

$$d_{se} = 2.02 h \left(\frac{D}{h}\right)^{0.98} Fr^{0.21} \sigma^{-0.24} \quad (2.9)$$

Gao (1993) introduced and confirmed the Chinese-Equation which has been utilized by expressway and railroad engineers in China for the uppermost twenty years. This equation depends on lab researches and a large range of field databases, also it is useful for both clear and live-bed water scour (Gao et al., 1999). The CSU-Equation (1995) contains two new K-factors K_{bed} and $K_{armoring}$. K_{shape} , K_{angle} and $K_{armoring}$ become 1.0 for circular piers in uniform material, $K_{bed} = 1.1$ for Clear-water scour without sand dunes, as shown,

$$d_{se} = 2.0 K_{shape} K_{angle} K_{bed} K_{armoring} \left(\frac{h}{D}\right)^{0.35} Fr^{0.43} D \quad (2.10)$$

where K_{bed} the correction factor for bedform is effects, and $K_{armoring}$ is the correction factor for armoring effects.

2.5 ANN in Scour Prediction

An artificial neural network (ANN) is a vast parallel-distributed information-processing system that has an assured function characteristic that looks like the human brain's biological neural networks (Haykin, 1994), Which is presented by McCulloch and Pitts (1943). The capability of the artificial neural network in characterizing a relationship from a given style makes it potential in resolving wide-ranging complicated problems such as modeling, classification, sample recognition, and nonlinear problems. The characterizes of an ANN are known by its procedure of selecting the connection weight, architecture, and activation function. The mechanism of artificial neural networks is one of the famed soft computing approaches. The traditional trails of experimentally and theoretic frameworks have been superseded predominately in the increased activities of engineering by the alternate artificial intelligence. ANN has considerable usefulness over compared to the traditional

approaches accompanied by the advantages of their data-driven technicality, the model-free form of estimation, and forbearance to data mistakes. Over and above that, it has been indicated that ANN performs well in dealing with situations wheresoever the obtainable data are deficient or fuzzy from its sources. A little while back, ANN has been vastly utilized to fix risqué issues in the different areas of water resources and hydrology. Trent et al. (1993) employed neural networks to presage the deepness of scour at the pile of the bridge. Wu and Lim (1993) executed an endeavor in the estimation of superior scouring deepness at the spur of a dam utilizing ANN. Liriano and Day (2001) utilized artificial intelligence for the estimation of scouring deepness at culvert outlets, and they have contrasted the outputs of actual forecasting equations with outcomes gained from ANN. Khosronejad et al., (2004) harnessed ANN in the foretelling scour hole features at vertical piles, also they employed radial basis and multilayer perception neural networks in their study. They indicated that ANN could model non-linear relations between output variables (width of scour hole and scour hole depth) and input variables (maximum shear velocity, maximum velocity, wave period, water depth, wave height, and shields parameters). Lockett (2005) carried out the neural network estimation for scouring deepness at viaduct piles. They presented that ANN outcomes at a great scale of precision in resolving a specific problem in contrast to theoretical and experimental outcomes. Meanwhile, Jeng et al., (2005) have employed ANN evaluation for the prediction of scouring deepness at viaduct piles, they established ANN models as a role of five parameters; flow depth, flow velocity, pier diameter, mean grain size, and critical flow velocity. Choi and Cheong (2006) offered a process for estimation local scour at viaduct piers employing an artificial neural network with an assertion on determining input parameters, learning process, calibrations of network control variables, and verifications. Furthermore, Bateni et al., (2007) utilized artificial intelligence for the prediction of equilibrium and time-dependent scour depth with different data. Moreover, Lee et al. (2007) applied ANN to foretell scour depth around a viaduct pier, and they used scour depth data from thirteen states in the USA. Azmatullah et al. (2008) employed neural networks to predict the scour amidst spillways, the inputs of the network were flux strength atop the spillways and characteristic head while they have set scour depth at downstream of the bucket as output, the search presented that ANN predicts the design scour downstream of a ski-jump bucket better than conventional equation-based methods. Guven and Gunal (2008) have used ANN trained with the back-propagation algorithm

in the prediction of maximum scour depth, and they found that ANN models give better results than traditional nonlinear equations, also, they utilized sigmoid transfer function in the modeling of ANN. Guven et al. (2012) have established ANN multilayer perceptron (MLP) models, and consisted of three layers with a back-propagation algorithm to estimate the deepness of local scour around circular pile because of waves, moreover, they developed gene-expression programming (GEP) models, they found that both ANN and GEP have provided a good accuracy better than conventional equations with $R = 0.994$ for GEP and $R = 0.992$ for ANN, respectively. Sarshari and Mullhaupt (2015) used ANN and empirical methods to foretell equilibrium scour deepness at viaduct piles, and they pointed out that ANN proffers better outputs than empirical procedures. Khassaf and Abdulwhab (2016) indicated that the artificial neural network with feedforward backpropagation provides a good estimation method for the local scour depth around bridge piers. Also, Amini et al. (2020) presented that ANN could be utilized to estimate the deepness of scour at complex piles as a delicate tool. However, the literature on the application of artificial neural networks to estimate scour depth at the abutment of the bridge is not reported over a large range.

CHAPTER THREE

CASE STUDY

3.1 Introduction

This chapter indicates the selection procedures of input parameters, and the laboratory data of local scour that used for modeling with the artificial neural network, then shows the details of the artificial neural network (ANN) that utilized for the prediction of local scour depth around bridge piers, moreover, clarifies the steps of modeling using MATLAB software, also presents methods that employed to evaluate the artificial neural network models.

3.2 Choosing of Input Parameters

The equilibrium local scour deepness at piles of the bridge is affected by flux, properties of bottom sediment of stream, and geometry of the pier (Melville and Coleman, 2000). In a functional relation, this can be presented as the following:

$$d_{se} = fn [flow (\rho, \mu, V, y, g, \gamma), sediment (d_{50}, \sigma_g, \rho_s, V_c), pier\ geometry (b, \alpha, \beta)] \quad (3.1)$$

where d_{se} equilibrium scour depth, μ and ρ are dynamic viscosity of water (m^2/s) and fluid density (kg/m^3), respectively, y and V are flow depth (m) and mean velocity (m/s^2), respectively, g is gravitational acceleration, γ is the correction factor for bed form, σ_g and d_{50} are standard deviation and median of the particle size distribution (mm), respectively, V_c is the critical mean velocity for entrainment of bed sediment (m/s), ρ_s is the sediment particle density (kg/m^3), b is the pier width or pier diameter, and β and α are correction factors for flow angle of attack and pier shape. For uniform sediment, and neglected impact of bedform, γ and σ_g can be neglected and subscript in d_{50} can be eliminated in Eq.3.1. Value of α range between 0.9 for sharp-nose pier and 1.1 for a circular pier, also the scope of β is between 1.0 – 1.08 for 0° and 60° of attack angle (Melville and Colman, 2000). Furthermore, in this research, the local scour around a cylindrical pier for the bridge has been assumed with 0 angle of attack,

therefore, relying on β and α could be neglected. Furthermore, with a steady value of ρ_s and ρ , and the insignificant effect of viscous, Eq. (3.1) could be written as following (Choi et al., 2017):

$$d_{se} = f_1 (V, y, d, V_c, b) \quad (3.2)$$

The Buckingham pi theory was utilized to gain the functional relationship for d_{se} . As the number of parameters is six with two essential dimensions in the Eq. (3.2), the number of dimensionless parameters will be 4 as shown in Eq (3.3). The dimensional analysis of Eq. (3.2) could be written as following (Choi et al., 2017):

$$\frac{d_{se}}{b} = f_2 \left(\frac{V}{V_c}, \frac{y}{b}, \frac{d}{b} \right) \quad (3.3)$$

The (V/V_c) linked to the stage of the local scour, the (y/b) clarifies the interaction of the horseshoe vortex, the counter-rotating water surface roller near the top of the pier and downflow, also, (d/b) describes the porosity of the scour hole boundary and relative roughness (Ettema et al. 1998).

3.3 Dataset

In this study, 400 laboratory measurements of pier scour data were used for the modeling of artificial neural networks. These data include parameters pier width (b), flow velocity (V), flow depth (y), the sediment critical mean velocity (V_c), the particle diameter (d) as input parameters and equilibrium scour depth (d_{se}) as a target parameter. Table 3.1 shows the range of data of each dimensional variable utilized for the ANN modeling in this research.

Table 3.1 Range of dimensional variables.

Dimensional variable	Range
V (ft/s ²)	0.54 – 5.28
y (ft)	0.066 – 3.281
d (mm)	0.24 – 7.8
V_c (ft/s)	0.73 – 4.81
b (ft)	0.095 – 2.5
d_{se} (ft)	0.049 – 1.497

While the range of the dimensionless variables used in the artificial neural network modeling has been illustrated in Table 3.2.

Table 3.2 Range of dimensionless variables.

Dimensionless variable	Range
d_{se}/b	0 – 3.084
V/V_C	0.445 – 4.690
y/b	0.052 – 20.947
d/b	0.304 – 82.978

The dataset has obtained from the USGS pier-scour database (Benedict and Caldwell, 2014), which include laboratory pier-scour data obtained from previous studies, as shown in Table 3.3.

Table 3.3 Sources of dataset.

Source of dataset	Number of datasets
Chabert and Engeldinger (1956)	93
Chee (1982)	37
Chiew (1984)	101
Coleman (unpublished)	6
Dey et. al, (1995)	18
Ettema (1980)	97
Ettema et. al, (2006)	6
Ettema (1976)	19
Graf (1995)	3
Jain and Fischer (1979)	20

Also, both dimensional and dimensionless parameters have normalized with the min-max method to increase the performance of deep learning. Min-max normalization is one of the most well-known methods for normalization. The dataset is scaled to a range of 0 to 1. A min-max scaling is done as the following equation (Dogan et al., 2008).

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3.4)$$

where X_{norm} is the normalized value of a variable, X is any value of the dataset, X_{max} is the maximum value of the whole dataset, and X_{min} is the minimum value of the whole dataset. Also, the relation between input parameters (V, y, d, V_C, b) and target parameter (d_{se}) is not strong enough to be a linear relationship as shown in Figure 3.1 to Figure 3.5. It is clear from these figures that the relation between input parameters and target parameters is not strong based on values of regression (R^2) which its low and far from 1, therefore, ANN could be used as a useful technique in this case.

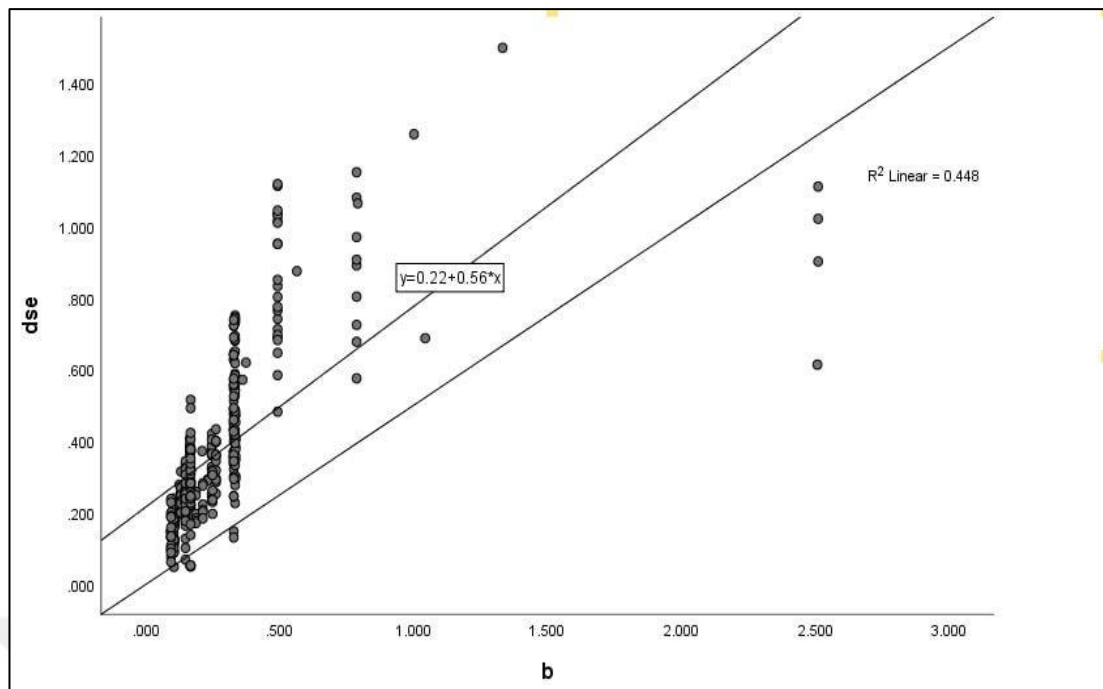


Figure 3.1 Relation between equilibrium scour depth and pier with.

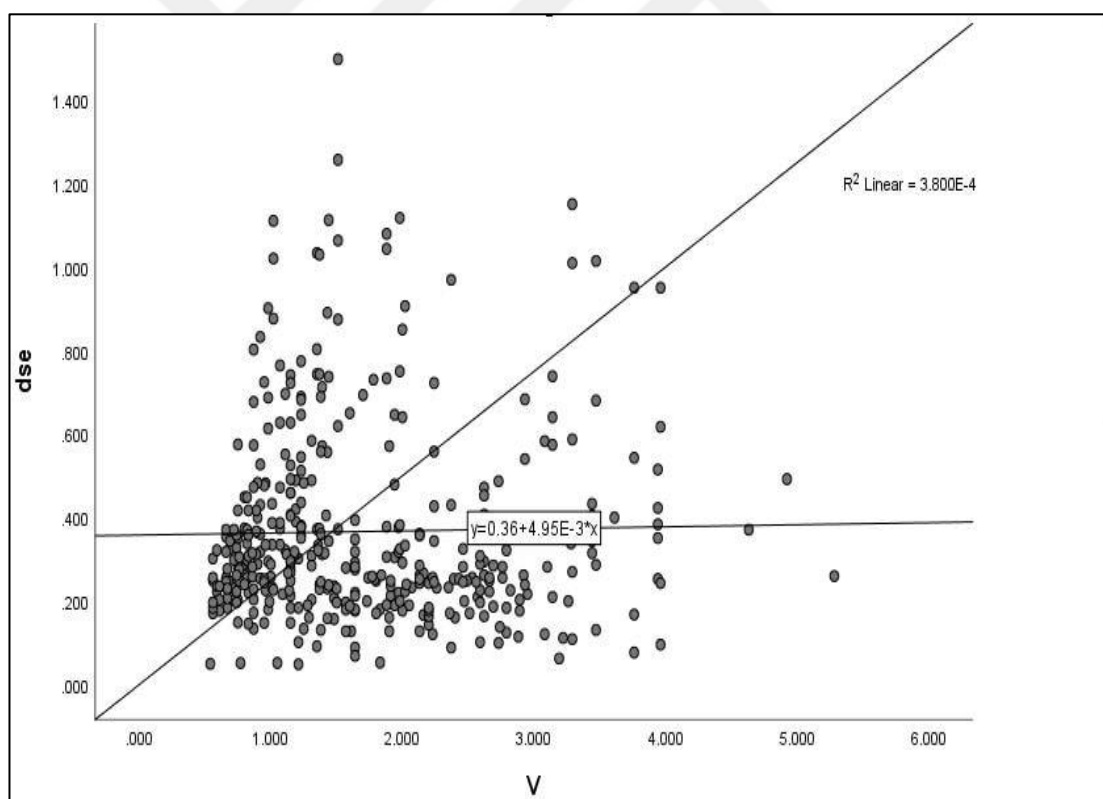


Figure 3.2 Relation between equilibrium scour depth and flow velocity.

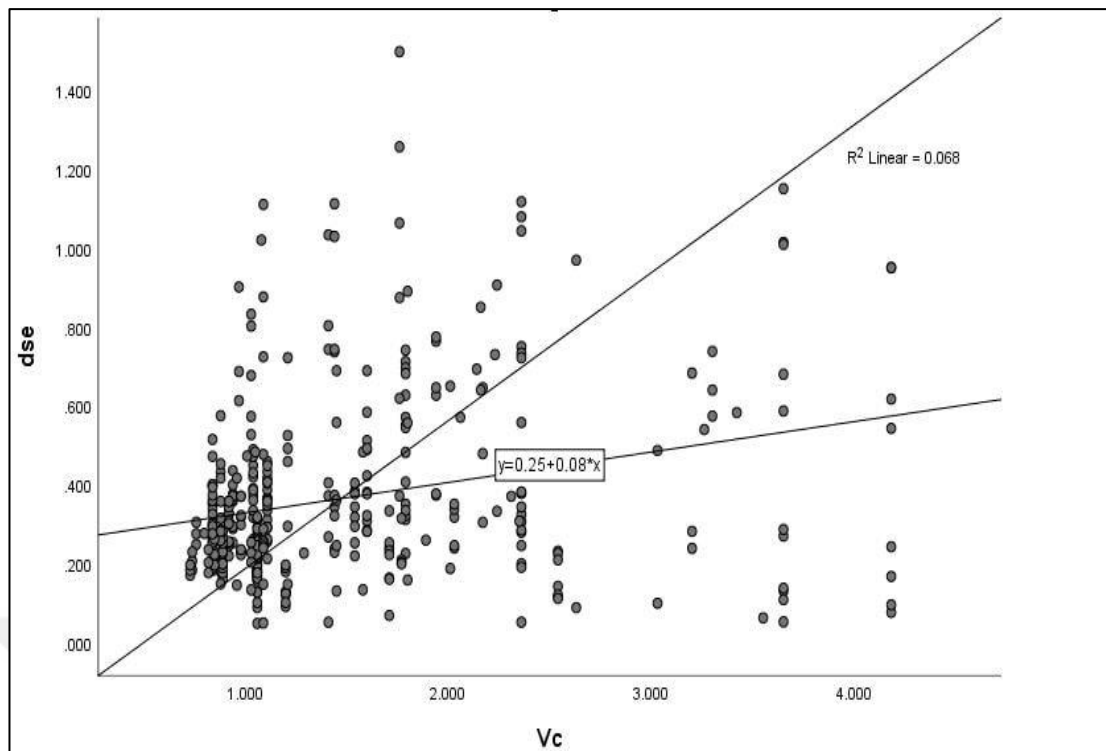


Figure 3.3 Relation between equilibrium scour depth and sediment critical velocity.

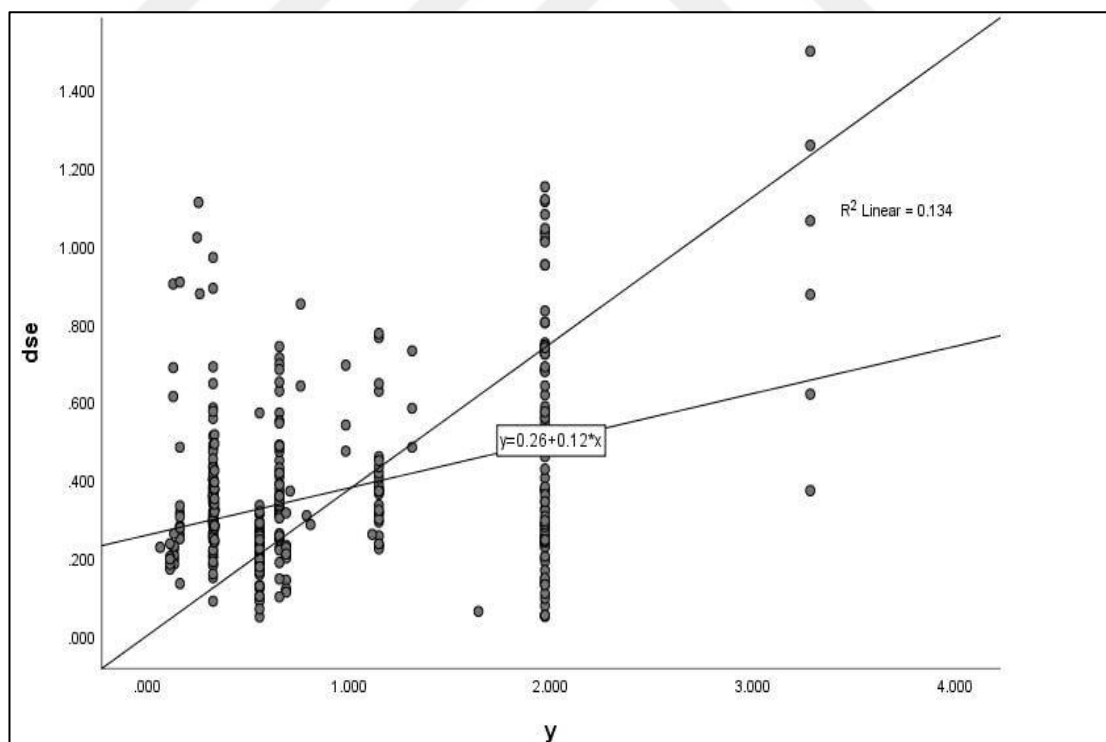


Figure 3.4 Relation between equilibrium scour depth and flow depth.

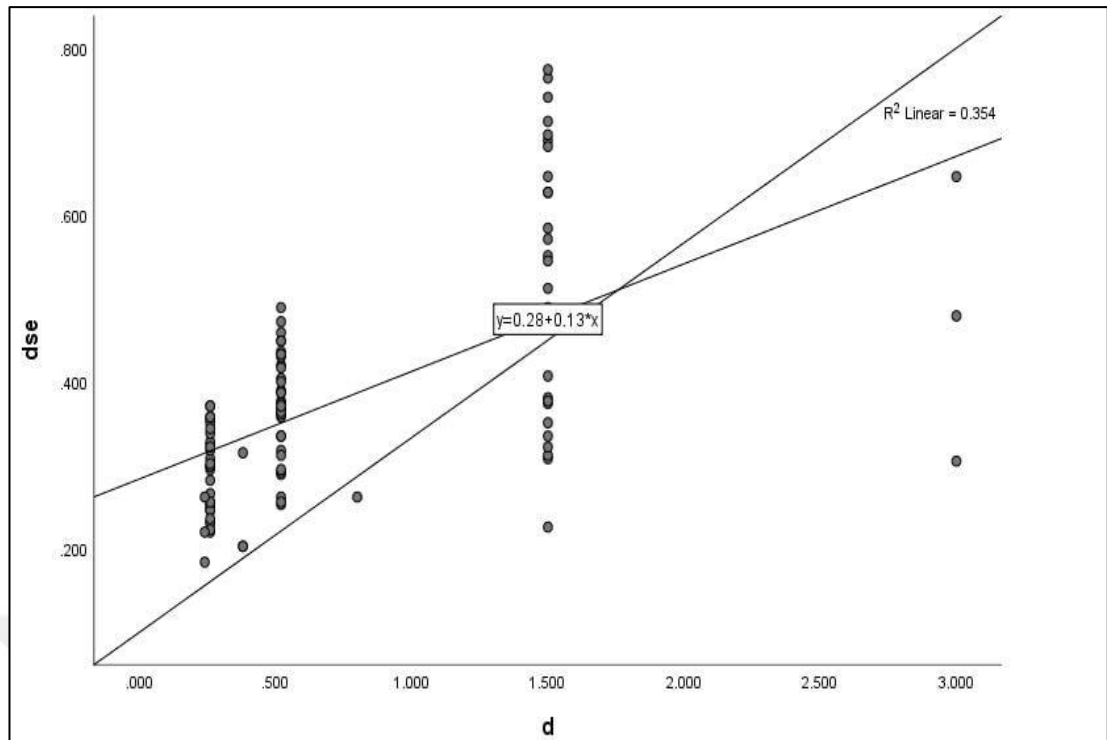


Figure 3.5 Relation between equilibrium scour depth and particle diameter.

3.4 Artificial Neural Network

An ideal ANN contains many nodes that are managed within a specific order. In a feed-forward neural network, the nodes are mostly organized in stratum, beginning from an initial input layer and finishing at the ending output layer. Over one or just a single hidden layer could be found in ANN structure, with each layer comprising more than one node or just one. Datums move from the input to the output side. In general, the input layer takes the input variables for the issue. This contains all the facts and datums that can affect the outcome. So on, the input layer is obvious, and it is an implying of supplying data to the network. The output layer contains results estimated by the network and thus symbolizes the nodular's outcome. An ANN consists of many connected nodes, and each node is a separate computational unit. As shown in Figure 3.6 (Khassaf and Abdulwhab, 2016), neurons put together in layers and many of ANN models contain 3 layers. The ANN understands by selecting the suitable number of neurons in the hidden layer and regulating the weights of the connections according to the training data.

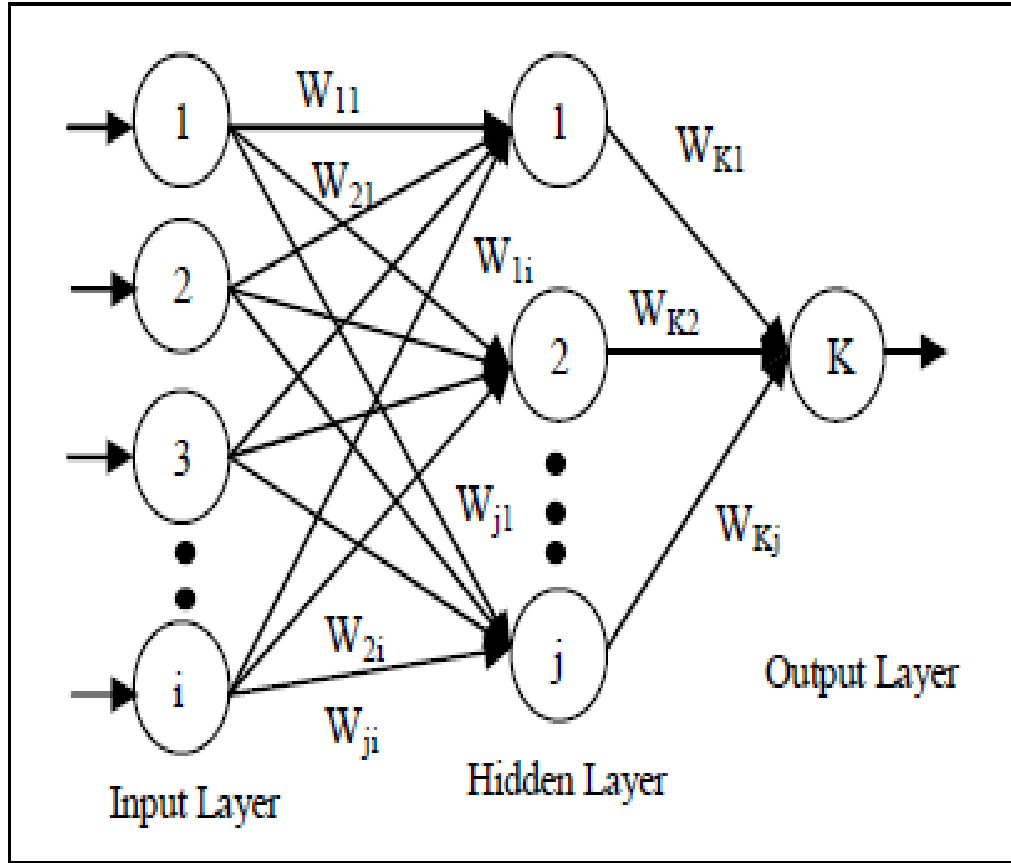


Figure 3.6 Artificial neural network model (Khassaf and Abdulwhab, 2016).

where W_{ji} is the weight of the connection between the j th hidden layer neuron and i th input layer neuron. W_{kj} is the weight of the connection between the k th output layer neuron and the j th hidden layer neuron.

3.4.1 Backpropagation Algorithm

In this study, a feedforward neural network with backpropagation algorithms and a single hidden layer has been utilized in the modeling. It provides a precise approach to any uninterrupted function there are enough hidden neurons in the layers (Hornik, 1991). In backpropagation neural networks, the relations amidst the different parameters are not identified mathematically. As an alternative, they learn from the samples fed to them. Also, they can popularize the right rejoinders that only largely resembles the information in the learning stage (Goh, 1995). The backpropagation neural network algorithm is a repeated gradient descent training process. It is executed in twain phases. In the initial phase, after all the network weightiness has been indiscriminately initialized, the selected datums are introduced to the network and conveyed forward to predict the outcome value of every paradigm which set. In the

latter phase, the variation (error) between recognized and predicted outcome is supplied backward through the network then the weightiness being varied in a method that the variance is reduced. The entire procedure is iterative with weights being calculated again at every and each rectification until the inaccuracy is low, or minimum than a particular threshold value. A treated neuron aggregates the inputs multiplied by the weights of correlations and then predicts the outcome of a neuron by utilizing the activation function between layers, as the following equations (Beg, 2008).

$$net_{pj} = \sum w_{ji} i_{pi} \quad (3.5)$$

$$o_{pj} = f(net_{pj}) \quad (3.6)$$

Where net_{pj} is the sum of the inputs, w_{ji} is weight vector, i_{pi} is the value of i^{th} the element of the input pattern, o_{pj} is the outcome of the node j for pattern p, and $f(.)$ is the activation function. In this study, the sigmoid transfer function has been applied in the hidden layer, the sigmoid function is a fixed and monotonically rising function that supplies a graded nonlinear response allowing the ANN to deal with any nonlinear procedure. Also, the purlin function was utilized as a transfer function between the output and hidden layer. The neural network acquires skills by adjusting the weights of the neurons in response to the errors between the target and actual outcome values. This is executed through the gradient descent on the entirety of squares of the errors for all the training models (Rumelhart, 1986). A single push through the group of training models besides the updating of the weights is known as an epoch or cycle. training is executed frequently introducing the whole assortment of training models (with the weights updated at the end of each cycle) till the mean total squared error over all the training models is reduced and within the ability particular for the issue (Caudill and Butler, 1990). At the final procedure of the training stage, the neural network must in a correct way replicate the target outcome values for the training data on the condition that the inaccuracies are low, i.e. concurrence takes place. The linked trained weights of the nodes are thereafter stocked in the neural network memory. In the posterior stage, the trained neural network is supplied with a combination set of datums. In this testing stage, the neural network estimation (using the trained weights) is compared with the target outcome values. This evaluates the accuracy of the neural network to popularize the right rejoinders for the testing models that only, in general, look like the dataset in the training collection. No further learning or weight

modifications take place throughout this stage. When the testing and training stages are discovered to be felicitous, the neural network can thereafter be put to utilize in workable implementations. The neural network will provide well-nigh instant outcomes of the output for the supplied workable inputs. The estimation must be credible on the condition the input values are in the scope employed in the training collection. A training algorithm figures out a decision function that the network's weights (Cömert and Kocamaz, 2017). There are different training algorithms. Also, there are different backpropagation algorithms, several of these backpropagation algorithms have been utilized in this study. All of the algorithms in this study run in the batch mode and performing with using the train, besides, the faster of the backpropagation algorithms are divided into two major categories. The first division utilizes heuristic techniques, which were enhanced from a test of the efficiency of the standard steepest descent algorithm, and the second employs standard numerical optimization techniques. Moreover, recent developments in the coding techniques in the MATLAB software have provided a wide range of back-propagation training algorithms which could be utilized in the modeling artificial neural network for various purposes. Table 3.4 shows these seven back-propagation algorithms that have been used in the modeling ANN using *MATLAB*®.

Table 3.4 Training algorithms functions.

Function name	Algorithm
trainlm	Levenberg-Marquardt backpropagation
trainrp	Resilient backpropagation
traingda	Gradient descent with adaptive lr backpropagation
traincgf	Fletcher-Powell conjugate gradient backpropagation
traincgp	Polak-Ribiere conjugate gradient backpropagation
traincgb	Powell -Beale conjugate gradient backpropagation
trainbfg	BFGS quasi-Newton backpropagation

3.5 ANN Modelling

Deep learning toolbox in *MATLAB*® offers a framework for designing and performing artificial neural network models with different learning algorithms. At first, the input variables (b , V , y , V_c , d) and output variable (d_{se}) should be entered into the workplace, besides, each variable (inputs and output) should be transposed from row

to column because the deep learning tool considers each column as observation, as shown in Figure 3.7.

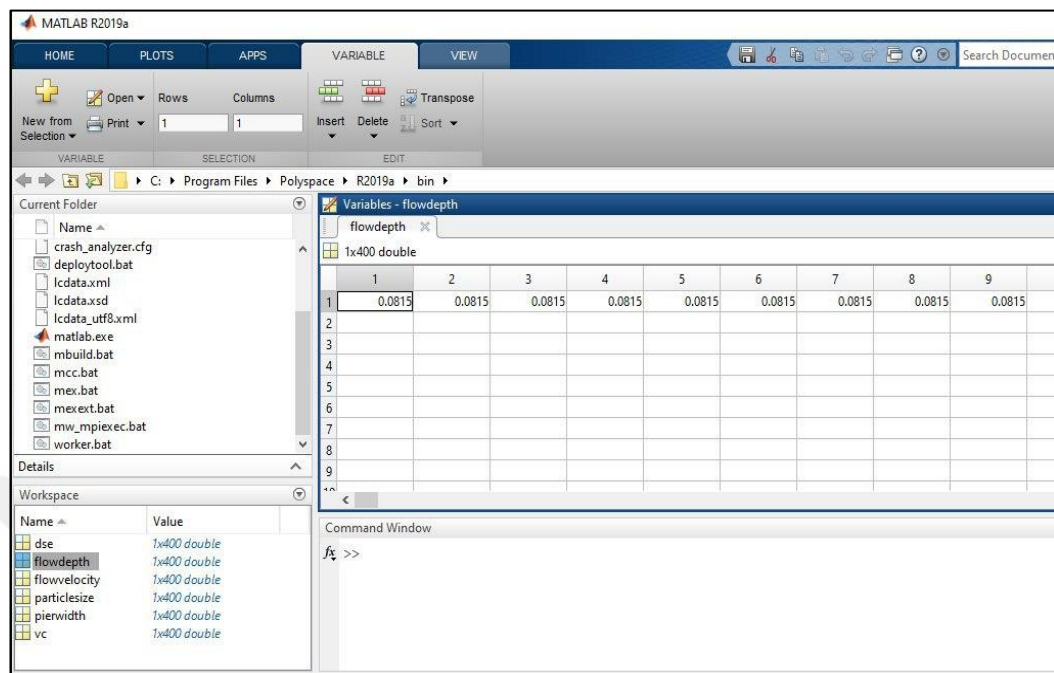


Figure 3.7 Feeding MATLAB with data.

Then the input variables should be collected as “input”, as shown in Figure 3.8. In the next step, the modeling window could be opened from the apps, then defining the input and target variables , as shown in Figure 3.9.

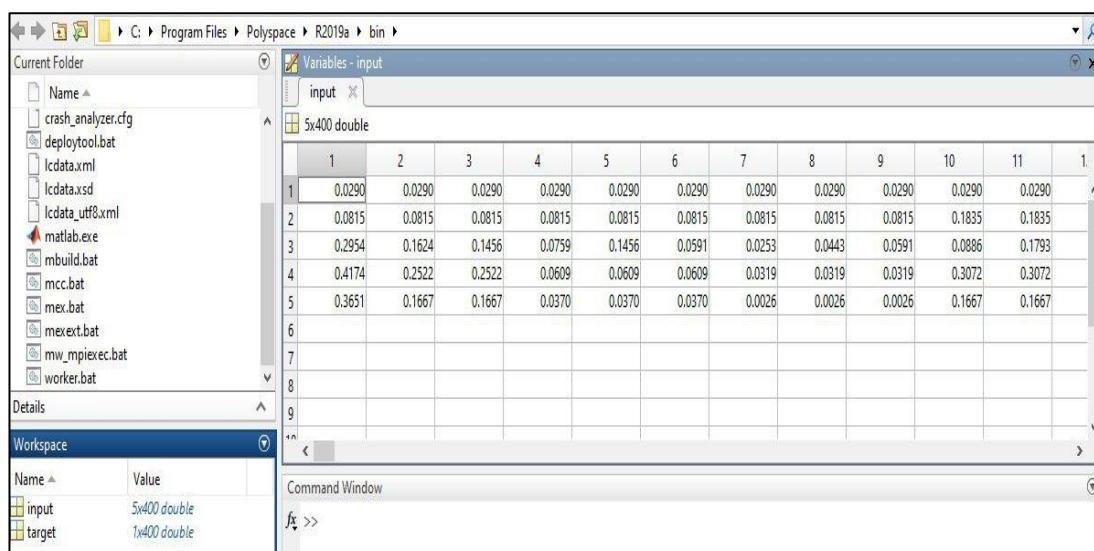


Figure 3.8 Arranging of variables.

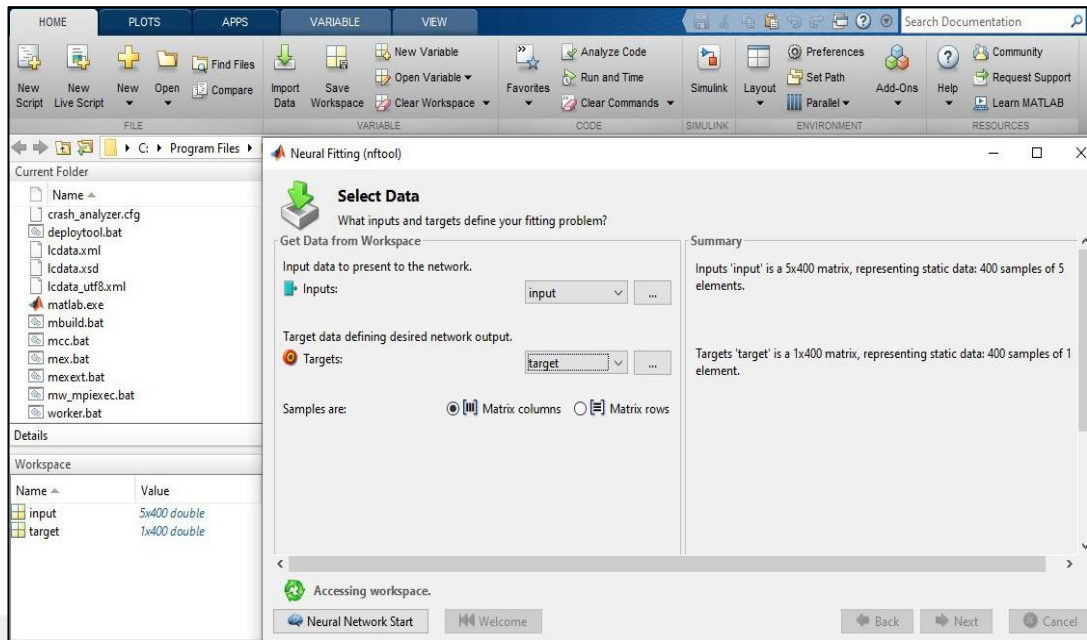


Figure 3.9 Defining of input and output data.

In the modeling of ANN, the dataset is divided into training, validation, and testing dataset. Training dataset using in the training the model (biases and weights in the situation of neural network), while, validation dataset supplies an unbiased assessment of an ANN model fit on the training data. Testing dataset using in the evolution of the accuracy of prediction. In this study, the 400-laboratory dataset was divided randomly into 70 percent for training, 15 percent for validation, and 15 percent for testing. Figure 3.10 illustrates the dividing of data in the MATLAB software before training artificial neural network models.

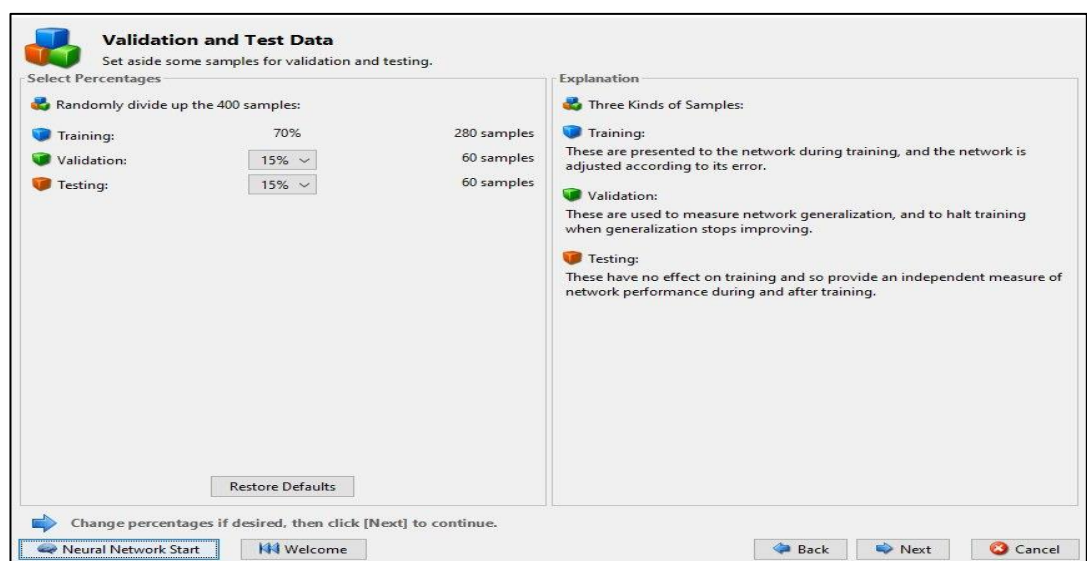


Figure 3.10 Dividing of dataset.

Then, the number of neurons in the hidden layer could be chosen, as shown in Figure 3.11.

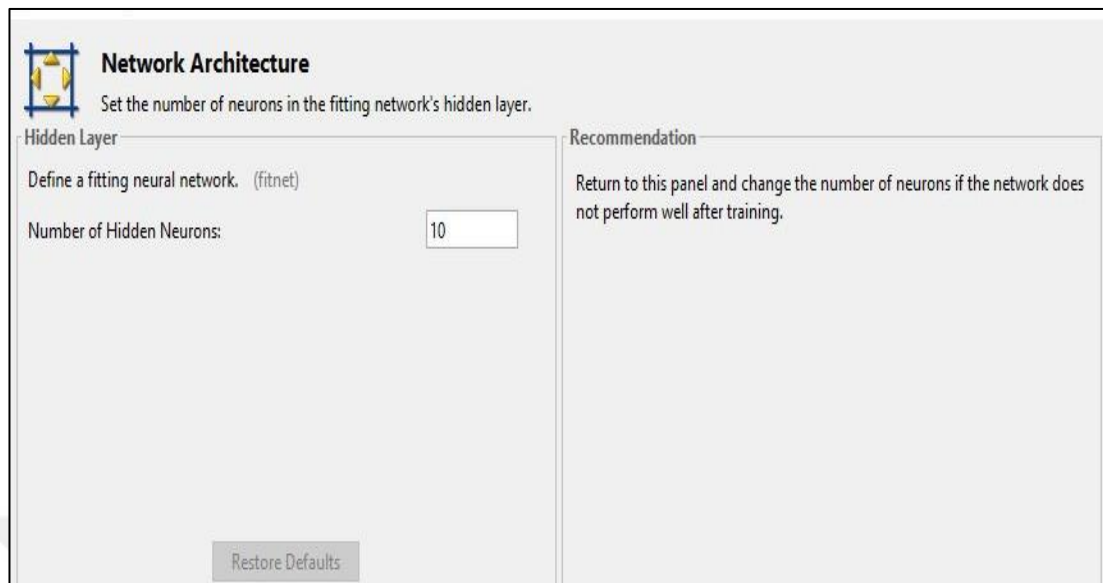


Figure 3.11 Determining number of neurons in the hidden layer.

Finally, the neural network could be trained, and results will be obtained such as regression value (R) and mean squared error (mse) for training, validation, and testing, as shown in Figure 3.12.

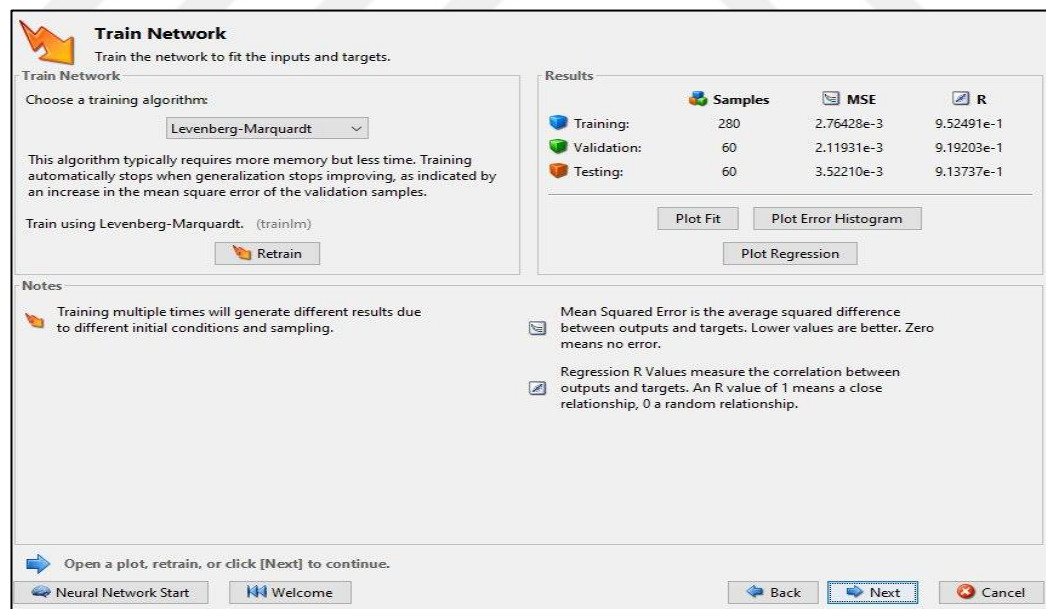


Figure 3.12 Training of ANN model.

Also, the additional results such as predicted values (output), errors, and advanced transcript of code could be saved, as shown in Figure 3.13.

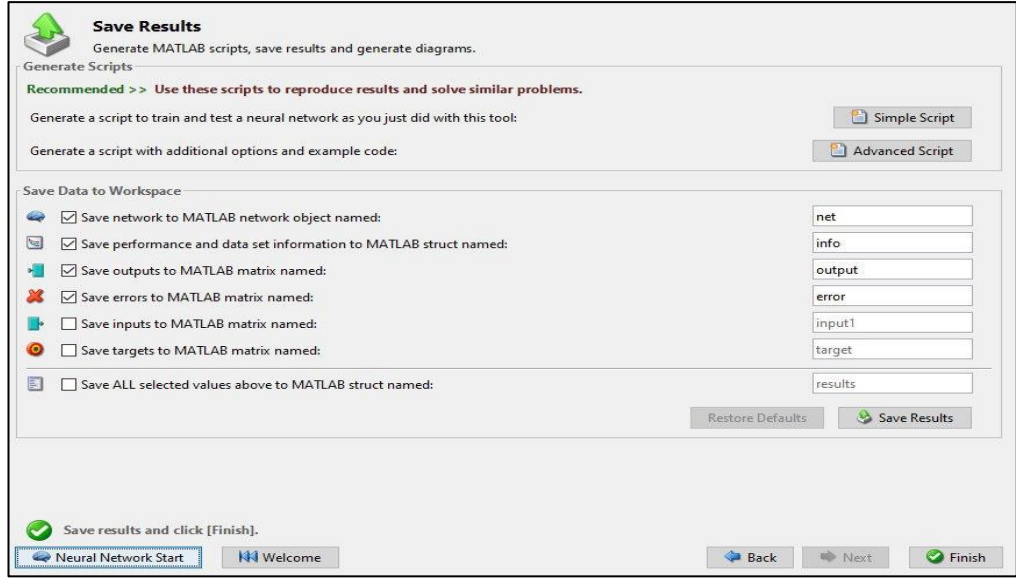


Figure 3.13 Saving of modeling results.

In this study, seven ANN models trained with six-dimensional parameters (d_{se} , b , V , y , V_c , d), different backpropagation training algorithms, and various nodes in hidden layers have been developed. Besides, one model with non-dimensional parameters ($\frac{d_{se}}{b}$, $\frac{V}{V_c}$, $\frac{y}{b}$, $\frac{d}{b}$) has developed to compare its performance with the best model that is trained with dimensional parameters. The ANN models have been evaluated according to mean squared error (mse) which counts the average of the squares of the errors, that is, the average squared variations between the predicted values and the measured value, also, it has been evaluated according to regression (R) values, as shown in the following equations (Hagan et al., 2002; Hagan et al., 2009).

$$MSE = \frac{1}{n} \sum_{k=1}^n (T_K - O_K)^2 \quad (3.7)$$

$$R = \frac{\sum_{k=1}^n (T_K - \bar{T})(O_K - \bar{O})}{(n-1)S_T S_O} \quad (3.8)$$

$$S_T = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (T_K - \bar{T})^2} \quad (3.9)$$

$$S_O = \sqrt{\frac{1}{n-1} \sum_{k=1}^n (O_K - \bar{O})^2} \quad (3.10)$$

$$\bar{T} = \frac{1}{n} \sum_{k=1}^n T_K \quad (3.11)$$

$$\bar{O} = \frac{1}{n} \sum_{k=1}^n O_K \quad (3.12)$$

where n is the number of data, O_K is the network output, T_K is the actual target, $\bar{O}$ is the mean value of the network output, $\bar{T}$ is the mean value of the targets. Besides, the best value of MSE is zero while R is one.



CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

In this study, different ANN models were established for the prediction of equilibrium depth around bridge piers. The results of ANN models have been compared with each other to determine the best prediction model. The ANN models have been trained with dimensional and non-dimensional data, the models with dimensional parameters have been called “DM”, while the ANN model with non-dimensional parameters has called “NDM”. Table 4.1 shows the characterizes of these ANN models.

Table 4.1 Characterizes of ANN models.

Model name	Training algorithm	Number of nodes in the hidden layer	Variables
DM-1	trainlm	23	d_{se}, b, V, y, V_c, d
DM-2	trainrp	16	d_{se}, b, V, y, V_c, d
DM-3	traingda	15	d_{se}, b, V, y, V_c, d
DM-4	traincgf	11	d_{se}, b, V, y, V_c, d
DM-5	traincgp	15	d_{se}, b, V, y, V_c, d
DM-6	traincgb	16	d_{se}, b, V, y, V_c, d
DM-7	trainbfg	17	d_{se}, b, V, y, V_c, d
NDM-1	trainlm	28	$\frac{d_{se}}{b}, \frac{V}{V_c}, \frac{y}{b}, \frac{d}{b}$

4.2 Regression Analysis

Regression analysis is a form of predictive modeling method that examines the relationship between an independent parameter (s) (predictor) and a dependent (target). Regression values of training, validation, and testing dataset of each ANN models have been obtained using *MATLAB*®. It was clear from the results that model DM-1, which trained with Levenberg-Marquardt training algorithm (tainlm) and 23 nodes on the hidden layer, is the best among ANN models with dimensional and non-

dimensional parameters with R (training) and R (test) value equal to 0.9529 and 0.9176, respectively. While the model DM-2 and DM-3 were the worst with R (test) equal to 0.6215 and 0.4210, respectively. Furthermore, in the ANN model DM-1, the predicted and measured scour depth values near to the fit line (dotted line) which indicate good accuracy in the prediction, as shown in Figure 4.1. Also, the regression value of training (0.8151) and test (0.7110) of model NDM-1 (ANN model with non-dimensional parameters) lower than model DM-1, which shows that the ANN model with dimensional parameters more accurate than the ANN model with non-dimensional parameters. Figure 4.1 to 4.8 Figure shows the regression values of each ANN model developed in the study.

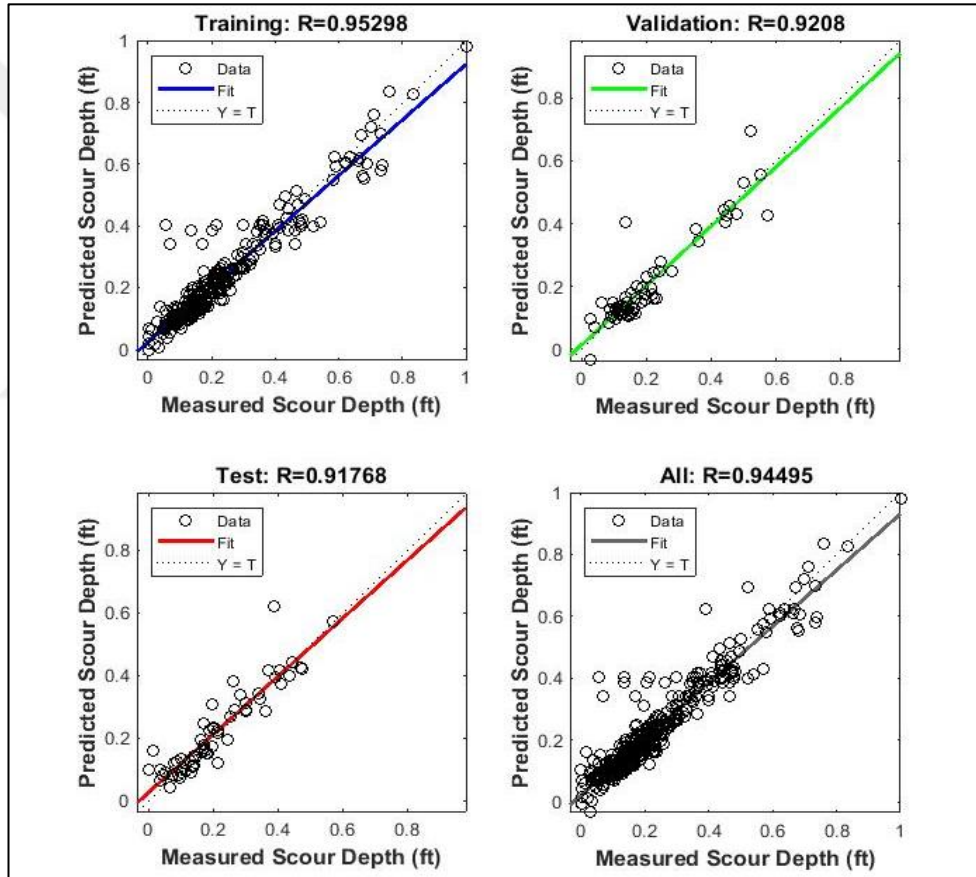


Figure 4.1 Regression values of DM-1 model.

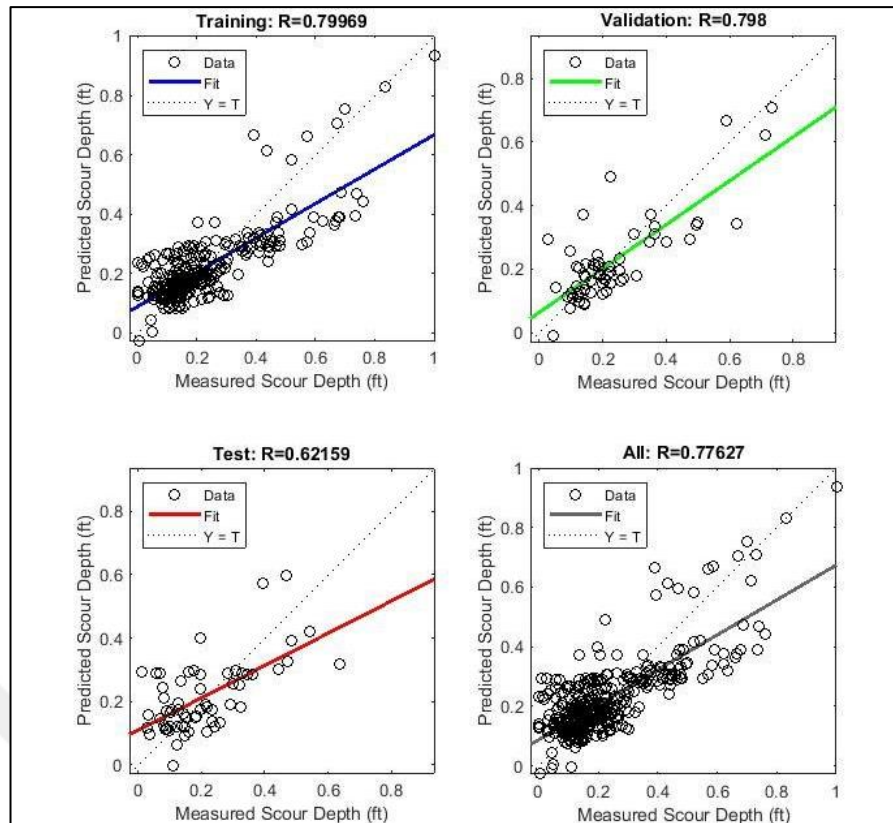


Figure 4.2 Regression values of DM-2 model.

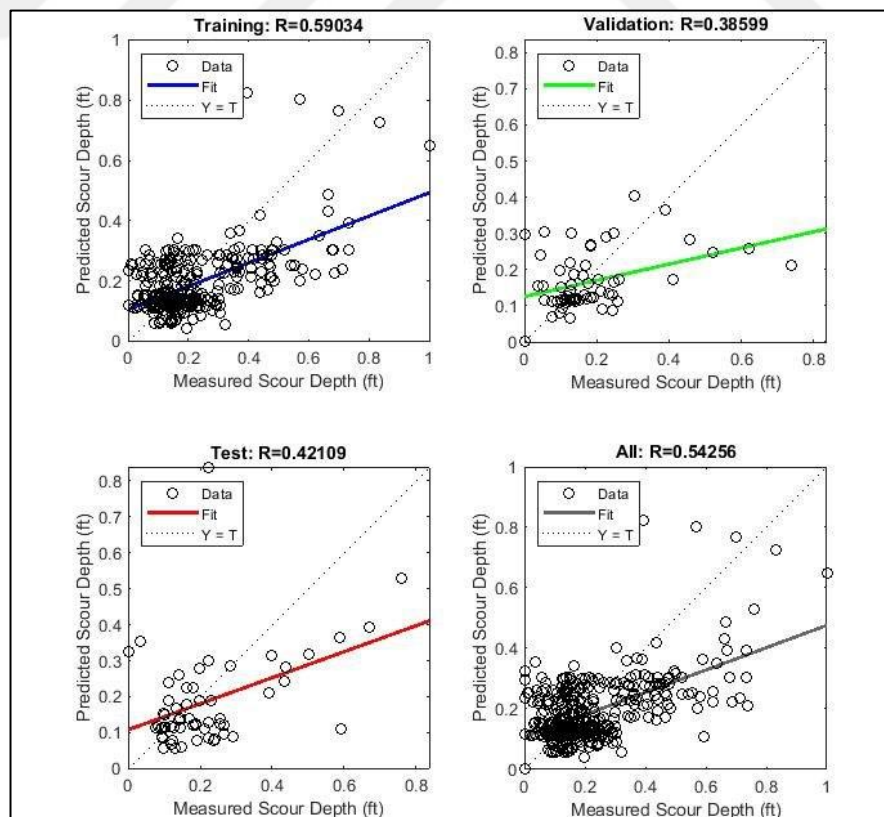


Figure 4.3 Regression values of DM-3 model.

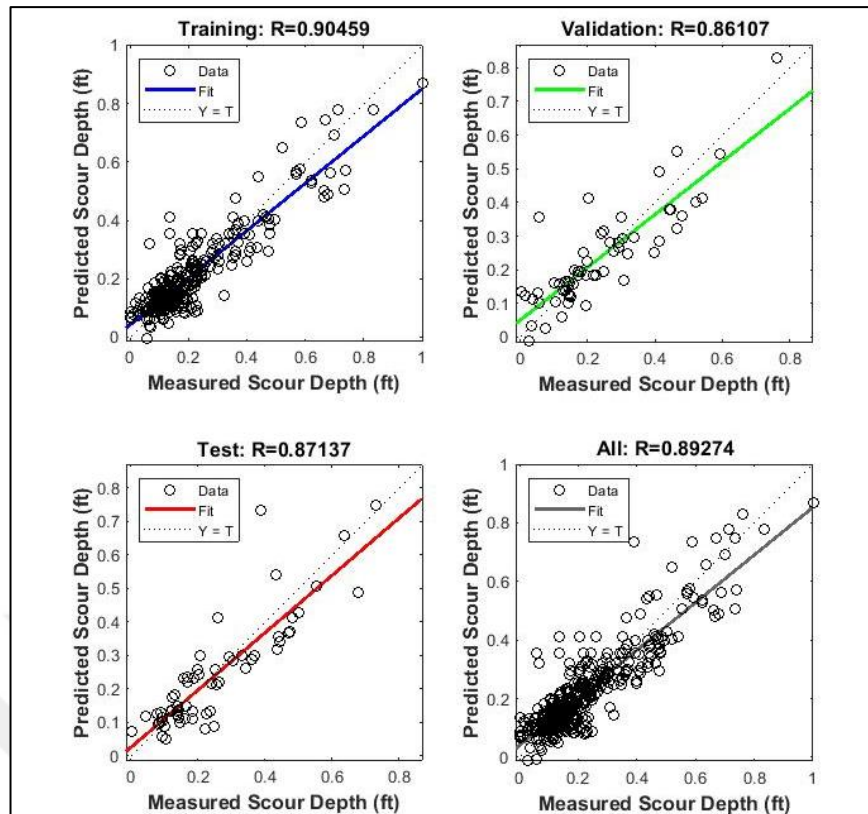


Figure 4.4 Regression values of DM-4 model.

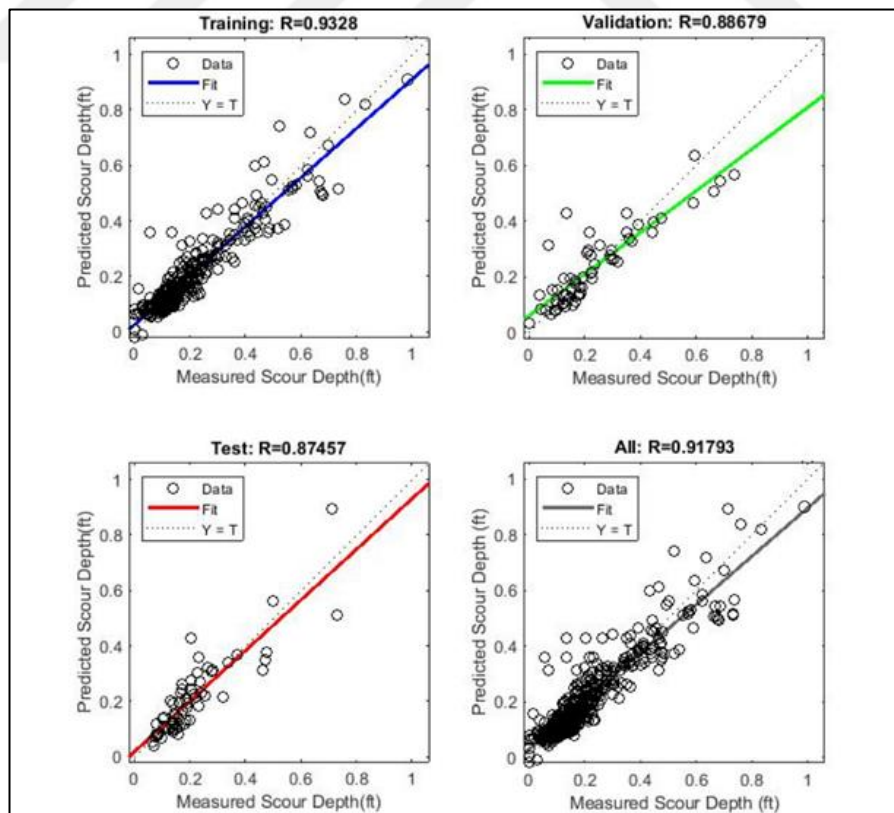


Figure 4.5 Regression values of DM-5 model.

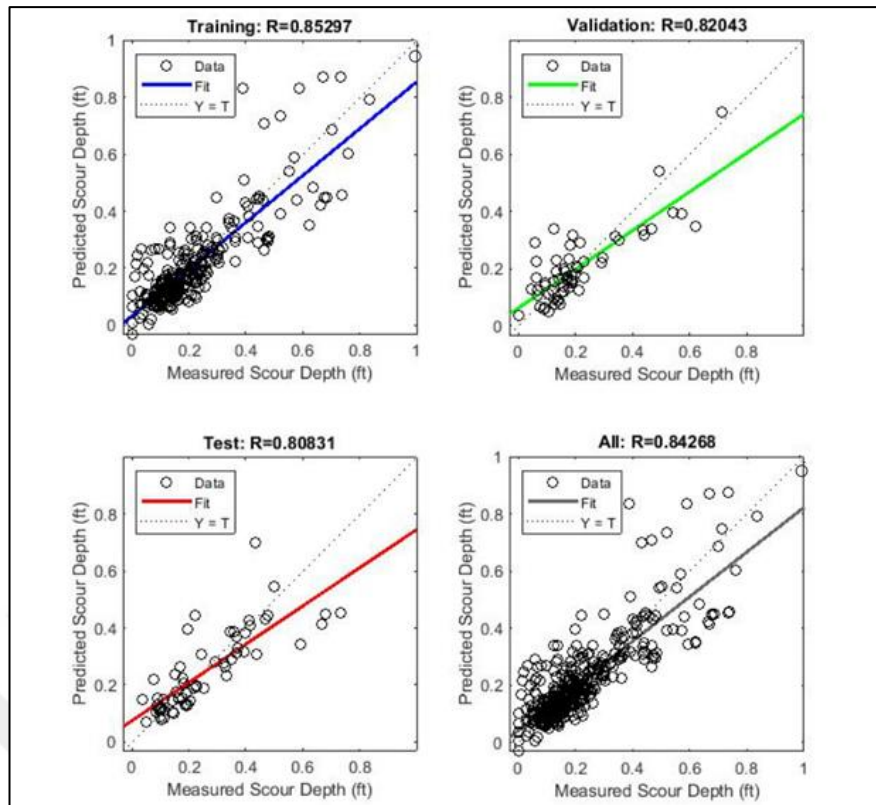


Figure 4.6 Regression values of DM-6 model.

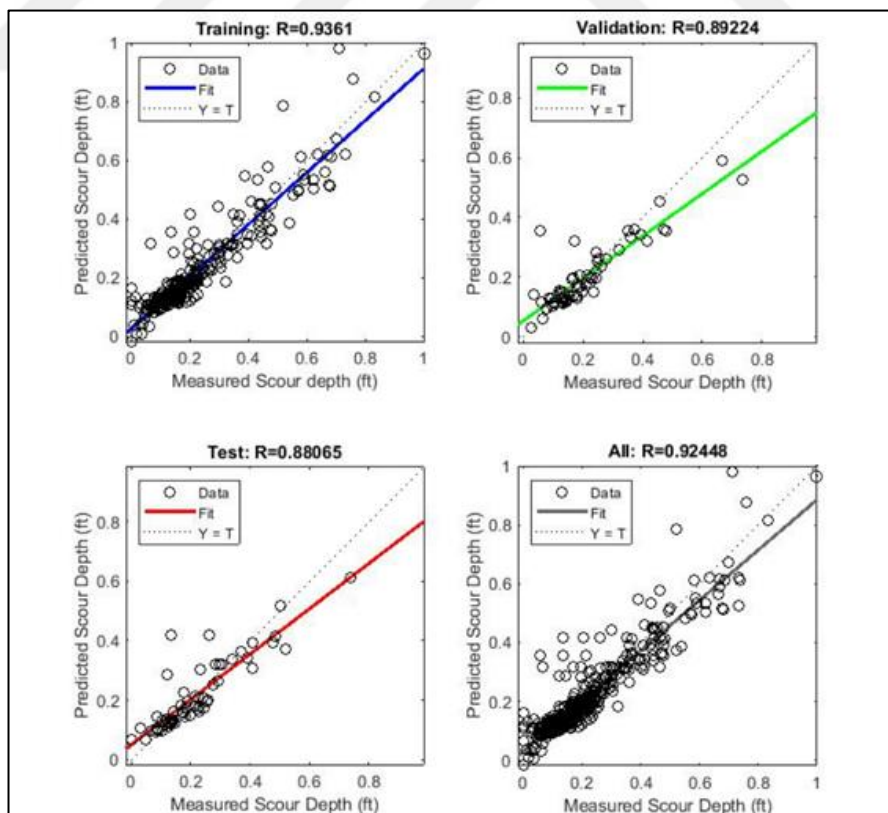


Figure 4.7 Regression values of DM-7 model.

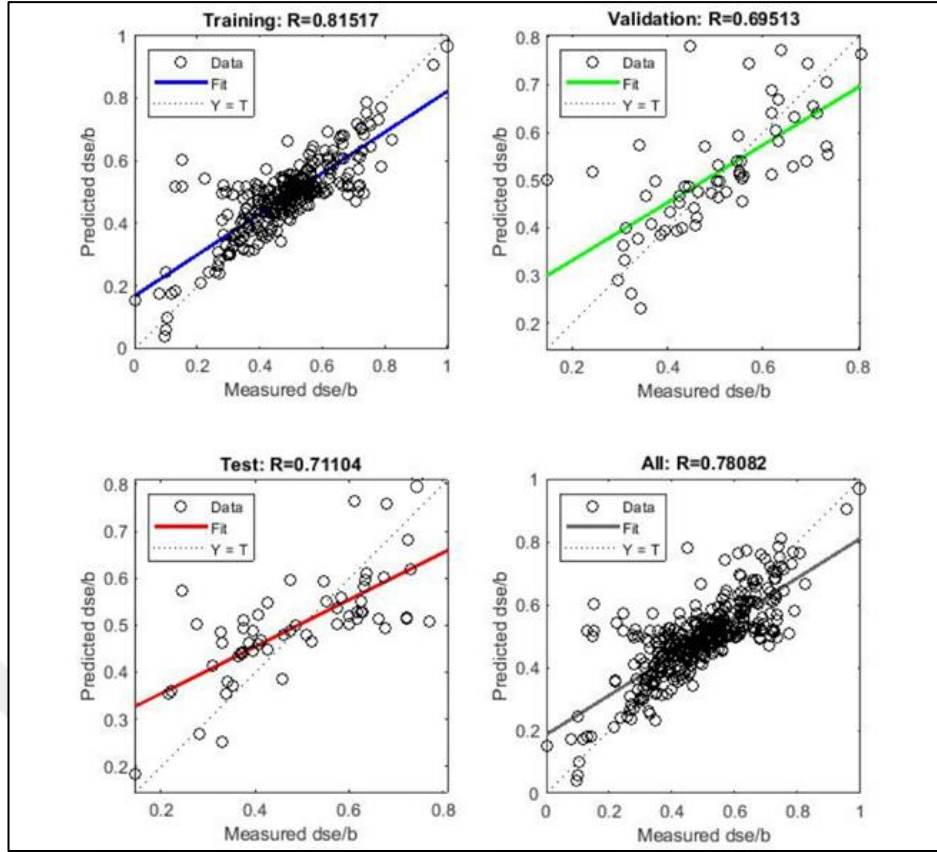


Figure 4.8 Regression values of NDM-1 model.

4.3 Performance Analysis

The performance evaluation plot of ANN models presents the progress of training, validation, and testing. In this analysis, the training procedures stop when the validation error approach steady-state. The blue, green, and red lines present the mean squared error (mse) value for the training, validation, and test, respectively. If any of the training, validation, and testing lines reach near the best (dotted) line or meet it, it indicates that the concourse has been done. These outcomes present that the network performs satisfactorily when it is presented with unknown values. Figure 4.9 to Figure 4.16 shows the performance of ANN models.

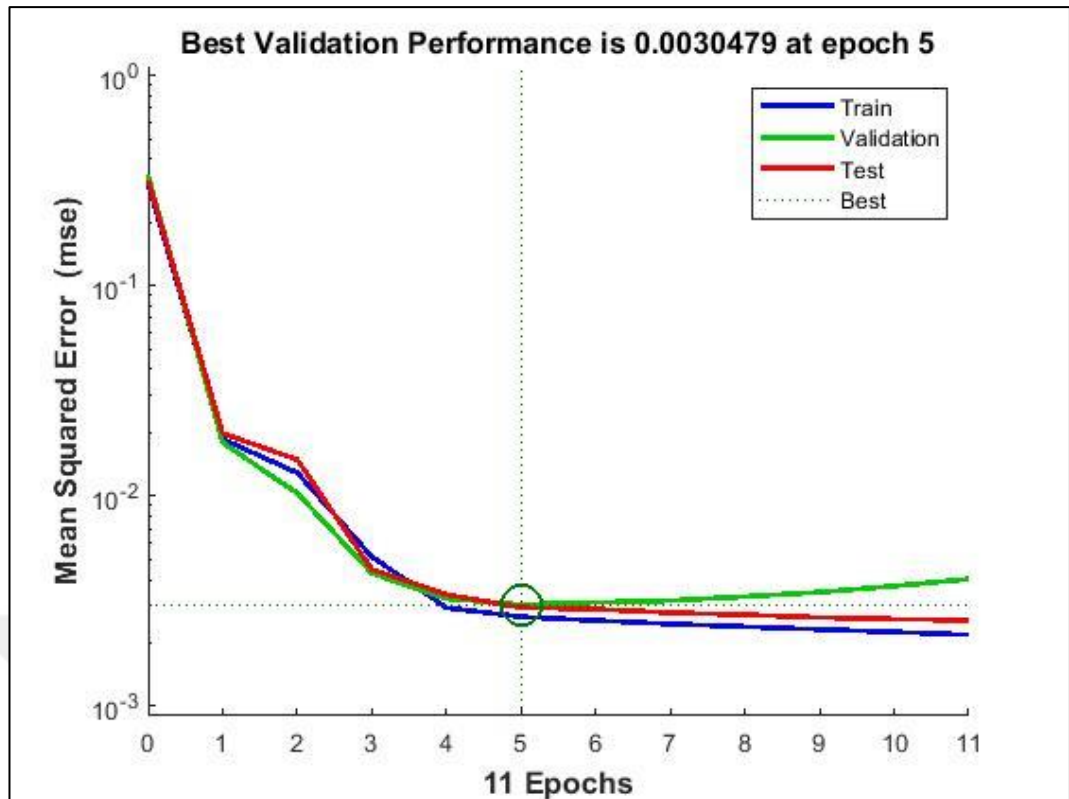


Figure 4.9 Performance of DM-1 model.

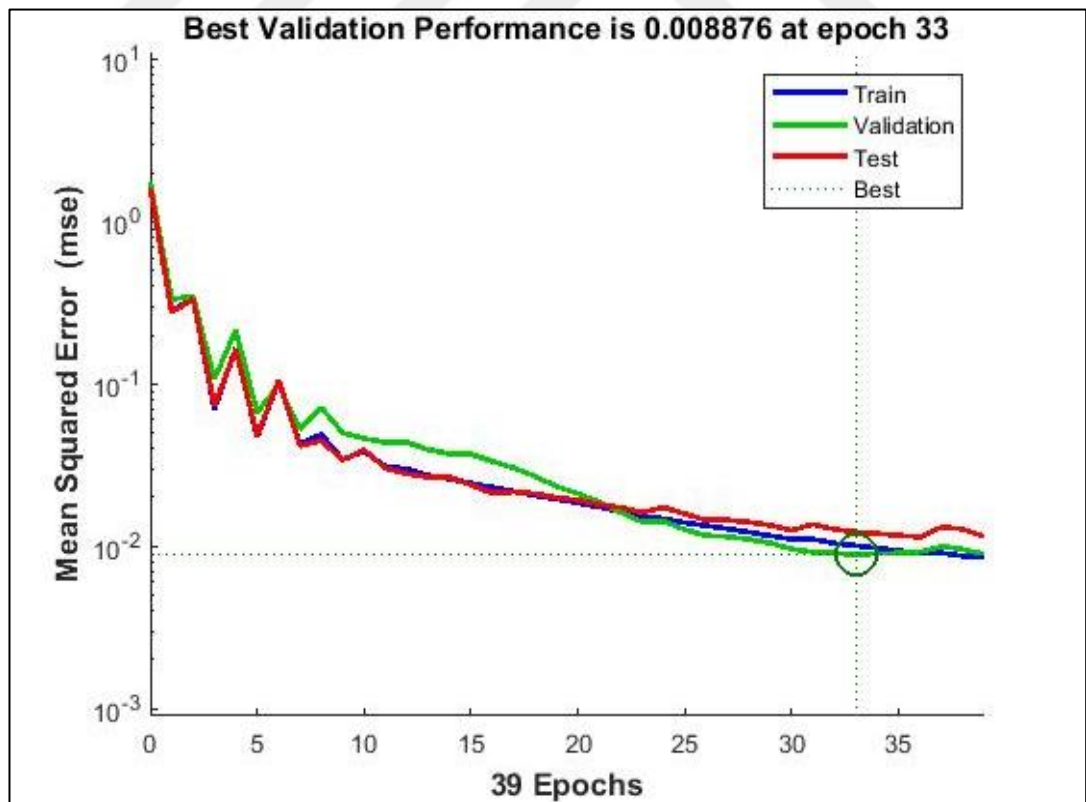


Figure 4.10 Performance of DM-2 model.

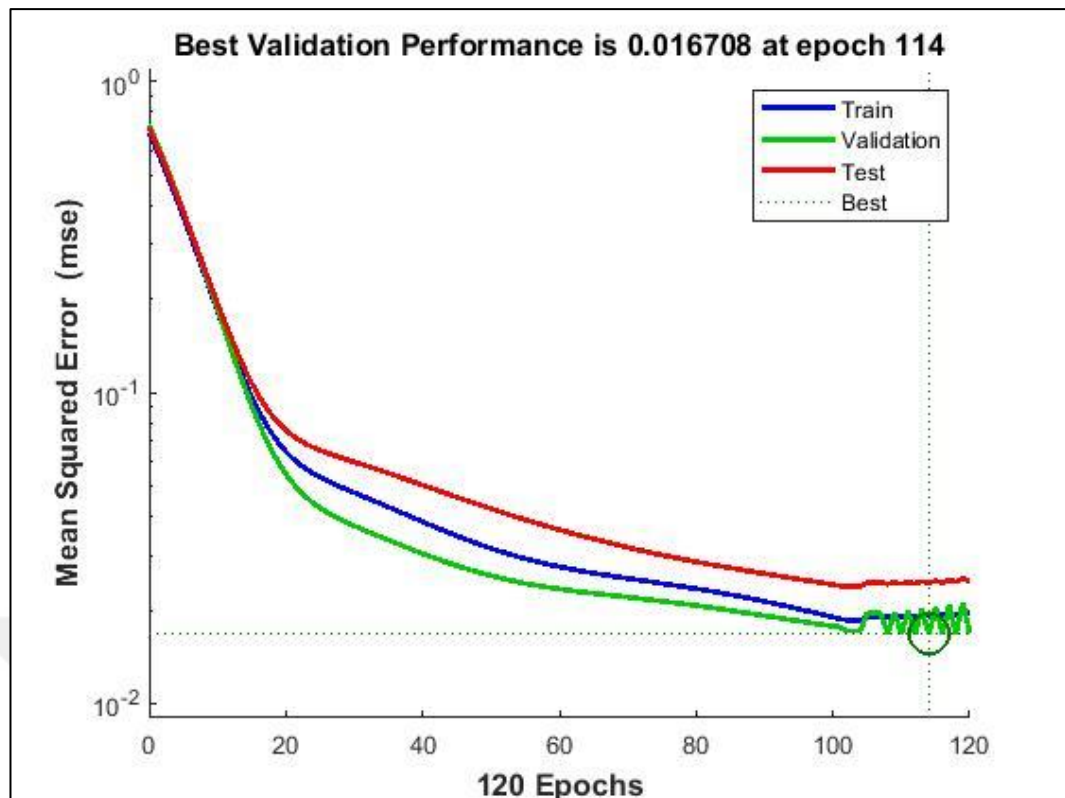


Figure 4.11 Performance of DM-3 model.

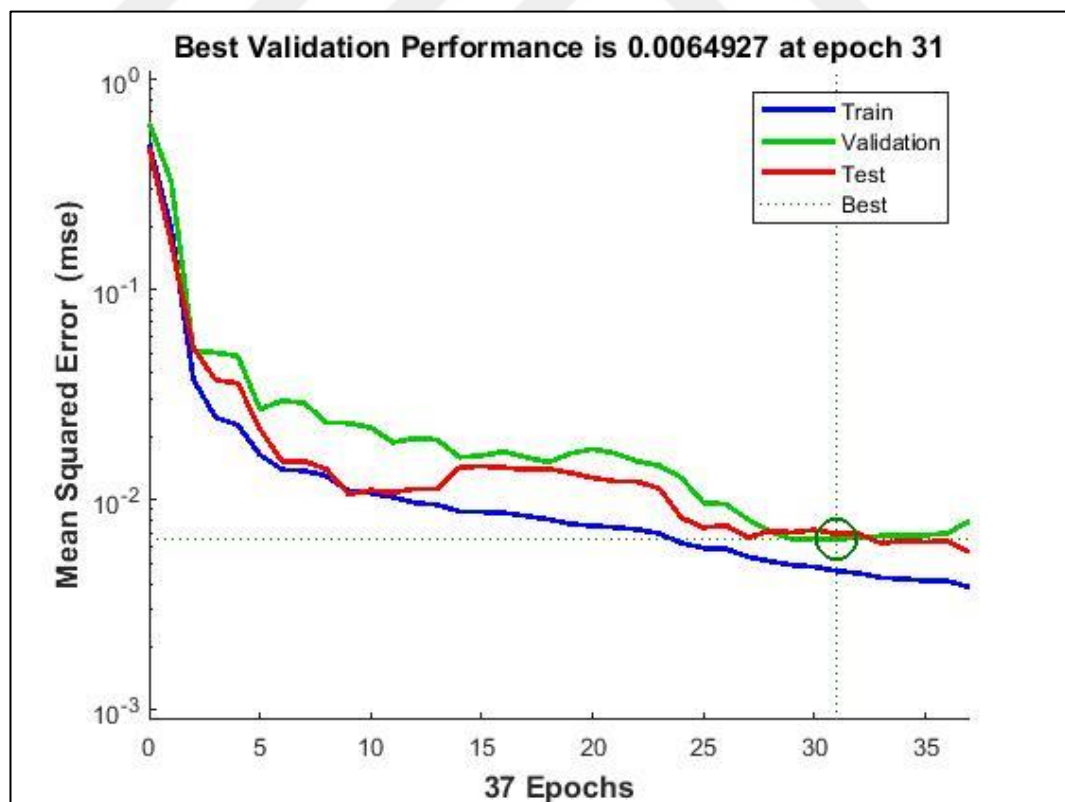


Figure 4.12 Performance of DM-4 model.

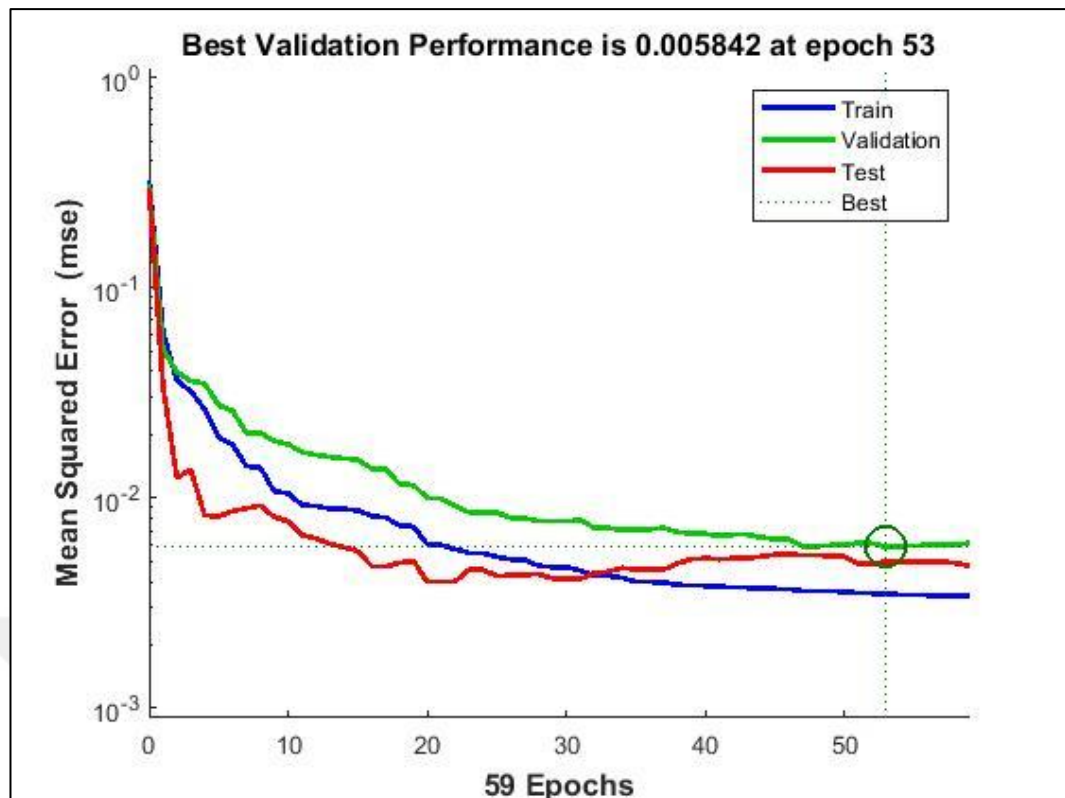


Figure 4.13 Performance of DM-5 model.

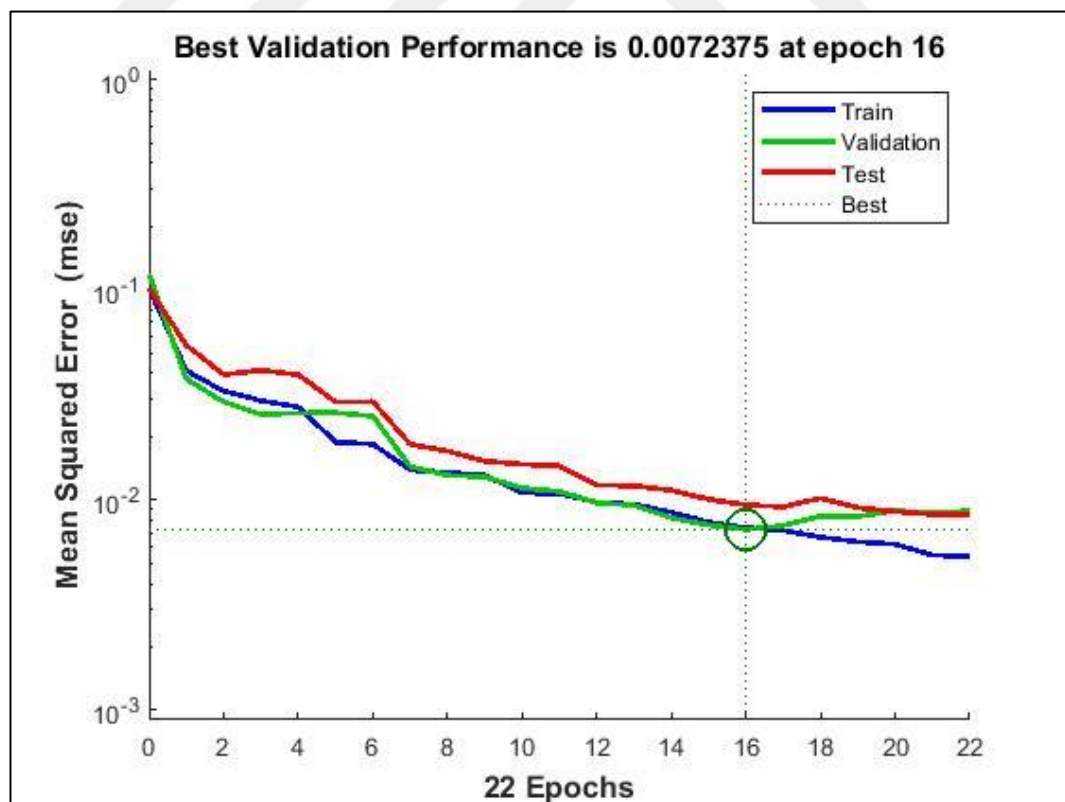


Figure 4.14 Performance of DM-6 model.

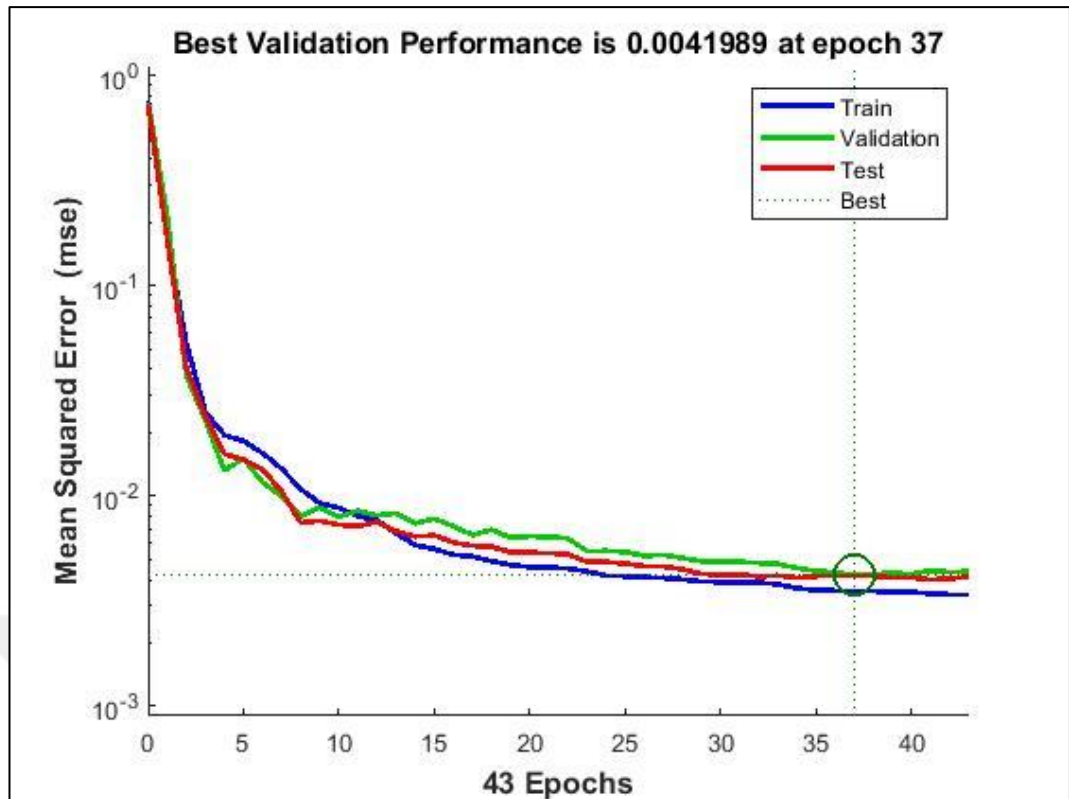


Figure 4.15 Performance of DM-7 model.

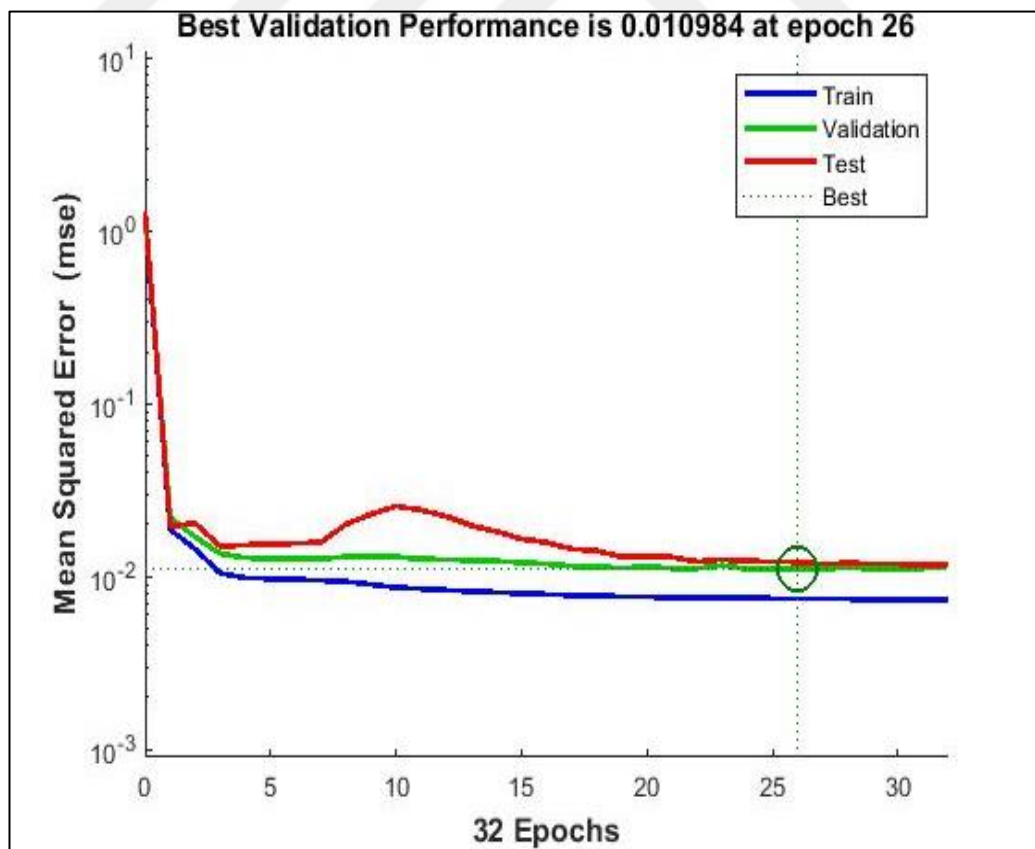


Figure 4.16 Performance of NDM-1 model.

Also, the mean squared error (MSE) is a measurement to assess the performance of a regression model. Table 4.2 shows the values of MSE of ANN models.

Table 4.2 MSE values of ANN models.

ANN Model	R (training)	MSE (training)	R (test)	MSE (test)
DM-1	0.9529	0.00270	0.9176	0.0029
DM-2	0.7996	0.0101	0.6215	0.0122
DM-3	0.5903	0.1920	0.4210	0.0244
DM-4	0.9045	0.0046	0.8713	0.0069
DM-5	0.9328	0.0035	0.8745	0.0050
DM-6	0.8529	0.00740	0.8083	0.0095
DM-7	0.9361	0.0035	0.8806	0.0042
NDM-1	0.8151	0.00746	0.7110	0.0121

It is clear from Table 4.2 that the ANN model DM-1 has the lowest MSE value with the highest R-value which means it's the best model compared to other ANN models in this study. Meanwhile, both ANN model DM-2 and DM-3 have presented a weak performance in the estimation, the MSE (test) for both of them less than other ANN models. Moreover, other ANN models (DM-4, DM-5, DM-6, and DM-7) have presented good accuracy but not too high as the model DM-1 depending on the results of MSE (test). Also, it's obvious that an ANN model with dimensional parameters trained with the Levenberg-Marquardt backpropagation algorithm (trainlm) provides less MSE (test) value than an ANN model with non-dimensional parameters trained with the same algorithm according to the results of Table 4.2.

4.4 Error Histogram Analysis

Error histogram is the histogram of the errors between measured values and estimated values after training a feedforward artificial neural network. As these error values present how estimated values are varying from the target values, as a consequence, these can be negative. Bins are the number of vertical bars you are observing on the graph. Y-axis represents the number of samples from the dataset, which lies down in a specific bin. Figure 4.17 to Figure 4.24 shows the error histogram of each ANN model.

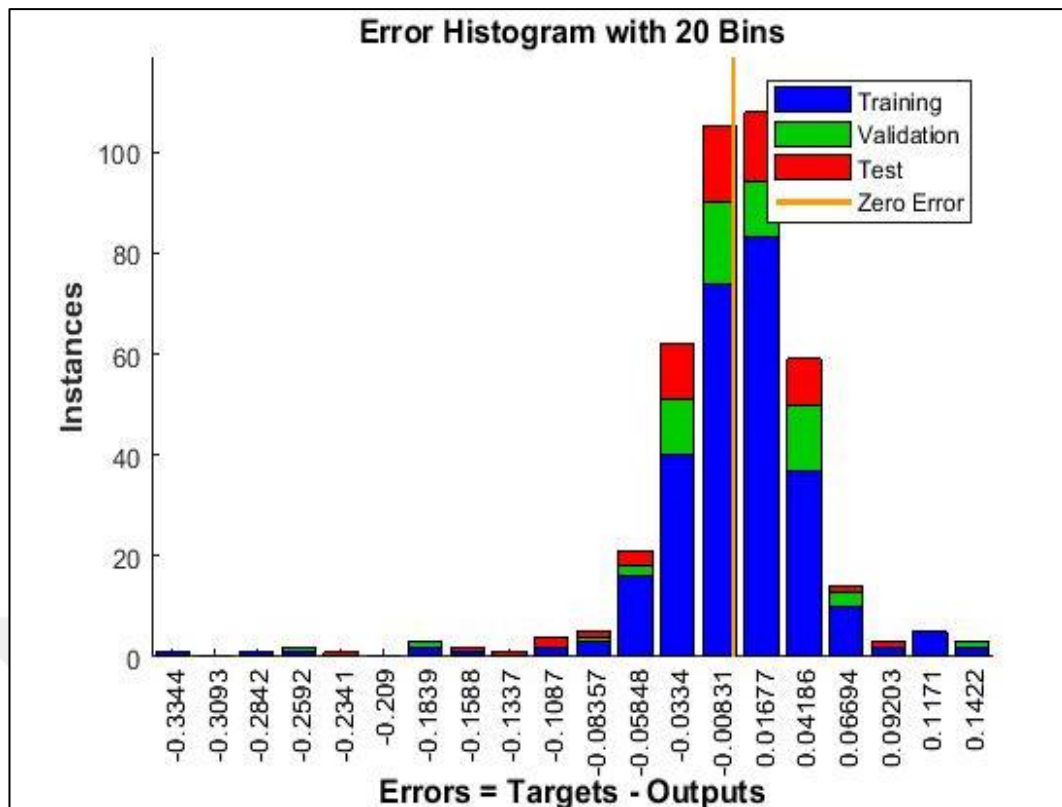


Figure 4.17 Error histogram of DM-1 model.

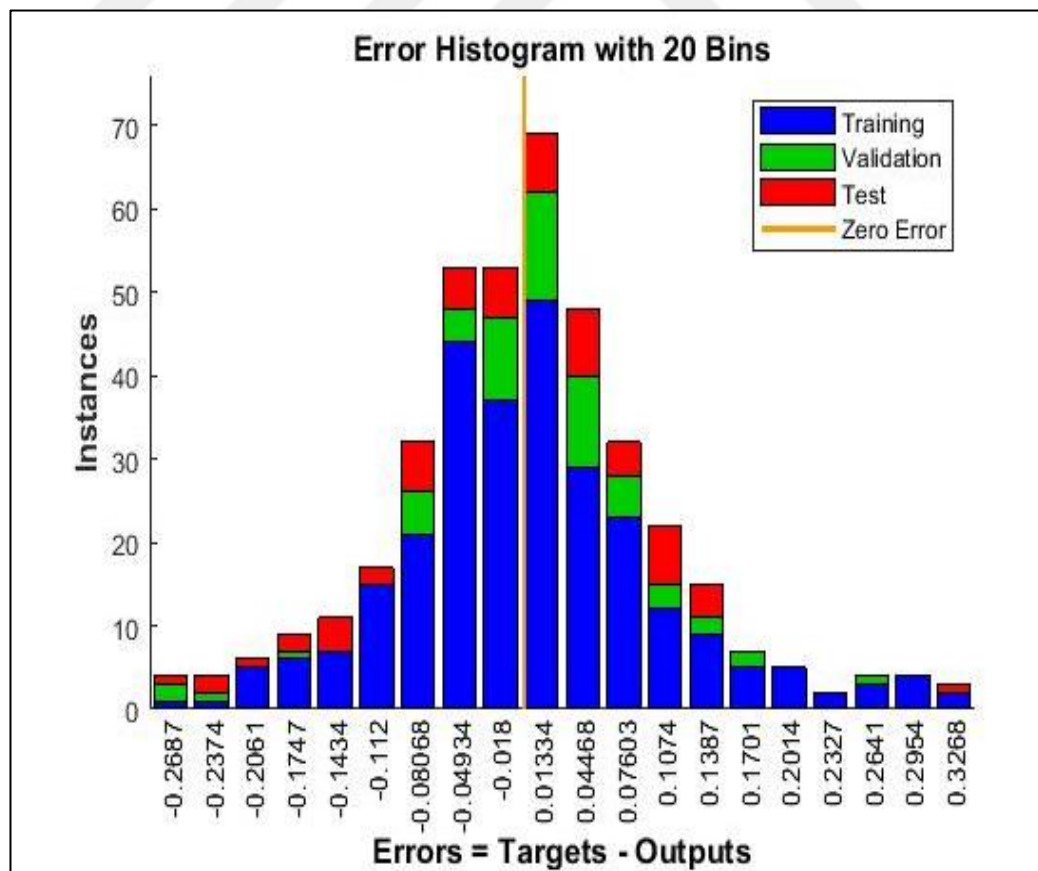


Figure 4.18 Error histogram of DM-2 model.

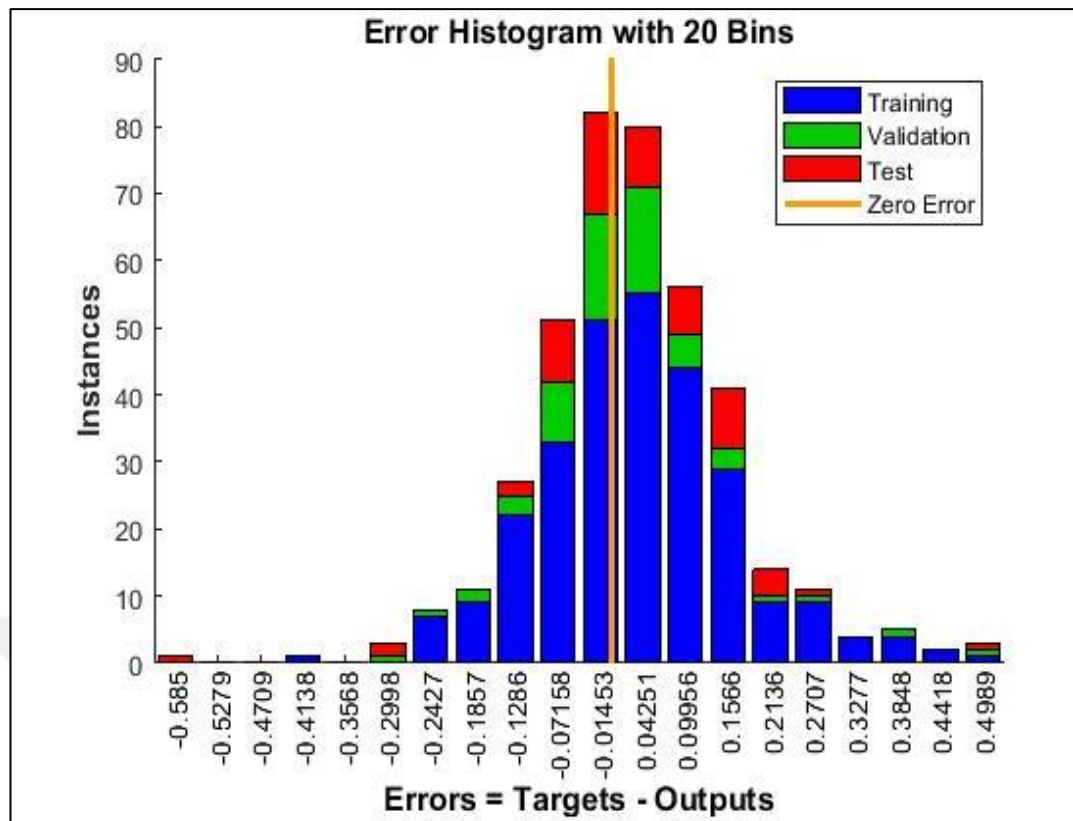


Figure 4.19 Error histogram of DM-3 model.

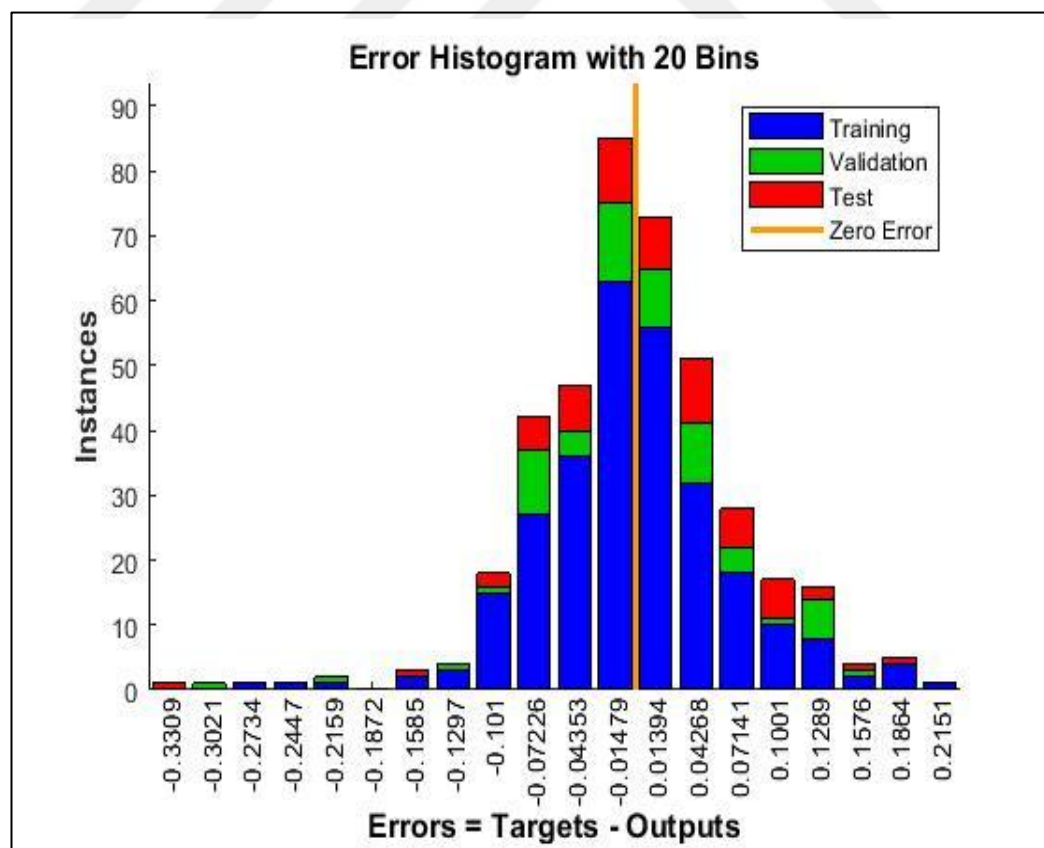


Figure 4.20 Error histogram of DM-4 model.

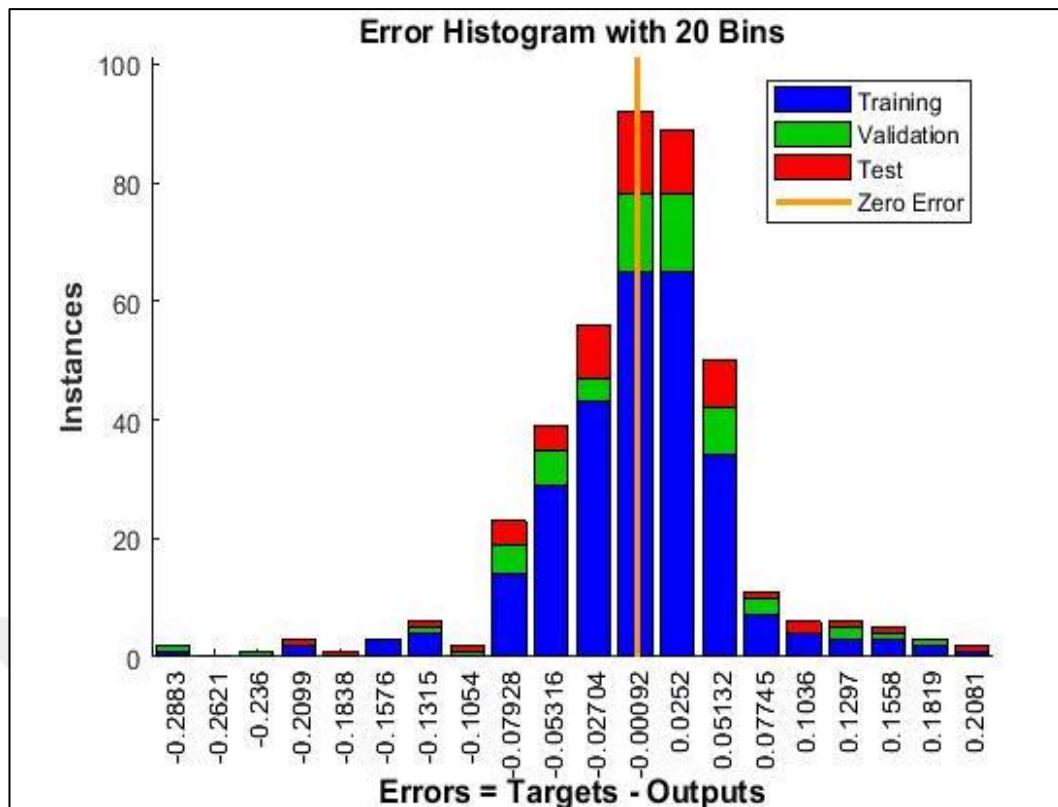


Figure 4.21 Error histogram of DM-5 model.

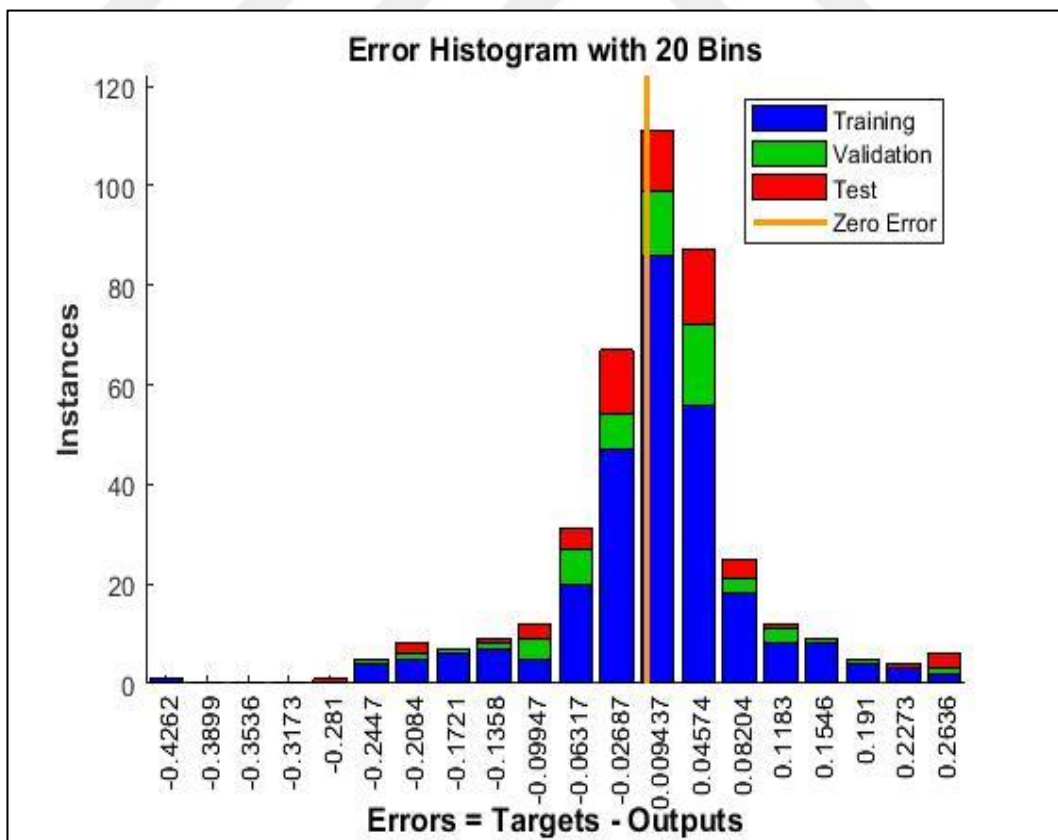


Figure 4.22 Error histogram of DM-6 model.

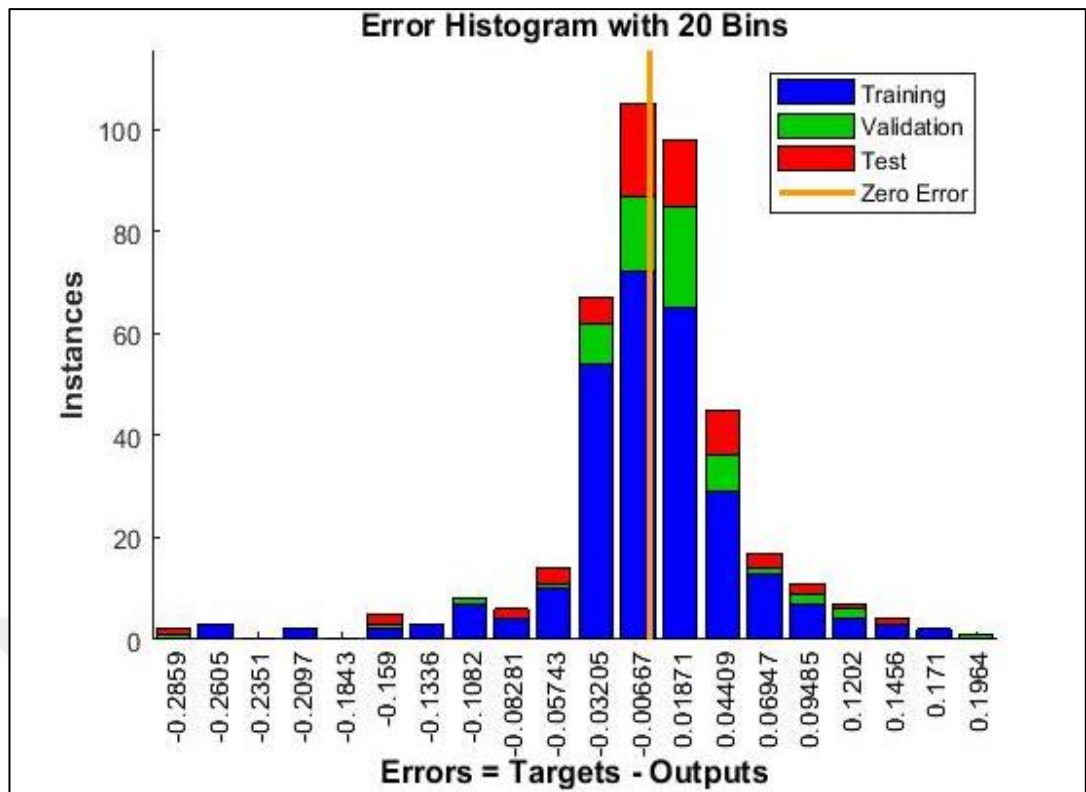


Figure 4.23 Error histogram of DM-7 model.

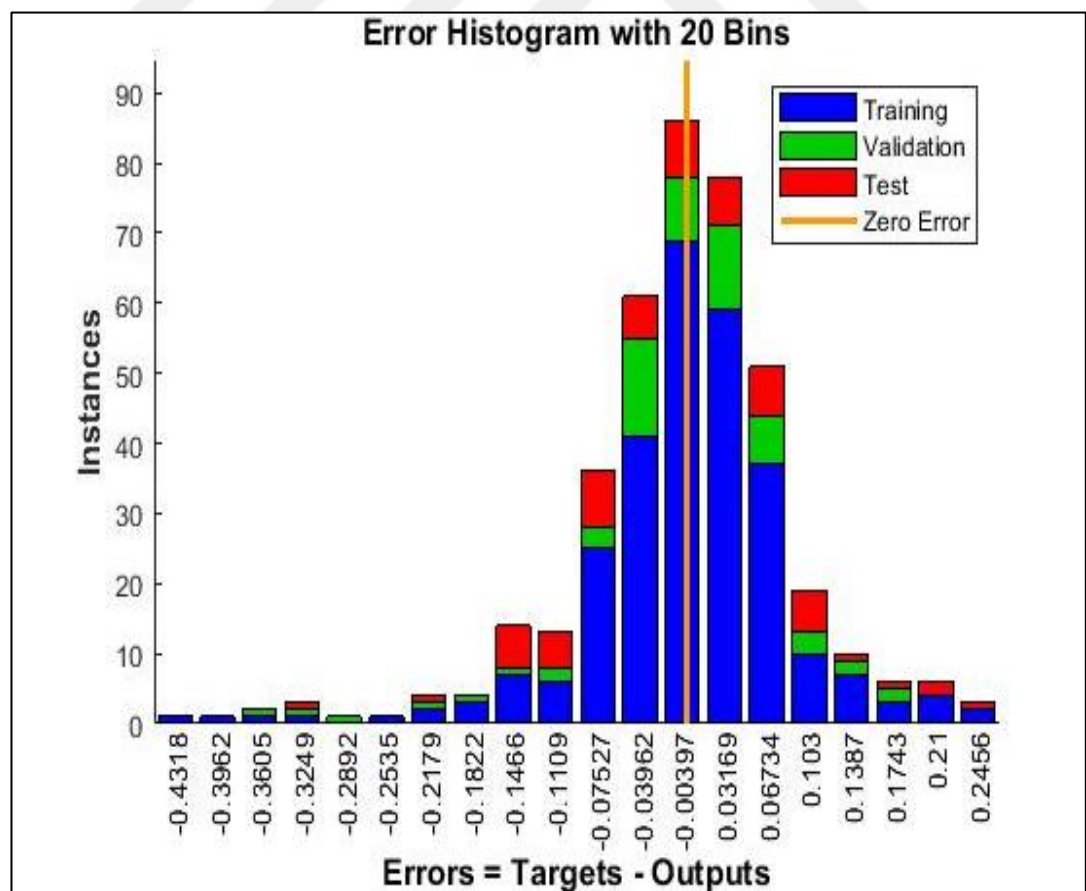


Figure 4.24 Error histogram of NDM-1 model.

4.5 Sensitivity Analysis

An artificial neural network could be utilized to examine the importance of each input parameter in the prediction. The effect of input parameters used in the DM-1 model (b , V , y , V_c , d) have been investigated in the prediction of equilibrium scour depth (d_{se}). Five ANN models have been established with a single hidden layer and feedforward backpropagation algorithm for sensitivity analysis. Table 4.3 shows the characterizes of these five ANN models.

Table 4.3 Characterizes of DM-1 models for sensitivity analysis.

Model name	Training algorithm	Number of nodes in the hidden layer	Input variable
DM-1	trainlm	23	b, V, y, V_c, d
DM-1a	trainlm	23	b, V, y, d
DM-1b	trainlm	23	b, y, V_c, d
DM-1c	trainlm	23	V, y, V_c, d
DM-1d	trainlm	23	b, V, V_c, d
DM-1e	trainlm	23	b, V, y, V_c

Moreover, the regression values of DM-1 models used in the sensitivity analysis have been obtained, as shown in Figure 4.25 to Figure 4.29.

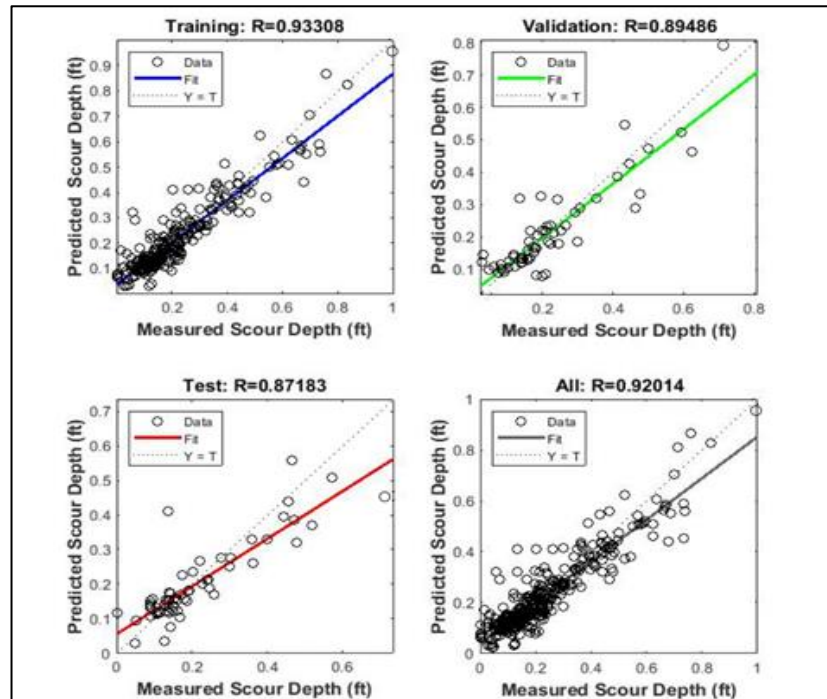


Figure 4.25 Regression values of DM-1a model.

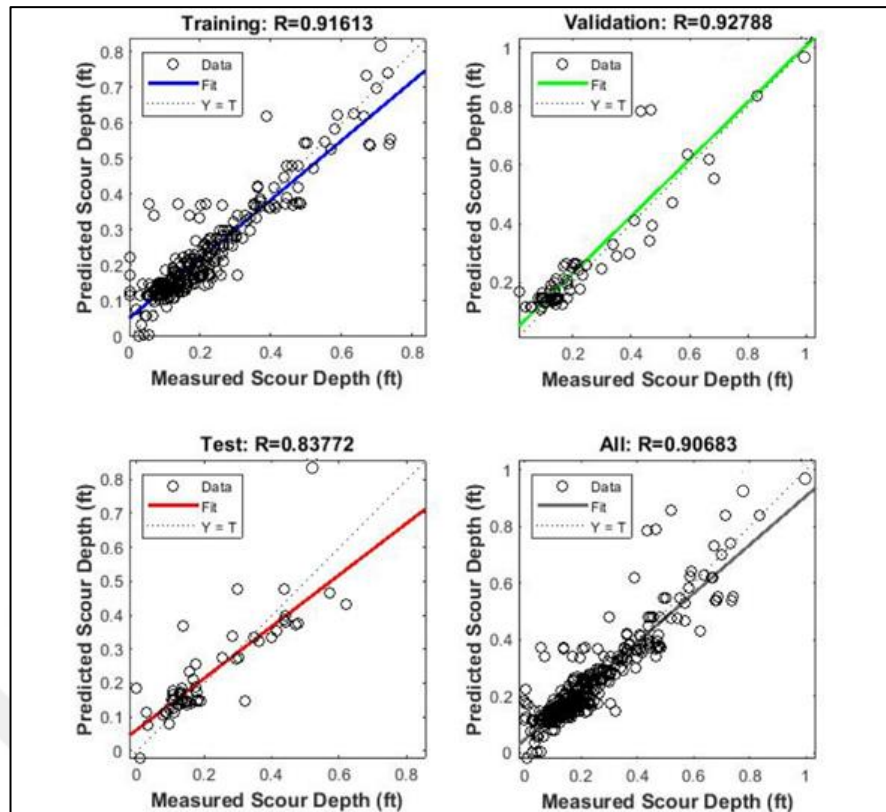


Figure 4.26 Regression values of DM-1b model.

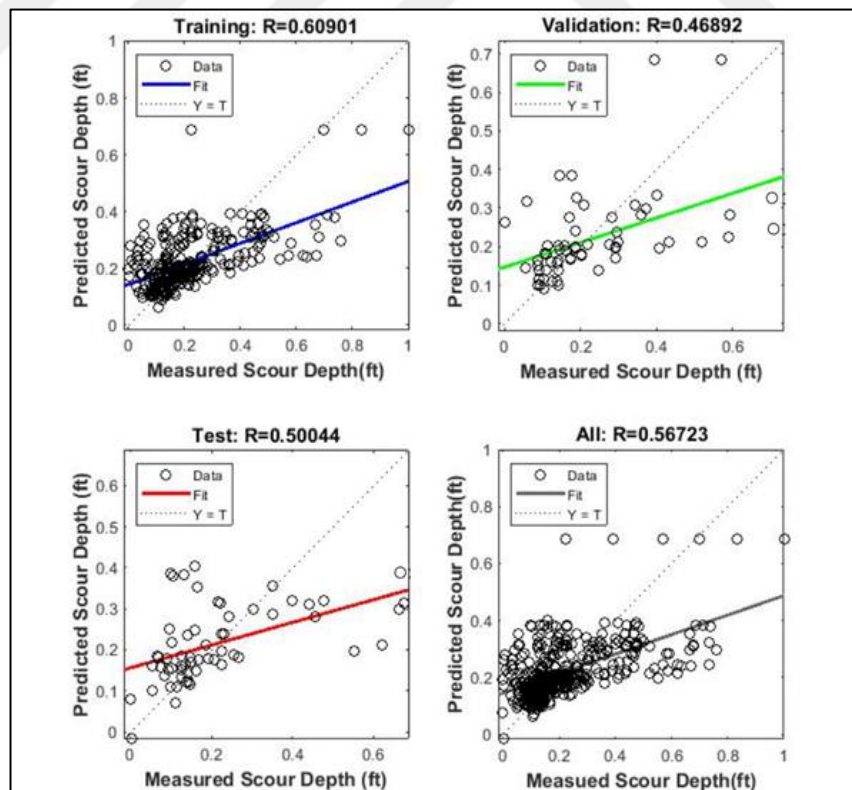


Figure 4.27 Regression values of DM-1c model.

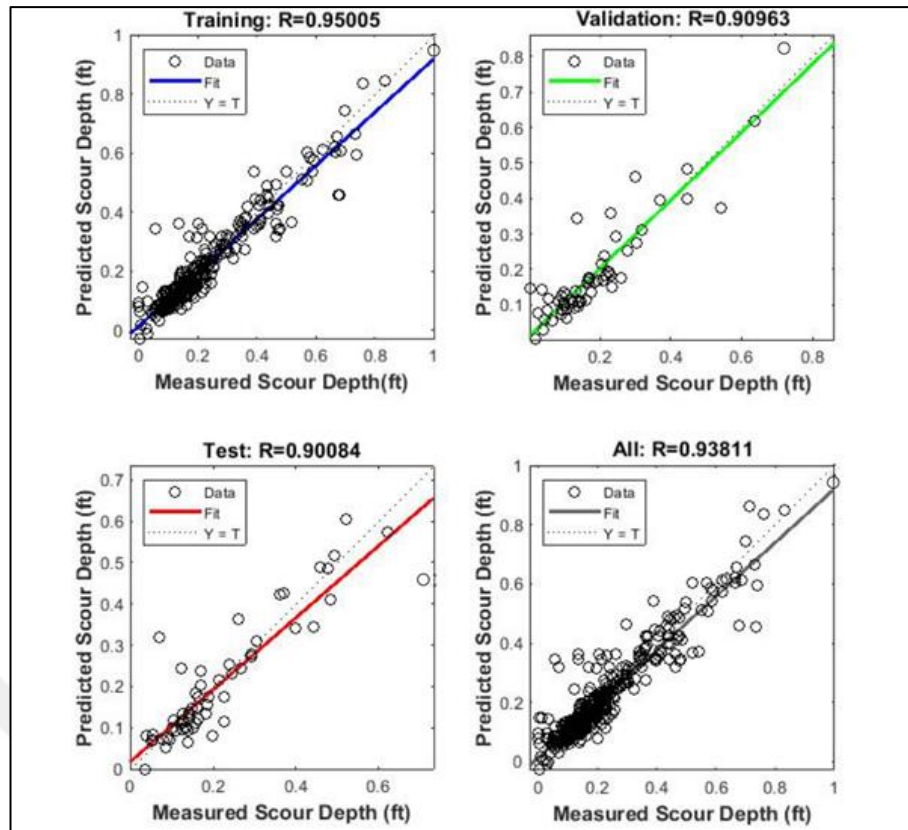


Figure 4.28 Regression values of DM-1d model.

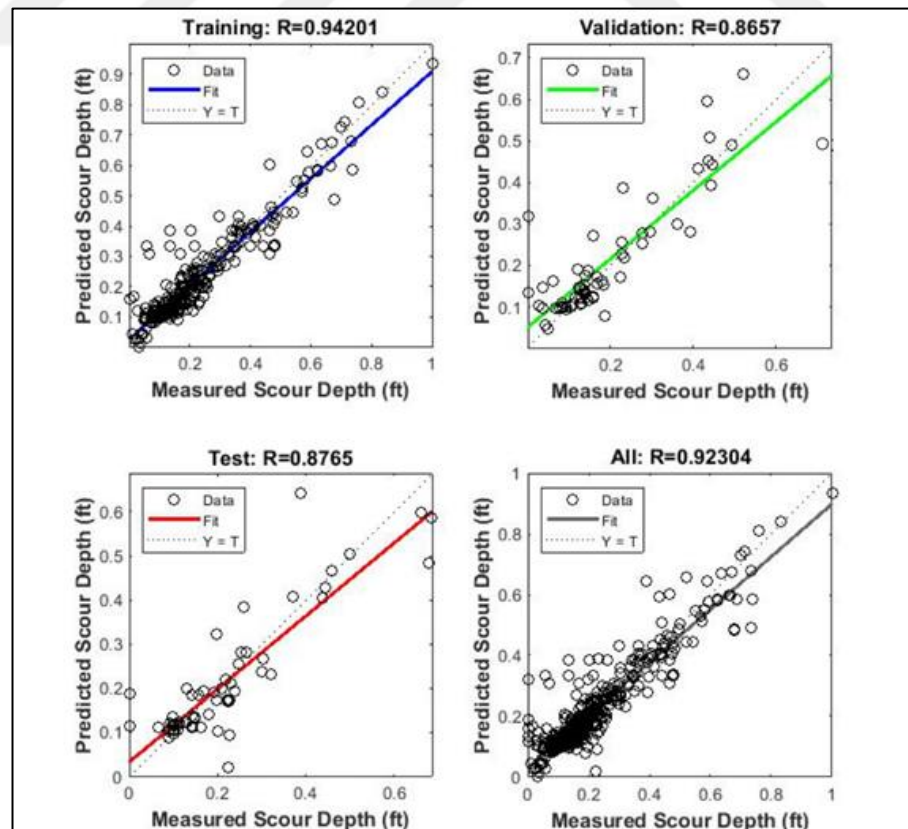


Figure 4.29 Regression values of DM-1e model.

Meanwhile, Table 4.4 shows the MSE values and number of epochs of DM-1 models which utilized for sensitivity analysis.

Table 4.4 MSE values and epoch of DM-1 models.

Model Name	R (training)	MSE (training)	R (test)	MSE (test)	Epochs
DM-1	0.9529	0.00270	0.9176	0.0029	11
DM-1a	0.9330	0.00361	0.8718	0.00530	11
DM-1b	0.9161	0.00370	0.8377	0.00744	10
DM-1c	0.6090	0.01580	0.5004	0.02040	8
DM-1d	0.9500	0.00272	0.9008	0.00440	16
DM-1e	0.9420	0.00305	0.8765	0.00524	9

It's obvious from Table 4.4 that the absence of pier width (b) in the model DM-1c has a great impact on the accuracy of the prediction of equilibrium scour depth around bridge piers. When the pier width (b) was removed from input parameters in model DM-1c, the regression value of the test of model DM-1, which equal to 0.9176, has lowered to 0.5004 (R -test value of ANN model DM-1c). While the removing of other input parameters (V , y , V_c , d) did not show a big effect on regression values of training and test. In addition, another three ANN models have been established to examine the importance of each non-dimensional parameter of NDM-1 model in the prediction. Table 4.5 shows the characterizes of NDM-1 models for sensitivity analysis.

Table 4.5 Characterizes of NDM-1 models for sensitivity analysis.

Model name	Training algorithm	Number of nodes in the hidden layer	Input variable
NDM-1	trainlm	28	$\frac{V}{V_c}, \frac{y}{b}, \frac{d}{b}$
NDM-1a	trainlm	28	$\frac{V}{V_c}, \frac{y}{b}$
NDM-1b	trainlm	28	$\frac{V}{V_c}, \frac{d}{b}$
NDM-1c	trainlm	28	$\frac{y}{b}, \frac{d}{b}$

Besides, the regression values of training, validation, and testing for the dataset of ANN model NDM-1 (non-dimensional model) have been obtained, as shown in Figure 4.30 to Figure 4.32.

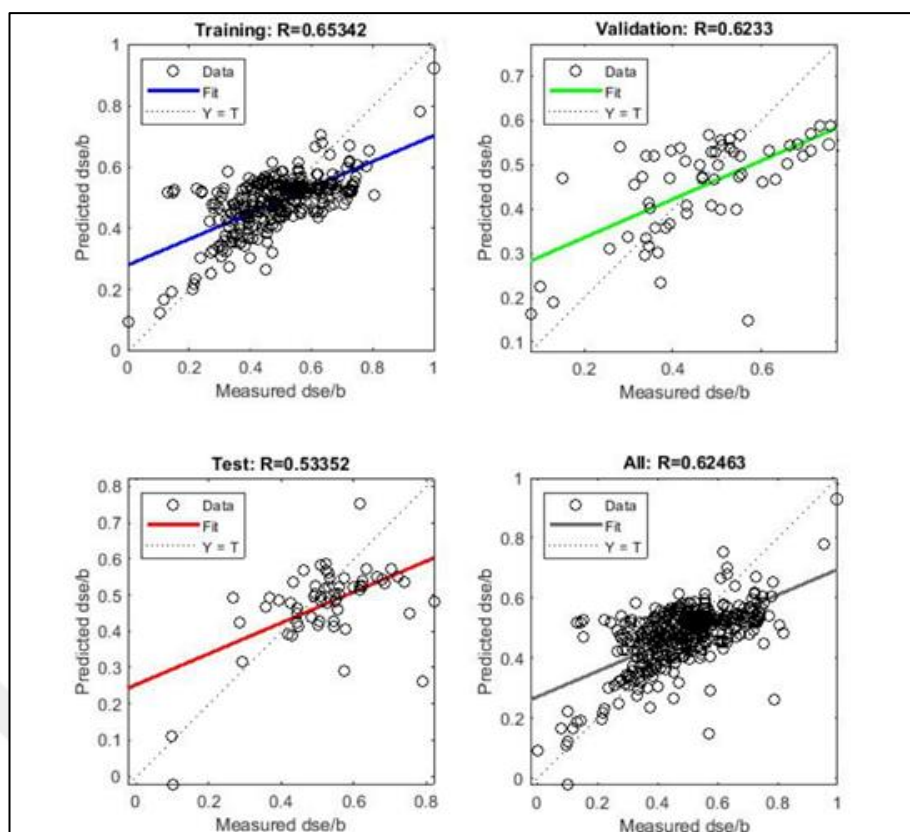


Figure 4.30 Regression values of NDM-1a model.

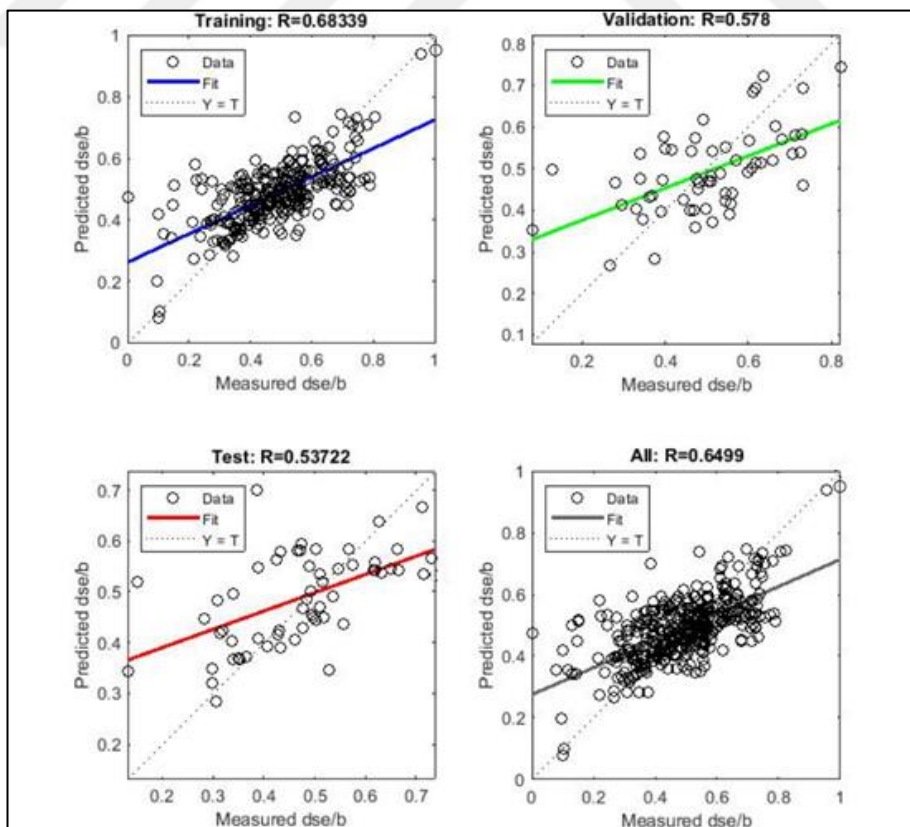


Figure 4.31 Regression values of NDM-1b model.

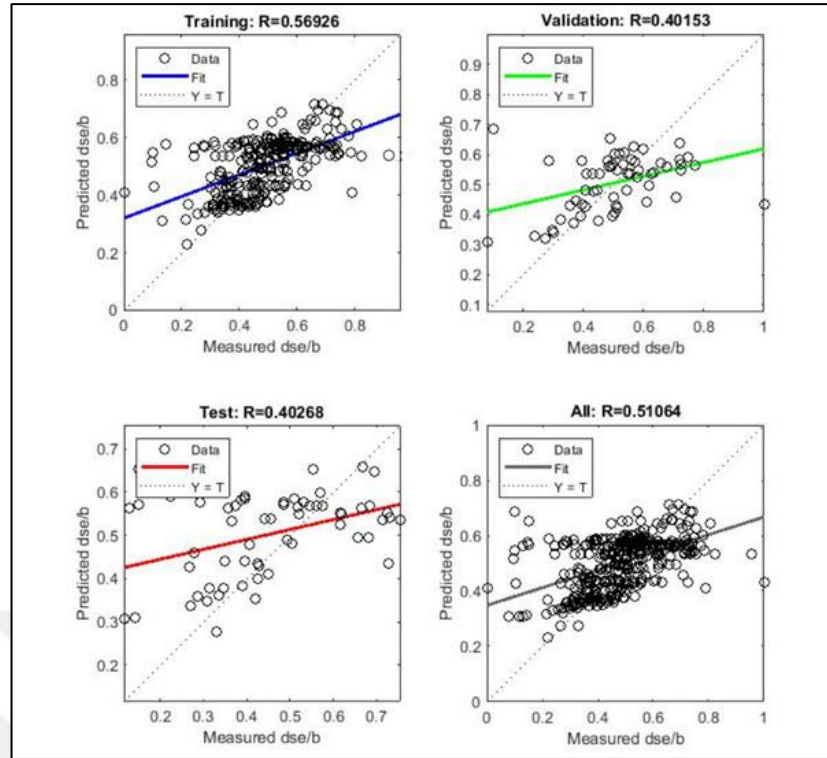


Figure 4.32 Regression values of NDM-1c model.

Meanwhile, Table 4.6 shows the MSE values and number of epochs of NDM-1 models which utilized for sensitivity analysis.

Table 4.6 MSE values and epoch of NDM-1 models.

Model Name	R (training)	MSE (training)	R (test)	MSE (test)	Epochs
NDM-1	0.8151	0.00746	0.7110	0.0121	32
NDM-1a	0.6534	0.0125	0.5335	0.0173	26
NDM-1b	0.6833	0.0123	0.5372	0.0135	36
NDM-1c	0.5692	0.0137	0.4026	0.0267	8

It's clear from Table 4.6 that the absence of $\frac{d}{b}$ in model NDM-1a and $\frac{y}{b}$ in model NDM-1b have approximately the same effect on the reliability of prediction, also, the elimination of $\frac{V}{V_c}$ in model NDM-1c has shown a decrease in the performance of prediction.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Precise estimation of the local scour depth around bridge piers are important for the effective design of the bridge piers foundation. Approximately, 60 percent of the down falling of bridges around the world due to flooding or scouring. Therefore, the quantity of local scour is one of the major considerations in the bridges' design. The rising advantage of soft computing technicality has encouraged scientific researchers to examine the possibility of applying hydro informatics technicalities to aid in the prediction of the scour depth at the bridge piers. In this study, an artificial neural network (ANN) has been utilized in the prediction of equilibrium local scour depth around bridge piers. Several ANN models have been developed using MATLAB, moreover, feed-forward backpropagations with a single hidden layer have been employed in the modeling. The ANN models have been trained with 400 laboratories scour data, the dataset has included pier width (b), flow velocity (V), flow depth (y), the sediment critical mean velocity (V_c), and the particle diameter (d) as input variables, while equilibrium scour depth (d_{se}) has been set as a target variable. The most important points from this study are showing in the following:

- The feed-forward neural network with backpropagation learning algorithms has shown good performance in the modeling.
- Training ANN models with a large range of data effects and increases the accuracy of estimation.
- Levenberg-Marquardt backpropagation algorithm proffers acceptable results in the ANN modeling related to hydraulic problems such as scouring.
- The model DM-1 which trained with Levenberg-Marquardt backpropagation and 23 nodes in the single hidden layer has shown good accuracy in the prediction, which provided a training regression value equal to 0.9529 (mse = 0.00270), and test regression value equal to 0.9176 (mse = 0.0029). While DM-

2 and DM-3 models have shown a low performance in the prediction, which was the lowest compared to the other ANN models in this study.

- It has been found that determining the number of nodes in the hidden layer could be done with the trial-and-error process.
- The comparison of results between NDM-1 and DM-1 models has shown that dimensional parameters in the modeling provide better outcomes than non-dimensional parameters. Also, Zounemat et al.(2009) has reached the same results, and they found that the ANN model trained with dimensional parameters gives better results than ANN trained with dimensionless parameters. In addition, the performance of ANN with dimensional parameters and non-dimensional parameters has examined by different researchers and it depends on the type of neural network and characteristics of the neural network such as the architecture of ANN and the type of training algorithm. Also, Khassaf and Abdulwhab (2016) found that ANN trained with the Levenberg-Marquardt backpropagation algorithm and dimensional parameters gives better results than other backpropagation algorithms.
- The regression value between input parameters (V, y, d, V_c, b) and target value (dse) is not strong sufficiently. Therefore, linear regression does not have the ability to predict the equilibrium scour depth accurately and ANN could be utilized to obtain a precise prediction.
- Sensitivity analysis of dimensional parameters have shown that the elimination of pier width from input parameters decreases the performance of modeling, while the sensitivity analysis of non-dimensional parameters has shown that removing any of the three input parameters $(\frac{V}{V_c}, \frac{y}{b}, \frac{d}{b})$ reduces the efficiency of prediction in the same way.
- The artificial neural network could be utilized as a reliable technique for the prediction of local scour depth around bridge piers.

5.2 Recommendations

Generally, studying scouring around various hydraulic structures is an essential topic in the field of hydraulic engineering. Pioneers' researchers have utilized empirical equations for the prediction of local scour depth around bridge piers using physical models at the laboratory, but recent developments in numerical modeling have aid to

enhance prediction techniques. For further studying regarding local scour depth around bridge piers, these aspects could be recommended for more investigation:

- Comparing the results of this study with various prediction techniques such as adaptive network-based fuzzy inference system (ANFIS), genetic algorithm (GA), and radial basis function neural network.
- Training the ANN models with field local scour depth data and compare the outcomes with ANN models trained with laboratory data to examine the efficiency of field data in the prediction.



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APPENDIX A

Table A.1 Laboratory measurements of Pier Scour (Sheppard and Others).

Data Source	Pier width bn (ft)	Approach flow velocity, V_o (ft/s)	Sediment critical velocity, V_c (ft/s)	Approach flow depth, y_o (ft)	D50 (mm)	Pier- scour depth, y_s (ft)
Chabert and Engeldinger (1956)	0.164	1.94	2.17	0.328	3	0.305
Chabert and Engeldinger (1956)	0.164	1.31	1.6	0.328	1.5	0.308
Chabert and Engeldinger (1956)	0.164	1.23	1.6	0.328	1.5	0.381
Chabert and Engeldinger (1956)	0.164	0.9	0.94	0.328	0.52	0.289
Chabert and Engeldinger (1956)	0.164	1.23	0.94	0.328	0.52	0.358
Chabert and Engeldinger (1956)	0.164	0.82	0.94	0.328	0.52	0.253
Chabert and Engeldinger (1956)	0.164	0.66	0.84	0.328	0.26	0.256
Chabert and Engeldinger (1956)	0.164	0.75	0.84	0.328	0.26	0.282
Chabert and Engeldinger (1956)	0.164	0.82	0.84	0.328	0.26	0.266
Chabert and Engeldinger (1956)	0.164	0.96	1.79	0.656	1.5	0.226
Chabert and Engeldinger (1956)	0.164	1.39	1.79	0.656	1.5	0.312
Chabert and Engeldinger (1956)	0.164	1.11	1.79	0.656	1.5	0.322
Chabert and Engeldinger (1956)	0.164	1.23	1.79	0.656	1.5	0.351
Chabert and Engeldinger (1956)	0.164	1.15	1.79	0.656	1.5	0.407
Chabert and Engeldinger (1956)	0.164	0.8	1.04	0.656	0.52	0.262
Chabert and Engeldinger (1956)	0.164	1.19	1.04	0.656	0.52	0.39
Chabert and Engeldinger (1956)	0.164	0.92	1.04	0.656	0.52	0.318
Chabert and Engeldinger (1956)	0.164	1.07	1.04	0.656	0.52	0.335

Chabert and Engeldinger (1956)	0.164	0.56	0.92	0.656	0.26	0.249
Chabert and Engeldinger (1956)	0.164	0.69	0.92	0.656	0.26	0.246
Chabert and Engeldinger (1956)	0.164	0.74	0.92	0.656	0.26	0.253
Chabert and Engeldinger (1956)	0.164	0.83	0.92	0.656	0.26	0.22
Chabert and Engeldinger (1956)	0.164	1.07	1.94	1.148	1.5	0.374
Chabert and Engeldinger (1956)	0.164	1.23	1.94	1.148	1.5	0.377
Chabert and Engeldinger (1956)	0.164	0.89	1.11	1.148	0.52	0.312
Chabert and Engeldinger (1956)	0.164	1.01	1.11	1.148	0.52	0.335
Chabert and Engeldinger (1956)	0.164	1.15	1.11	1.148	0.52	0.292
Chabert and Engeldinger (1956)	0.164	0.82	1.11	1.148	0.52	0.256
Chabert and Engeldinger (1956)	0.164	0.66	0.98	1.148	0.26	0.233
Chabert and Engeldinger (1956)	0.164	0.72	0.98	1.148	0.26	0.23
Chabert and Engeldinger (1956)	0.164	0.59	0.98	1.148	0.26	0.223
Chabert and Engeldinger (1956)	0.246	0.9	0.94	0.328	0.52	0.364
Chabert and Engeldinger (1956)	0.246	1.23	0.94	0.328	0.52	0.377
Chabert and Engeldinger (1956)	0.246	0.82	0.94	0.328	0.52	0.295
Chabert and Engeldinger (1956)	0.246	0.66	0.84	0.328	0.26	0.246
Chabert and Engeldinger (1956)	0.246	0.75	0.84	0.328	0.26	0.295
Chabert and Engeldinger (1956)	0.246	0.82	0.84	0.328	0.26	0.299
Chabert and Engeldinger (1956)	0.246	0.8	1.04	0.656	0.52	0.374
Chabert and Engeldinger (1956)	0.246	1.19	1.04	0.656	0.52	0.42
Chabert and Engeldinger (1956)	0.246	0.92	1.04	0.656	0.52	0.361
Chabert and Engeldinger (1956)	0.246	1.07	1.04	0.656	0.52	0.387
Chabert and Engeldinger (1956)	0.246	0.56	0.92	0.656	0.26	0.256
Chabert and Engeldinger (1956)	0.246	0.69	0.92	0.656	0.26	0.325
Chabert and Engeldinger (1956)	0.246	0.74	0.92	0.656	0.26	0.328
Chabert and Engeldinger (1956)	0.246	0.83	0.92	0.656	0.26	0.308
Chabert and Engeldinger (1956)	0.246	0.89	1.11	1.148	0.52	0.367
Chabert and Engeldinger (1956)	0.246	1.01	1.11	1.148	0.52	0.387

Chabert and Engeldinger (1956)	0.246	1.15	1.11	1.148	0.52	0.404
Chabert and Engeldinger (1956)	0.246	0.82	1.11	1.148	0.52	0.364
Chabert and Engeldinger (1956)	0.246	0.66	0.98	1.148	0.26	0.318
Chabert and Engeldinger (1956)	0.246	0.72	0.98	1.148	0.26	0.299
Chabert and Engeldinger (1956)	0.246	0.59	0.98	1.148	0.26	0.236
Chabert and Engeldinger (1956)	0.328	1.94	2.17	0.328	3	0.479
Chabert and Engeldinger (1956)	0.328	1.31	1.6	0.328	1.5	0.489
Chabert and Engeldinger (1956)	0.328	1.23	1.6	0.328	1.5	0.512
Chabert and Engeldinger (1956)	0.328	0.9	0.94	0.328	0.52	0.4
Chabert and Engeldinger (1956)	0.328	1.23	0.94	0.328	0.52	0.436
Chabert and Engeldinger (1956)	0.328	0.82	0.94	0.328	0.52	0.371
Chabert and Engeldinger (1956)	0.328	0.66	0.84	0.328	0.26	0.354
Chabert and Engeldinger (1956)	0.328	0.75	0.84	0.328	0.26	0.351
Chabert and Engeldinger (1956)	0.328	0.82	0.84	0.328	0.26	0.338
Chabert and Engeldinger (1956)	0.328	0.96	1.79	0.656	1.5	0.335
Chabert and Engeldinger (1956)	0.328	1.39	1.79	0.656	1.5	0.571
Chabert and Engeldinger (1956)	0.328	1.11	1.79	0.656	1.5	0.551
Chabert and Engeldinger (1956)	0.328	1.23	1.79	0.656	1.5	0.545
Chabert and Engeldinger (1956)	0.328	1.15	1.79	0.656	1.5	0.627
Chabert and Engeldinger (1956)	0.328	0.8	1.04	0.656	0.52	0.449
Chabert and Engeldinger (1956)	0.328	1.19	1.04	0.656	0.52	0.489
Chabert and Engeldinger (1956)	0.328	0.92	1.04	0.656	0.52	0.43
Chabert and Engeldinger (1956)	0.328	1.07	1.04	0.656	0.52	0.472
Chabert and Engeldinger (1956)	0.328	0.56	0.92	0.656	0.26	0.302
Chabert and Engeldinger (1956)	0.328	0.69	0.92	0.656	0.26	0.344
Chabert and Engeldinger (1956)	0.328	0.74	0.92	0.656	0.26	0.358
Chabert and Engeldinger (1956)	0.328	0.83	0.92	0.656	0.26	0.358
Chabert and Engeldinger (1956)	0.328	1.07	1.94	1.148	1.5	0.627
Chabert and Engeldinger (1956)	0.328	1.23	1.94	1.148	1.5	0.646

Chabert and Engeldinger (1956)	0.328	0.89	1.11	1.148	0.52	0.417
Chabert and Engeldinger (1956)	0.328	1.01	1.11	1.148	0.52	0.433
Chabert and Engeldinger (1956)	0.328	1.15	1.11	1.148	0.52	0.459
Chabert and Engeldinger (1956)	0.328	0.82	1.11	1.148	0.52	0.449
Chabert and Engeldinger (1956)	0.328	0.66	0.98	1.148	0.26	0.371
Chabert and Engeldinger (1956)	0.328	0.72	0.98	1.148	0.26	0.371
Chabert and Engeldinger (1956)	0.328	0.59	0.98	1.148	0.26	0.322
Chabert and Engeldinger (1956)	0.492	1.94	2.17	0.328	3	0.646
Chabert and Engeldinger (1956)	0.492	1.31	1.6	0.328	1.5	0.584
Chabert and Engeldinger (1956)	0.492	1.23	1.6	0.328	1.5	0.689
Chabert and Engeldinger (1956)	0.492	0.96	1.79	0.656	1.5	0.482
Chabert and Engeldinger (1956)	0.492	1.39	1.79	0.656	1.5	0.712
Chabert and Engeldinger (1956)	0.492	1.11	1.79	0.656	1.5	0.696
Chabert and Engeldinger (1956)	0.492	1.23	1.79	0.656	1.5	0.682
Chabert and Engeldinger (1956)	0.492	1.15	1.79	0.656	1.5	0.741
Chabert and Engeldinger (1956)	0.492	1.07	1.94	1.148	1.5	0.764
Chabert and Engeldinger (1956)	0.492	1.23	1.94	1.148	1.5	0.774
Chee (1982)	0.167	1.15	0.84	0.328	0.24	0.184
Chee (1982)	0.167	1.64	0.84	0.328	0.24	0.22
Chee (1982)	0.167	2.13	0.84	0.328	0.24	0.262
Chee (1982)	0.167	0.75	0.88	0.328	0.38	0.203
Chee (1982)	0.167	1.31	0.88	0.328	0.38	0.203
Chee (1982)	0.167	3.44	0.88	0.328	0.38	0.315
Chee (1982)	0.167	2.62	1.11	0.328	0.8	0.262
Chee (1982)	0.167	1.21	0.84	0.328	0.24	0.184
Chee (1982)	0.167	1.48	0.84	0.328	0.24	0.207
Chee (1982)	0.167	0.98	0.88	0.328	0.38	0.18
Chee (1982)	0.167	1.64	1.11	0.328	0.8	0.213
Chee (1982)	0.167	1.97	1.54	0.328	1.4	0.22
Chee (1982)	0.167	1.28	0.84	0.328	0.24	0.19
Chee (1982)	0.167	3.94	1.54	0.328	1.4	0.253
Chee (1982)	0.262	0.98	0.84	0.328	0.24	0.253
Chee (1982)	0.262	2.62	0.84	0.328	0.24	0.397
Chee (1982)	0.262	2.13	0.88	0.328	0.38	0.358
Chee (1982)	0.262	3.44	1.11	0.328	0.8	0.361
Chee (1982)	0.262	1.97	1.54	0.328	1.4	0.318
Chee (1982)	0.262	2.62	1.54	0.328	1.4	0.295

Chee (1982)	0.262	3.44	1.54	0.328	1.4	0.344
Chee (1982)	0.262	3.61	0.84	0.328	0.24	0.4
Chee (1982)	0.262	3.44	0.88	0.328	0.38	0.433
Chee (1982)	0.262	2.13	0.84	0.328	0.24	0.361
Chee (1982)	0.262	2.66	0.84	0.328	0.24	0.4
Chee (1982)	0.262	1.31	0.88	0.328	0.38	0.285
Chee (1982)	0.262	1.64	1.11	0.328	0.8	0.292
Chee (1982)	0.335	1.21	0.84	0.328	0.24	0.302
Chee (1982)	0.335	1.64	1.11	0.328	0.8	0.348
Chee (1982)	0.335	3.94	1.54	0.328	1.4	0.384
Chee (1982)	0.335	2.62	0.84	0.328	0.24	0.472
Chee (1982)	0.335	2.13	1.11	0.328	0.8	0.358
Chee (1982)	0.335	3.44	1.54	0.328	1.4	0.404
Chee (1982)	0.335	0.98	0.84	0.328	0.24	0.295
Chee (1982)	0.335	2.62	0.88	0.328	0.38	0.453
Chee (1982)	0.335	2.62	1.11	0.328	0.8	0.407
Chee (1982)	0.335	1.97	1.54	0.328	1.4	0.377
Chiew (1984)	0.104	2.2	2.54	0.689	3.2	0.143
Chiew (1984)	0.104	0.87	0.89	0.558	0.24	0.172
Chiew (1984)	0.104	0.99	1.06	0.558	0.6	0.199
Chiew (1984)	0.104	1.09	1.06	0.558	0.6	0.217
Chiew (1984)	0.104	1.37	1.71	0.558	1.45	0.24
Chiew (1984)	0.105	2.88	2.54	0.689	3.2	0.115
Chiew (1984)	0.105	3.08	2.54	0.689	3.2	0.121
Chiew (1984)	0.105	3.22	2.54	0.689	3.2	0.112
Chiew (1984)	0.105	1.29	0.89	0.558	0.24	0.161
Chiew (1984)	0.105	1.57	1.06	0.558	0.6	0.197
Chiew (1984)	0.105	1.64	0.89	0.558	0.24	0.177
Chiew (1984)	0.105	1.83	1.06	0.558	0.6	0.18
Chiew (1984)	0.105	1.92	1.06	0.558	0.6	0.194
Chiew (1984)	0.105	1.9	1.06	0.558	0.6	0.161
Chiew (1984)	0.105	2.05	0.89	0.558	0.24	0.19
Chiew (1984)	0.105	2.16	1.06	0.558	0.6	0.167
Chiew (1984)	0.105	2.2	1.71	0.558	1.45	0.164
Chiew (1984)	0.105	2.4	1.71	0.558	1.45	0.161
Chiew (1984)	0.105	2.47	0.89	0.558	0.24	0.2
Chiew (1984)	0.105	2.51	1.06	0.558	0.6	0.171
Chiew (1984)	0.105	1.15	1.06	0.558	0.6	0.213
Chiew (1984)	0.105	1.21	1.06	0.558	0.6	0.049
Chiew (1984)	0.105	1.35	1.2	0.558	0.8	0.092
Chiew (1984)	0.105	1.48	1.06	0.558	0.6	0.157
Chiew (1984)	0.105	1.61	1.2	0.558	0.8	0.128
Chiew (1984)	0.105	1.64	1.06	0.558	0.6	0.089
Chiew (1984)	0.105	1.64	1.06	0.558	0.6	0.18
Chiew (1984)	0.105	1.8	1.06	0.558	0.6	0.171
Chiew (1984)	0.105	1.9	1.2	0.558	0.8	0.128
Chiew (1984)	0.105	2.13	1.06	0.558	0.6	0.128
Chiew (1984)	0.105	2.2	1.06	0.558	0.6	0.177

Chiew (1984)	0.105	2.2	1.06	0.558	0.6	0.184
Chiew (1984)	0.105	2.23	1.2	0.558	0.8	0.121
Chiew (1984)	0.105	2.59	1.06	0.558	0.6	0.102
Chiew (1984)	0.105	2.69	1.06	0.558	0.6	0.187
Chiew (1984)	0.105	2.79	1.06	0.558	0.6	0.184
Chiew (1984)	0.105	2.79	1.2	0.558	0.8	0.125
Chiew (1984)	0.125	1.15	1.06	0.558	0.6	0.278
Chiew (1984)	0.125	1.5	1.06	0.558	0.6	0.197
Chiew (1984)	0.125	1.91	1.06	0.558	0.6	0.213
Chiew (1984)	0.125	2.95	1.06	0.558	0.6	0.217
Chiew (1984)	0.131	1.41	1.77	0.689	1.45	0.315
Chiew (1984)	0.131	2.57	1.77	0.689	1.45	0.21
Chiew (1984)	0.131	2.89	1.77	0.689	1.45	0.203
Chiew (1984)	0.131	3.26	1.77	0.689	1.45	0.2
Chiew (1984)	0.131	0.72	0.89	0.558	0.24	0.203
Chiew (1984)	0.131	1.14	0.89	0.558	0.24	0.226
Chiew (1984)	0.131	1.73	0.89	0.558	0.24	0.2
Chiew (1984)	0.131	1.91	0.89	0.558	0.24	0.236
Chiew (1984)	0.131	2.39	0.89	0.558	0.24	0.253
Chiew (1984)	0.131	2.43	0.89	0.558	0.24	0.253
Chiew (1984)	0.131	2.53	0.89	0.558	0.24	0.256
Chiew (1984)	0.131	2.76	0.89	0.558	0.24	0.256
Chiew (1984)	0.131	1.15	1.06	0.558	0.6	0.269
Chiew (1984)	0.131	1.48	1.06	0.558	0.6	0.236
Chiew (1984)	0.131	1.8	1.06	0.558	0.6	0.249
Chiew (1984)	0.131	2.07	1.06	0.558	0.6	0.233
Chiew (1984)	0.131	2.59	1.06	0.558	0.6	0.226
Chiew (1984)	0.148	5.28	1.89	1.115	1.45	0.26
Chiew (1984)	0.148	2.26	2.54	0.689	3.2	0.232
Chiew (1984)	0.148	2.82	2.54	0.689	3.2	0.226
Chiew (1984)	0.148	3.14	2.54	0.689	3.2	0.21
Chiew (1984)	0.148	1.12	1.06	0.558	0.6	0.312
Chiew (1984)	0.148	1.36	1.71	0.558	1.45	0.334
Chiew (1984)	0.148	1.01	0.89	0.558	0.24	0.233
Chiew (1984)	0.148	1.43	0.89	0.558	0.24	0.23
Chiew (1984)	0.148	1.5	1.06	0.558	0.6	0.23
Chiew (1984)	0.148	1.74	1.06	0.558	0.6	0.256
Chiew (1984)	0.148	1.79	0.89	0.558	0.24	0.253
Chiew (1984)	0.148	1.91	1.06	0.558	0.6	0.249
Chiew (1984)	0.148	2.13	1.06	0.558	0.6	0.243
Chiew (1984)	0.148	2.16	0.89	0.558	0.24	0.266
Chiew (1984)	0.148	2.13	1.71	0.558	1.45	0.253
Chiew (1984)	0.148	2.49	1.06	0.558	0.6	0.249
Chiew (1984)	0.148	2.35	1.71	0.558	1.45	0.233
Chiew (1984)	0.148	2.76	0.89	0.558	0.24	0.282
Chiew (1984)	0.148	2.66	1.71	0.558	1.45	0.223
Chiew (1984)	0.148	2.92	1.06	0.558	0.6	0.262
Chiew (1984)	0.148	1.15	1.06	0.558	0.6	0.249

Chiew (1984)	0.148	1.21	1.2	0.558	0.8	0.102
Chiew (1984)	0.148	1.57	1.06	0.558	0.6	0.128
Chiew (1984)	0.148	1.57	1.2	0.558	0.8	0.18
Chiew (1984)	0.148	1.64	1.71	0.558	1.45	0.069
Chiew (1984)	0.148	1.77	1.06	0.558	0.6	0.259
Chiew (1984)	0.148	1.84	1.06	0.558	0.6	0.262
Chiew (1984)	0.148	1.94	1.2	0.558	0.8	0.19
Chiew (1984)	0.148	2	1.06	0.558	0.6	0.177
Chiew (1984)	0.148	2.2	1.06	0.558	0.6	0.243
Chiew (1984)	0.148	2.23	1.06	0.558	0.6	0.256
Chiew (1984)	0.148	2.36	1.06	0.558	0.6	0.171
Chiew (1984)	0.148	2.59	1.2	0.558	0.8	0.197
Chiew (1984)	0.148	2.62	1.06	0.558	0.6	0.164
Chiew (1984)	0.148	2.66	1.06	0.558	0.6	0.249
Chiew (1984)	0.148	2.66	1.06	0.558	0.6	0.256
Chiew (1984)	0.148	2.89	1.06	0.558	0.6	0.177
Chiew (1984)	0.164	1.18	1.06	0.558	0.6	0.312
Chiew (1984)	0.167	1.18	1.06	0.558	0.6	0.318
Chiew (1984)	0.167	2.02	1.06	0.558	0.6	0.223
Chiew (1984)	0.167	2.56	1.06	0.558	0.6	0.246
Chiew (1984)	0.23	2	1.06	0.558	0.6	0.292
Chiew (1984)	0.23	2.59	1.06	0.558	0.6	0.289
Coleman (unpublished)	1.043	1.02	1.09	0.262	0.84	0.876
Coleman (unpublished)	1.043	0.98	0.97	0.131	0.84	0.687
Coleman (unpublished)	2.507	0.98	0.97	0.131	0.84	0.613
Coleman (unpublished)	2.51	1.02	1.09	0.256	0.84	1.11
Coleman (unpublished)	2.51	1.02	1.08	0.249	0.84	1.02
Coleman (unpublished)	2.51	0.98	0.97	0.131	0.84	0.901
Dey and others (1995)	0.187	0.86	0.88	0.164	0.58	0.259
Dey and others (1995)	0.187	0.76	0.76	0.164	0.26	0.249
Dey and others (1995)	0.187	0.74	0.85	0.135	0.58	0.197
Dey and others (1995)	0.187	0.67	0.74	0.135	0.26	0.184
Dey and others (1995)	0.187	0.61	0.82	0.115	0.58	0.177
Dey and others (1995)	0.187	0.56	0.73	0.115	0.26	0.171
Dey and others (1995)	0.213	0.86	0.88	0.164	0.58	0.282
Dey and others (1995)	0.213	0.76	0.76	0.164	0.26	0.276
Dey and others (1995)	0.213	0.74	0.85	0.135	0.58	0.223
Dey and others (1995)	0.213	0.67	0.74	0.135	0.26	0.207

Dey and others (1995)	0.213	0.61	0.82	0.115	0.58	0.203
Dey and others (1995)	0.213	0.56	0.73	0.115	0.26	0.184
Dey and others (1995)	0.249	0.86	0.88	0.164	0.58	0.315
Dey and others (1995)	0.249	0.76	0.76	0.164	0.26	0.305
Dey and others (1995)	0.249	0.74	0.85	0.135	0.58	0.262
Dey and others (1995)	0.249	0.67	0.74	0.135	0.26	0.23
Dey and others (1995)	0.249	0.61	0.82	0.115	0.58	0.236
Dey and others (1995)	0.249	0.56	0.73	0.115	0.26	0.197
Ettema (1980)	0.094	1.44	1.44	1.969	0.84	0.238
Ettema (1980)	0.094	1.98	2.36	1.969	1.9	0.2
Ettema (1980)	0.094	0.87	1.03	1.969	0.24	0.134
Ettema (1980)	0.094	1.37	1.44	1.969	0.84	0.229
Ettema (1980)	0.094	3.47	3.65	1.969	5.35	0.131
Ettema (1980)	0.094	3.76	4.18	1.969	7.8	0.077
Ettema (1980)	0.094	3.96	4.18	1.969	7.8	0.096
Ettema (1980)	0.094	0.95	1.09	1.969	0.38	0.148
Ettema (1980)	0.094	1.88	2.36	1.969	1.9	0.191
Ettema (1980)	0.094	3.29	3.65	1.969	5.35	0.109
Ettema (1980)	0.094	3.19	3.55	1.64	5.35	0.063
Ettema (1980)	0.094	0.83	0.96	0.656	0.38	0.146
Ettema (1980)	0.094	1.6	2.01	0.656	1.9	0.188
Ettema (1980)	0.094	2.73	3.03	0.656	5.35	0.1
Ettema (1980)	0.094	0.75	0.88	0.328	0.38	0.149
Ettema (1980)	0.094	1.43	1.8	0.328	1.9	0.159
Ettema (1980)	0.094	2.37	2.63	0.328	5.35	0.089
Ettema (1980)	0.094	1.25	1.58	0.164	1.9	0.134
Ettema (1980)	0.148	0.92	1.03	1.969	0.24	0.254
Ettema (1980)	0.148	1	1.09	1.969	0.38	0.258
Ettema (1980)	0.148	1.44	1.44	1.969	0.84	0.344
Ettema (1980)	0.148	1.98	2.36	1.969	1.9	0.325
Ettema (1980)	0.148	3.1	3.2	1.969	3.8	0.282
Ettema (1980)	0.148	0.87	1.03	1.969	0.24	0.204
Ettema (1980)	0.148	0.95	1.09	1.969	0.38	0.252
Ettema (1980)	0.148	1.36	1.44	1.969	0.84	0.322
Ettema (1980)	0.148	1.88	2.36	1.969	1.9	0.306
Ettema (1980)	0.148	2.93	3.2	1.969	3.8	0.239
Ettema (1980)	0.167	0.87	1.03	1.969	0.24	0.228
Ettema (1980)	0.167	0.95	1.09	1.969	0.38	0.245
Ettema (1980)	0.167	1.35	1.41	1.969	0.8	0.372
Ettema (1980)	0.167	1.37	1.44	1.969	0.84	0.373
Ettema (1980)	0.167	1.88	2.36	1.969	1.9	0.378
Ettema (1980)	0.167	3.29	3.65	1.969	5.35	0.27
Ettema (1980)	0.167	3.76	4.18	1.969	7.8	0.168

Ettema (1980)	0.167	1	1.09	1.969	0.38	0.288
Ettema (1980)	0.167	1.42	1.41	1.969	0.8	0.405
Ettema (1980)	0.167	0.8	1.09	1.969	0.38	0.24
Ettema (1980)	0.167	1.13	1.41	1.969	0.8	0.268
Ettema (1980)	0.167	1.57	2.36	1.969	1.9	0.28
Ettema (1980)	0.167	2.74	3.65	1.969	5.35	0.138
Ettema (1980)	0.167	0.54	1.09	1.969	0.38	0.05
Ettema (1980)	0.167	0.77	1.41	1.969	0.8	0.052
Ettema (1980)	0.167	1.05	2.36	1.969	1.9	0.052
Ettema (1980)	0.167	1.83	3.65	1.969	5.35	0.053
Ettema (1980)	0.167	1.98	2.36	1.969	1.9	0.382
Ettema (1980)	0.167	3.47	3.65	1.969	5.35	0.287
Ettema (1980)	0.167	3.96	4.18	1.969	7.8	0.243
Ettema (1980)	0.333	0.92	1.03	1.969	0.24	0.527
Ettema (1980)	0.333	1.44	1.44	1.969	0.84	0.737
Ettema (1980)	0.333	1.98	2.36	1.969	1.9	0.75
Ettema (1980)	0.333	3.47	3.65	1.969	5.35	0.68
Ettema (1980)	0.333	3.96	4.18	1.969	7.8	0.617
Ettema (1980)	0.333	0.87	1.03	1.969	0.24	0.573
Ettema (1980)	0.333	1.35	1.41	1.969	0.8	0.743
Ettema (1980)	0.333	1.37	1.44	1.969	0.84	0.743
Ettema (1980)	0.333	2.93	3.2	1.969	3.8	0.683
Ettema (1980)	0.333	3.76	4.18	1.969	7.8	0.543
Ettema (1980)	0.333	0.95	1.09	1.969	0.38	0.477
Ettema (1980)	0.333	1.88	2.36	1.969	1.9	0.733
Ettema (1980)	0.333	3.29	3.65	1.969	5.35	0.587
Ettema (1980)	0.333	0.9	1.05	1.312	0.38	0.483
Ettema (1980)	0.333	1.78	2.23	1.312	1.9	0.73
Ettema (1980)	0.333	3.08	3.42	1.312	5.35	0.583
Ettema (1980)	0.333	0.87	1.01	0.984	0.38	0.473
Ettema (1980)	0.333	1.7	2.14	0.984	1.9	0.693
Ettema (1980)	0.333	2.93	3.26	0.984	5.35	0.54
Ettema (1980)	0.333	0.83	0.96	0.656	0.38	0.417
Ettema (1980)	0.333	1.6	2.01	0.656	1.9	0.65
Ettema (1980)	0.333	2.73	3.03	0.656	5.35	0.487
Ettema (1980)	0.333	0.75	0.88	0.328	0.38	0.417
Ettema (1980)	0.333	1.43	1.8	0.328	1.9	0.557
Ettema (1980)	0.333	2.37	2.63	0.328	5.35	0.43
Ettema (1980)	0.333	0.67	0.8	0.164	0.38	0.277
Ettema (1980)	0.333	1.25	1.58	0.164	1.9	0.483
Ettema (1980)	0.333	2.02	2.24	0.164	5.35	0.333
Ettema (1980)	0.333	1.02	1.29	0.066	1.9	0.227
Ettema (1980)	0.492	0.92	1.03	1.969	0.24	0.832
Ettema (1980)	0.492	1.44	1.44	1.969	0.84	1.112
Ettema (1980)	0.492	1.98	2.36	1.969	1.9	1.117
Ettema (1980)	0.492	3.47	3.65	1.969	5.35	1.014
Ettema (1980)	0.492	3.96	4.18	1.969	7.8	0.95
Ettema (1980)	0.492	0.87	1.03	1.969	0.24	0.802

Ettema (1980)	0.492	1.35	1.41	1.969	0.8	1.033
Ettema (1980)	0.492	1.37	1.44	1.969	0.84	1.029
Ettema (1980)	0.492	1.88	2.36	1.969	1.9	1.043
Ettema (1980)	0.492	3.29	3.65	1.969	5.35	1.009
Ettema (1980)	0.492	3.76	4.18	1.969	7.8	0.95
Ettema (1980)	0.787	0.87	1.03	1.969	0.24	0.677
Ettema (1980)	0.787	0.95	1.09	1.969	0.38	0.724
Ettema (1980)	0.787	1.35	1.41	1.969	0.8	0.803
Ettema (1980)	0.787	1.88	2.36	1.969	1.9	1.079
Ettema (1980)	0.787	3.29	3.65	1.969	5.35	1.15
Ettema (1980)	0.787	0.75	0.88	0.328	0.38	0.575
Ettema (1980)	0.787	1.43	1.8	0.328	1.9	0.89
Ettema (1980)	0.787	2.37	2.63	0.328	5.35	0.969
Ettema (1980)	0.787	2.02	2.24	0.164	5.35	0.906
Ettema and others (2006)	0.21	1.51	1.76	3.281	1.05	0.372
Ettema and others (2006)	0.374	1.51	1.76	3.281	1.05	0.619
Ettema and others (2006)	0.564	1.51	1.76	3.281	1.05	0.874
Ettema and others (2006)	0.791	1.51	1.76	3.281	1.05	1.063
Ettema and others (2006)	1.001	1.51	1.76	3.281	1.05	1.256
Ettema and others (2006)	1.332	1.51	1.76	3.281	1.05	1.497
Ettema (1976)	0.328	1.15	1.21	1.969	0.55	0.525
Ettema (1976)	0.328	1.15	1.21	1.969	0.55	0.722
Ettema (1976)	0.328	1.15	1.21	1.969	0.55	0.492
Ettema (1976)	0.328	1.15	1.21	1.969	0.55	0.295
Ettema (1976)	0.328	1.15	1.21	1.969	0.55	0.148
Ettema (1976)	0.328	1.38	1.45	1.969	0.85	0.689
Ettema (1976)	0.328	1.38	1.45	1.969	0.85	0.558
Ettema (1976)	0.328	1.38	1.45	1.969	0.85	0.361
Ettema (1976)	0.328	1.38	1.45	1.969	0.85	0.246
Ettema (1976)	0.328	1.38	1.45	1.969	0.85	0.131
Ettema (1976)	0.328	2.24	2.36	1.969	1.9	0.722
Ettema (1976)	0.328	2.24	2.36	1.969	1.9	0.558
Ettema (1976)	0.328	2.24	2.36	1.969	1.9	0.427
Ettema (1976)	0.328	2.24	2.36	1.969	1.9	0.344
Ettema (1976)	0.328	2.24	2.36	1.969	1.9	0.246
Ettema (1976)	0.328	3.14	3.3	1.969	4.1	0.738
Ettema (1976)	0.328	3.14	3.3	1.969	4.1	0.64
Ettema (1976)	0.328	3.14	3.3	1.969	4.1	0.574
Ettema (1976)	0.328	1.15	1.21	1.969	0.55	0.459
Graf (1995)	0.328	2	2.16	0.761	2.1	0.64
Graf (1995)	0.361	1.9	2.06	0.558	2.1	0.571
Graf (1995)	0.492	2	2.16	0.761	2.1	0.85
Jain and Fischer (1979)	0.167	2.69	2.36	0.81	2.5	0.285

Jain and Fischer (1979)	0.167	2.59	2.35	0.791	2.5	0.308
Jain and Fischer (1979)	0.167	4.63	2.31	0.709	2.5	0.371
Jain and Fischer (1979)	0.167	1.64	0.84	0.335	0.25	0.276
Jain and Fischer (1979)	0.167	2.46	0.84	0.335	0.25	0.325
Jain and Fischer (1979)	0.167	3.28	0.84	0.335	0.25	0.374
Jain and Fischer (1979)	0.167	3.94	0.84	0.335	0.25	0.515
Jain and Fischer (1979)	0.167	1.64	1.6	0.335	1.5	0.282
Jain and Fischer (1979)	0.167	2.13	1.6	0.335	1.5	0.285
Jain and Fischer (1979)	0.167	2.46	1.6	0.335	1.5	0.282
Jain and Fischer (1979)	0.167	2.79	1.6	0.335	1.5	0.322
Jain and Fischer (1979)	0.167	3.28	1.6	0.335	1.5	0.377
Jain and Fischer (1979)	0.167	3.94	1.6	0.335	1.5	0.423
Jain and Fischer (1979)	0.167	4.92	1.6	0.335	1.5	0.492
Jain and Fischer (1979)	0.167	1.64	2.03	0.335	2.5	0.318
Jain and Fischer (1979)	0.167	2.03	2.03	0.335	2.5	0.24
Jain and Fischer (1979)	0.167	2.46	2.03	0.335	2.5	0.246
Jain and Fischer (1979)	0.167	3.28	2.03	0.335	2.5	0.338
Jain and Fischer (1979)	0.167	3.94	2.03	0.335	2.5	0.351
Jain and Fischer (1979)	0.333	1.64	0.84	0.335	0.25	0.394

APPENDIX B

Table B.1 Predicted local scour depth by ANN models.

DM-1	DM-2	DM-3	DM-4	DM-5	DM-6	DM-7	NDM-1
0.142	0.287	0.162	0.164	0.114	0.223	0.157	0.497
0.163	0.227	0.223	0.099	0.136	0.215	0.159	0.632
0.164	0.228	0.222	0.090	0.133	0.225	0.164	0.644
0.115	0.154	0.129	0.109	0.109	0.142	0.137	0.505
0.121	0.132	0.112	0.135	0.129	0.122	0.135	0.472
0.111	0.160	0.135	0.100	0.104	0.147	0.136	0.506
0.109	0.156	0.129	0.102	0.090	0.144	0.119	0.432
0.116	0.148	0.120	0.113	0.097	0.138	0.123	0.455
0.120	0.142	0.114	0.120	0.102	0.134	0.126	0.464
0.184	0.258	0.270	0.062	0.194	0.337	0.184	0.780
0.198	0.253	0.267	0.116	0.188	0.282	0.164	0.694
0.193	0.259	0.270	0.082	0.192	0.318	0.178	0.772
0.197	0.257	0.269	0.097	0.190	0.303	0.172	0.745
0.195	0.258	0.270	0.087	0.191	0.313	0.176	0.765
0.143	0.176	0.133	0.098	0.127	0.160	0.146	0.541
0.160	0.146	0.110	0.135	0.136	0.129	0.149	0.508
0.152	0.166	0.124	0.111	0.131	0.149	0.149	0.528
0.159	0.155	0.116	0.126	0.134	0.138	0.150	0.515
0.127	0.176	0.130	0.087	0.102	0.154	0.125	0.443
0.143	0.165	0.116	0.103	0.108	0.142	0.134	0.472
0.148	0.161	0.111	0.109	0.110	0.138	0.136	0.479
0.155	0.153	0.103	0.119	0.113	0.131	0.140	0.488
0.161	0.261	0.301	0.084	0.219	0.312	0.181	0.786
0.182	0.265	0.289	0.110	0.221	0.299	0.177	0.810
0.152	0.181	0.136	0.115	0.160	0.139	0.165	0.529
0.168	0.174	0.131	0.129	0.167	0.131	0.170	0.527
0.180	0.166	0.126	0.144	0.175	0.123	0.174	0.533
0.141	0.184	0.139	0.105	0.155	0.145	0.161	0.531
0.130	0.178	0.123	0.101	0.129	0.120	0.145	0.423
0.141	0.175	0.120	0.109	0.133	0.114	0.151	0.442
0.116	0.182	0.128	0.091	0.123	0.126	0.138	0.391
0.175	0.167	0.134	0.183	0.173	0.167	0.178	0.443
0.182	0.144	0.117	0.211	0.195	0.155	0.186	0.412
0.171	0.173	0.140	0.174	0.166	0.170	0.174	0.436
0.167	0.170	0.135	0.174	0.151	0.165	0.150	0.367

0.175	0.162	0.126	0.185	0.159	0.161	0.157	0.399
0.180	0.156	0.119	0.193	0.165	0.158	0.162	0.412
0.197	0.192	0.138	0.174	0.198	0.194	0.187	0.473
0.216	0.162	0.115	0.214	0.209	0.175	0.200	0.491
0.207	0.183	0.129	0.189	0.203	0.187	0.193	0.487
0.214	0.171	0.121	0.204	0.207	0.179	0.198	0.493
0.177	0.194	0.136	0.160	0.170	0.184	0.154	0.354
0.195	0.183	0.122	0.178	0.177	0.176	0.167	0.417
0.200	0.179	0.117	0.184	0.180	0.173	0.171	0.434
0.209	0.171	0.108	0.195	0.184	0.168	0.178	0.457
0.217	0.206	0.139	0.194	0.238	0.199	0.214	0.506
0.234	0.200	0.134	0.209	0.246	0.194	0.222	0.506
0.248	0.191	0.129	0.225	0.253	0.189	0.229	0.506
0.206	0.209	0.143	0.184	0.234	0.203	0.208	0.505
0.191	0.205	0.127	0.177	0.205	0.175	0.184	0.436
0.203	0.202	0.123	0.186	0.209	0.172	0.191	0.451
0.177	0.209	0.132	0.166	0.199	0.180	0.175	0.413
0.316	0.308	0.168	0.337	0.264	0.306	0.318	0.538
0.289	0.248	0.227	0.258	0.261	0.267	0.290	0.483
0.289	0.250	0.226	0.249	0.255	0.273	0.292	0.479
0.227	0.180	0.140	0.250	0.232	0.190	0.219	0.395
0.236	0.157	0.121	0.280	0.255	0.186	0.236	0.363
0.222	0.186	0.145	0.240	0.224	0.192	0.212	0.384
0.218	0.183	0.141	0.238	0.208	0.184	0.179	0.321
0.226	0.176	0.132	0.250	0.217	0.182	0.189	0.357
0.232	0.170	0.125	0.258	0.223	0.180	0.197	0.370
0.310	0.283	0.277	0.226	0.325	0.397	0.318	0.516
0.343	0.279	0.275	0.282	0.336	0.365	0.309	0.551
0.327	0.284	0.277	0.247	0.329	0.385	0.317	0.539
0.336	0.283	0.277	0.263	0.332	0.376	0.314	0.548
0.330	0.284	0.277	0.252	0.330	0.382	0.316	0.543
0.240	0.209	0.144	0.243	0.264	0.226	0.226	0.427
0.262	0.179	0.120	0.284	0.278	0.218	0.251	0.466
0.251	0.200	0.135	0.257	0.270	0.222	0.236	0.454
0.259	0.189	0.126	0.273	0.275	0.219	0.245	0.467
0.218	0.211	0.142	0.225	0.234	0.212	0.180	0.298
0.236	0.201	0.128	0.244	0.243	0.207	0.198	0.379
0.242	0.197	0.123	0.251	0.245	0.205	0.204	0.401
0.251	0.189	0.114	0.262	0.250	0.202	0.214	0.430
0.341	0.302	0.314	0.258	0.391	0.430	0.345	0.612
0.374	0.307	0.303	0.285	0.399	0.426	0.345	0.609
0.271	0.232	0.143	0.265	0.315	0.258	0.261	0.471
0.289	0.226	0.138	0.281	0.322	0.256	0.273	0.484
0.305	0.217	0.132	0.298	0.329	0.256	0.283	0.493
0.259	0.235	0.147	0.254	0.310	0.260	0.253	0.461
0.242	0.233	0.131	0.244	0.279	0.230	0.219	0.396
0.253	0.230	0.127	0.254	0.283	0.228	0.229	0.419
0.227	0.236	0.136	0.233	0.273	0.232	0.207	0.364

0.468	0.330	0.174	0.490	0.398	0.384	0.459	0.468
0.388	0.271	0.231	0.387	0.369	0.314	0.413	0.387
0.385	0.273	0.230	0.377	0.362	0.317	0.412	0.377
0.403	0.305	0.285	0.357	0.441	0.449	0.444	0.359
0.455	0.304	0.283	0.419	0.465	0.441	0.453	0.456
0.427	0.308	0.284	0.380	0.451	0.445	0.450	0.405
0.441	0.308	0.284	0.398	0.457	0.443	0.452	0.432
0.432	0.308	0.284	0.386	0.453	0.444	0.451	0.415
0.486	0.340	0.327	0.401	0.549	0.541	0.509	0.452
0.528	0.345	0.317	0.429	0.562	0.546	0.516	0.480
0.132	0.116	0.088	0.149	0.127	0.118	0.130	0.448
0.136	0.092	0.069	0.159	0.146	0.105	0.125	0.449
0.159	0.091	0.070	0.147	0.150	0.111	0.126	0.512
0.113	0.156	0.129	0.106	0.099	0.145	0.129	0.473
0.127	0.116	0.093	0.149	0.134	0.115	0.132	0.445
0.220	0.169	0.092	0.143	0.171	0.205	0.169	0.765
0.132	0.158	0.159	0.162	0.164	0.111	0.121	0.534
0.133	0.112	0.084	0.152	0.130	0.116	0.130	0.444
0.134	0.098	0.073	0.159	0.141	0.107	0.127	0.437
0.124	0.138	0.111	0.128	0.116	0.131	0.134	0.477
0.115	0.144	0.148	0.145	0.155	0.118	0.128	0.469
0.130	0.209	0.225	0.158	0.167	0.134	0.120	0.548
0.133	0.108	0.081	0.155	0.134	0.113	0.129	0.439
0.191	0.136	0.105	0.212	0.214	0.145	0.183	0.664
0.200	0.145	0.106	0.223	0.190	0.158	0.177	0.401
0.235	0.119	0.084	0.215	0.225	0.220	0.207	0.484
0.198	0.112	0.091	0.238	0.224	0.177	0.194	0.432
0.226	0.183	0.132	0.262	0.253	0.238	0.219	0.528
0.208	0.219	0.228	0.252	0.249	0.188	0.200	0.460
0.205	0.215	0.213	0.284	0.264	0.172	0.190	0.397
0.229	0.171	0.154	0.292	0.276	0.188	0.224	0.458
0.278	0.177	0.082	0.204	0.263	0.307	0.234	0.494
0.254	0.172	0.097	0.220	0.245	0.281	0.226	0.538
0.214	0.102	0.074	0.235	0.224	0.180	0.195	0.439
0.236	0.121	0.085	0.214	0.226	0.224	0.209	0.497
0.197	0.130	0.099	0.236	0.209	0.156	0.191	0.372
0.184	0.157	0.152	0.235	0.232	0.166	0.199	0.389
0.251	0.140	0.095	0.297	0.257	0.181	0.227	0.330
0.232	0.166	0.155	0.299	0.286	0.202	0.256	0.341
0.271	0.136	0.120	0.328	0.358	0.267	0.304	0.441
0.265	0.127	0.087	0.281	0.279	0.280	0.263	0.387
0.216	0.162	0.162	0.311	0.294	0.219	0.251	0.318
0.277	0.173	0.159	0.353	0.335	0.247	0.282	0.387
0.246	0.158	0.111	0.281	0.242	0.180	0.213	0.365
0.248	0.134	0.103	0.290	0.277	0.273	0.261	0.380
0.220	0.172	0.167	0.316	0.295	0.249	0.254	0.384
0.262	0.227	0.231	0.321	0.305	0.228	0.264	0.407
0.081	0.199	0.195	0.120	0.070	0.223	0.060	0.431

0.105	0.132	0.095	0.065	0.055	0.102	0.106	0.512
0.099	0.153	0.128	0.052	0.075	0.124	0.113	0.574
0.101	0.146	0.123	0.061	0.077	0.114	0.111	0.543
0.131	0.233	0.252	0.048	0.116	0.229	0.112	0.720
0.047	0.044	0.217	0.118	0.062	0.127	0.059	0.468
0.063	0.004	0.229	0.109	0.063	0.109	0.069	0.440
0.081	0.010	0.240	0.102	0.065	0.099	0.078	0.412
0.109	0.098	0.067	0.094	0.066	0.072	0.104	0.540
0.092	0.120	0.112	0.090	0.084	0.079	0.099	0.500
0.102	0.081	0.057	0.101	0.069	0.057	0.101	0.594
0.083	0.113	0.112	0.097	0.084	0.068	0.094	0.515
0.081	0.112	0.113	0.099	0.083	0.066	0.094	0.520
0.082	0.112	0.113	0.099	0.083	0.066	0.094	0.519
0.106	0.076	0.058	0.098	0.068	0.057	0.104	0.602
0.081	0.111	0.115	0.103	0.081	0.065	0.095	0.522
0.087	0.209	0.227	0.127	0.114	0.121	0.080	0.464
0.082	0.201	0.213	0.142	0.114	0.102	0.081	0.456
0.133	0.087	0.065	0.091	0.069	0.076	0.118	0.642
0.094	0.117	0.117	0.109	0.079	0.073	0.105	0.492
0.102	0.142	0.121	0.066	0.079	0.109	0.111	0.528
0.102	0.138	0.119	0.071	0.080	0.104	0.109	0.517
0.098	0.155	0.151	0.072	0.095	0.117	0.106	0.522
0.095	0.123	0.113	0.086	0.084	0.084	0.101	0.499
0.088	0.145	0.151	0.086	0.096	0.096	0.097	0.487
0.089	0.117	0.112	0.092	0.084	0.075	0.097	0.503
0.089	0.117	0.112	0.092	0.084	0.075	0.097	0.503
0.084	0.113	0.112	0.097	0.084	0.069	0.095	0.513
0.076	0.139	0.153	0.098	0.096	0.080	0.090	0.485
0.081	0.111	0.115	0.102	0.082	0.065	0.095	0.523
0.082	0.112	0.116	0.103	0.081	0.065	0.096	0.520
0.082	0.112	0.116	0.103	0.081	0.065	0.096	0.520
0.071	0.137	0.153	0.109	0.094	0.071	0.090	0.497
0.099	0.119	0.116	0.111	0.079	0.076	0.108	0.492
0.105	0.122	0.115	0.113	0.080	0.080	0.112	0.504
0.111	0.125	0.113	0.116	0.081	0.085	0.116	0.531
0.092	0.142	0.140	0.131	0.093	0.077	0.109	0.462
0.119	0.146	0.122	0.087	0.098	0.119	0.123	0.522
0.111	0.126	0.114	0.108	0.103	0.096	0.114	0.498
0.096	0.115	0.114	0.119	0.102	0.082	0.107	0.512
0.129	0.131	0.110	0.138	0.101	0.112	0.135	0.559
0.161	0.245	0.264	0.086	0.160	0.257	0.135	0.731
0.103	0.185	0.189	0.184	0.149	0.133	0.116	0.466
0.100	0.156	0.154	0.197	0.149	0.109	0.130	0.471
0.099	0.110	0.113	0.202	0.154	0.083	0.153	0.481
0.116	0.151	0.111	0.077	0.073	0.127	0.116	0.492
0.132	0.114	0.077	0.113	0.087	0.096	0.121	0.509
0.121	0.083	0.058	0.128	0.092	0.075	0.117	0.556
0.121	0.080	0.058	0.126	0.092	0.076	0.118	0.560

0.140	0.087	0.065	0.116	0.090	0.095	0.130	0.550
0.143	0.088	0.066	0.115	0.090	0.097	0.132	0.560
0.149	0.092	0.067	0.113	0.091	0.104	0.136	0.595
0.165	0.103	0.071	0.111	0.095	0.122	0.145	0.670
0.123	0.147	0.122	0.094	0.104	0.122	0.127	0.521
0.117	0.128	0.114	0.113	0.108	0.100	0.119	0.498
0.104	0.117	0.113	0.123	0.108	0.088	0.112	0.505
0.098	0.115	0.116	0.127	0.106	0.086	0.112	0.516
0.112	0.121	0.117	0.134	0.102	0.100	0.124	0.484
0.133	0.217	0.159	0.124	0.196	0.163	0.288	0.744
0.128	0.193	0.200	0.165	0.116	0.252	0.107	0.534
0.098	0.061	0.218	0.154	0.111	0.178	0.102	0.437
0.120	0.003	0.238	0.136	0.113	0.149	0.116	0.405
0.137	0.152	0.124	0.109	0.118	0.133	0.137	0.521
0.173	0.240	0.254	0.094	0.157	0.251	0.148	0.685
0.144	0.128	0.087	0.121	0.099	0.112	0.130	0.499
0.141	0.098	0.064	0.142	0.107	0.092	0.129	0.515
0.129	0.130	0.115	0.131	0.124	0.110	0.129	0.497
0.119	0.121	0.114	0.139	0.124	0.102	0.125	0.498
0.133	0.084	0.058	0.144	0.107	0.087	0.128	0.541
0.113	0.118	0.115	0.142	0.123	0.100	0.123	0.505
0.109	0.117	0.117	0.144	0.121	0.101	0.124	0.513
0.137	0.083	0.061	0.137	0.105	0.098	0.134	0.528
0.134	0.215	0.234	0.163	0.159	0.162	0.115	0.528
0.116	0.121	0.119	0.148	0.117	0.112	0.131	0.501
0.125	0.207	0.220	0.178	0.159	0.143	0.114	0.516
0.171	0.105	0.071	0.126	0.109	0.138	0.155	0.690
0.123	0.191	0.193	0.196	0.159	0.120	0.121	0.512
0.137	0.132	0.112	0.157	0.120	0.132	0.147	0.537
0.137	0.150	0.123	0.111	0.119	0.131	0.137	0.518
0.136	0.170	0.155	0.106	0.133	0.151	0.140	0.544
0.126	0.127	0.114	0.134	0.124	0.107	0.128	0.496
0.126	0.153	0.153	0.129	0.137	0.126	0.128	0.503
0.162	0.232	0.252	0.122	0.158	0.216	0.133	0.601
0.118	0.120	0.114	0.139	0.124	0.101	0.124	0.499
0.115	0.119	0.115	0.141	0.124	0.100	0.124	0.502
0.109	0.144	0.155	0.142	0.137	0.111	0.120	0.494
0.111	0.117	0.116	0.143	0.122	0.100	0.123	0.509
0.109	0.117	0.118	0.145	0.120	0.102	0.125	0.515
0.110	0.117	0.118	0.145	0.119	0.103	0.125	0.515
0.112	0.119	0.119	0.146	0.118	0.107	0.128	0.511
0.107	0.144	0.150	0.161	0.131	0.113	0.129	0.508
0.122	0.124	0.118	0.150	0.117	0.117	0.136	0.492
0.124	0.125	0.118	0.151	0.117	0.119	0.137	0.491
0.124	0.125	0.118	0.151	0.117	0.119	0.137	0.491
0.135	0.131	0.113	0.156	0.119	0.130	0.146	0.526
0.149	0.151	0.123	0.129	0.134	0.137	0.146	0.513
0.151	0.151	0.123	0.132	0.137	0.138	0.148	0.512

0.123	0.120	0.117	0.162	0.139	0.115	0.136	0.504
0.129	0.124	0.120	0.166	0.133	0.132	0.146	0.507
0.163	0.129	0.120	0.222	0.194	0.165	0.182	0.474
0.159	0.131	0.123	0.225	0.186	0.192	0.191	0.521
0.428	0.306	0.201	0.569	0.526	0.393	0.495	0.238
0.455	0.294	0.192	0.551	0.492	0.347	0.448	0.209
0.622	0.667	0.364	0.735	0.467	0.834	0.549	0.173
0.700	0.708	0.395	0.747	0.512	0.873	0.621	0.182
0.694	0.706	0.392	0.747	0.508	0.871	0.617	0.183
0.623	0.668	0.364	0.735	0.467	0.834	0.550	0.173
0.104	0.158	0.138	0.121	0.120	0.144	0.147	0.425
0.111	0.145	0.125	0.135	0.116	0.139	0.129	0.375
0.091	0.164	0.146	0.105	0.107	0.148	0.142	0.404
0.099	0.151	0.134	0.124	0.107	0.142	0.123	0.346
0.074	0.171	0.156	0.086	0.090	0.152	0.132	0.363
0.086	0.158	0.146	0.109	0.093	0.146	0.114	0.291
0.126	0.162	0.140	0.145	0.139	0.150	0.160	0.400
0.132	0.149	0.127	0.158	0.135	0.145	0.139	0.355
0.112	0.168	0.147	0.128	0.125	0.153	0.153	0.377
0.121	0.154	0.136	0.146	0.125	0.147	0.132	0.325
0.095	0.175	0.157	0.108	0.108	0.157	0.142	0.333
0.107	0.162	0.148	0.131	0.111	0.151	0.122	0.269
0.154	0.167	0.142	0.176	0.164	0.158	0.177	0.371
0.160	0.154	0.129	0.188	0.160	0.153	0.153	0.331
0.140	0.173	0.149	0.159	0.150	0.160	0.168	0.347
0.149	0.160	0.139	0.176	0.149	0.154	0.145	0.303
0.123	0.179	0.159	0.138	0.132	0.163	0.154	0.301
0.136	0.167	0.151	0.161	0.135	0.157	0.132	0.245
0.106	0.157	0.300	0.112	0.171	0.101	0.129	0.153
0.068	0.267	0.185	0.155	0.101	0.111	0.135	0.540
0.038	0.157	0.256	0.061	0.080	0.004	0.085	0.475
0.094	0.152	0.301	0.100	0.149	0.090	0.122	0.580
0.067	0.262	0.304	0.091	0.125	0.218	0.086	0.451
0.013	0.224	0.112	0.117	0.069	0.248	0.010	0.265
0.004	0.242	0.150	0.132	0.095	0.267	0.044	0.252
0.045	0.146	0.267	0.061	0.087	0.021	0.090	0.534
0.074	0.267	0.196	0.145	0.075	0.089	0.126	0.679
0.069	0.255	0.261	0.093	0.083	0.197	0.041	0.495
0.061	0.294	0.255	0.076	0.064	0.170	0.036	0.354
0.097	0.146	0.109	0.039	0.054	0.107	0.108	0.556
0.151	0.259	0.260	0.059	0.111	0.268	0.091	0.613
0.067	0.095	0.353	0.032	0.073	0.037	0.008	0.233
0.054	0.145	0.124	0.034	0.041	0.123	0.097	0.551
0.127	0.245	0.224	0.024	0.075	0.219	0.105	0.570
0.035	0.294	0.223	0.013	0.009	0.025	0.033	0.310
0.074	0.227	0.184	0.007	0.053	0.176	0.115	0.479
0.113	0.196	0.259	0.127	0.136	0.057	0.137	0.537
0.121	0.184	0.270	0.128	0.143	0.074	0.143	0.582

0.184	0.187	0.300	0.176	0.218	0.144	0.181	0.712
0.154	0.295	0.189	0.213	0.160	0.154	0.195	0.720
0.133	0.259	0.181	0.136	0.248	0.198	0.185	0.606
0.100	0.191	0.255	0.119	0.119	0.050	0.128	0.468
0.108	0.179	0.266	0.120	0.127	0.067	0.135	0.520
0.169	0.182	0.302	0.162	0.194	0.132	0.174	0.655
0.160	0.295	0.201	0.204	0.134	0.134	0.187	0.678
0.132	0.177	0.167	0.146	0.201	0.181	0.151	0.541
0.121	0.203	0.255	0.138	0.133	0.067	0.143	0.484
0.129	0.191	0.266	0.140	0.141	0.084	0.151	0.546
0.195	0.194	0.301	0.184	0.214	0.147	0.193	0.707
0.197	0.194	0.302	0.185	0.213	0.149	0.193	0.703
0.189	0.305	0.203	0.225	0.155	0.150	0.209	0.706
0.179	0.275	0.294	0.157	0.155	0.237	0.136	0.475
0.126	0.245	0.130	0.184	0.151	0.268	0.100	0.484
0.142	0.196	0.269	0.148	0.157	0.091	0.159	0.620
0.209	0.198	0.301	0.196	0.235	0.158	0.199	0.768
0.089	0.173	0.255	0.114	0.091	0.064	0.124	0.341
0.144	0.176	0.302	0.144	0.145	0.114	0.170	0.526
0.179	0.294	0.245	0.188	0.080	0.089	0.189	0.517
0.150	0.188	0.152	0.167	0.061	0.167	0.032	0.307
0.016	0.132	0.235	0.066	0.007	0.036	0.067	0.039
0.040	0.127	0.296	0.073	0.034	0.068	0.120	0.243
0.067	0.234	0.324	0.086	0.020	0.007	0.162	0.059
0.005	0.028	0.000	0.134	0.066	0.031	0.018	0.098
0.184	0.304	0.190	0.233	0.181	0.169	0.217	0.750
0.180	0.283	0.340	0.150	0.198	0.254	0.179	0.525
0.118	0.266	0.167	0.195	0.177	0.283	0.134	0.471
0.299	0.316	0.254	0.299	0.269	0.231	0.278	0.468
0.423	0.295	0.302	0.371	0.379	0.304	0.364	0.517
0.421	0.390	0.202	0.412	0.373	0.312	0.413	0.620
0.424	0.331	0.418	0.307	0.372	0.335	0.394	0.609
0.375	0.321	0.211	0.355	0.378	0.316	0.343	0.501
0.286	0.310	0.250	0.289	0.255	0.225	0.268	0.457
0.400	0.292	0.302	0.356	0.358	0.294	0.356	0.515
0.406	0.291	0.303	0.359	0.360	0.296	0.359	0.517
0.398	0.242	0.162	0.319	0.389	0.309	0.379	0.656
0.382	0.294	0.175	0.355	0.353	0.311	0.308	0.512
0.296	0.296	0.262	0.295	0.265	0.240	0.284	0.477
0.427	0.391	0.215	0.406	0.350	0.297	0.410	0.641
0.418	0.321	0.367	0.324	0.330	0.330	0.358	0.645
0.286	0.237	0.142	0.281	0.308	0.246	0.267	0.470
0.469	0.324	0.246	0.368	0.406	0.433	0.360	0.614
0.376	0.335	0.312	0.301	0.327	0.368	0.364	0.599
0.268	0.216	0.121	0.268	0.296	0.234	0.245	0.457
0.444	0.303	0.274	0.341	0.397	0.455	0.337	0.603
0.344	0.197	0.360	0.296	0.341	0.359	0.338	0.584
0.247	0.197	0.125	0.257	0.259	0.213	0.221	0.433

0.392	0.294	0.273	0.309	0.343	0.408	0.322	0.582
0.311	0.124	0.403	0.291	0.321	0.297	0.314	0.536
0.223	0.184	0.141	0.245	0.220	0.188	0.198	0.359
0.324	0.276	0.229	0.271	0.265	0.301	0.311	0.509
0.260	0.309	0.285	0.261	0.251	0.195	0.312	0.395
0.206	0.180	0.150	0.231	0.201	0.175	0.182	0.282
0.265	0.258	0.188	0.234	0.225	0.235	0.305	0.429
0.173	0.399	0.041	0.185	0.198	0.160	0.284	0.261
0.183	0.243	0.164	0.172	0.193	0.195	0.286	0.360
0.412	0.421	0.251	0.411	0.386	0.395	0.386	0.457
0.579	0.392	0.302	0.505	0.516	0.452	0.525	0.496
0.597	0.470	0.210	0.570	0.565	0.460	0.613	0.553
0.621	0.376	0.487	0.481	0.545	0.415	0.592	0.606
0.601	0.374	0.258	0.526	0.583	0.348	0.534	0.579
0.400	0.416	0.247	0.401	0.373	0.390	0.373	0.445
0.551	0.390	0.302	0.487	0.494	0.447	0.513	0.493
0.560	0.389	0.303	0.491	0.499	0.448	0.518	0.494
0.604	0.472	0.225	0.563	0.545	0.450	0.612	0.561
0.612	0.364	0.430	0.504	0.507	0.421	0.562	0.632
0.608	0.343	0.224	0.535	0.561	0.353	0.502	0.603
0.494	0.612	0.242	0.540	0.598	0.700	0.533	0.411
0.512	0.596	0.254	0.552	0.612	0.709	0.578	0.427
0.695	0.581	0.302	0.647	0.740	0.734	0.787	0.461
0.760	0.620	0.237	0.778	0.895	0.747	0.981	0.486
0.835	0.441	0.528	0.828	0.837	0.604	0.878	0.597
0.368	0.264	0.175	0.477	0.440	0.293	0.345	0.242
0.550	0.336	0.241	0.575	0.531	0.442	0.611	0.312
0.622	0.319	0.349	0.659	0.719	0.485	0.620	0.426
0.593	0.389	0.110	0.545	0.637	0.342	0.535	0.374
0.192	0.490	0.837	0.227	0.281	0.445	0.197	0.592
0.395	0.572	0.823	0.400	0.388	0.511	0.341	0.494
0.573	0.660	0.802	0.558	0.516	0.588	0.501	0.499
0.722	0.754	0.767	0.692	0.673	0.687	0.675	0.478
0.827	0.831	0.726	0.777	0.821	0.792	0.816	0.458
0.982	0.936	0.650	0.869	0.810	0.986	0.984	0.433
0.340	0.291	0.286	0.322	0.312	0.265	0.319	0.501
0.340	0.291	0.286	0.322	0.312	0.265	0.319	0.501
0.340	0.291	0.286	0.322	0.312	0.265	0.319	0.501
0.340	0.291	0.286	0.322	0.312	0.265	0.319	0.501
0.404	0.289	0.303	0.355	0.358	0.292	0.355	0.518
0.404	0.289	0.303	0.355	0.358	0.292	0.355	0.518
0.404	0.289	0.303	0.355	0.358	0.292	0.355	0.518
0.404	0.289	0.303	0.355	0.358	0.292	0.355	0.518
0.404	0.289	0.303	0.355	0.358	0.292	0.355	0.518
0.384	0.371	0.171	0.412	0.426	0.341	0.418	0.574
0.384	0.371	0.171	0.412	0.426	0.341	0.418	0.574
0.384	0.371	0.171	0.412	0.426	0.341	0.418	0.574

0.384	0.371	0.171	0.412	0.426	0.341	0.418	0.574
0.384	0.371	0.171	0.412	0.426	0.341	0.418	0.574
0.417	0.335	0.214	0.294	0.409	0.306	0.391	0.632
0.417	0.335	0.214	0.294	0.409	0.306	0.391	0.632
0.417	0.335	0.214	0.294	0.409	0.306	0.391	0.632
0.340	0.291	0.286	0.322	0.312	0.265	0.319	0.501
0.403	0.271	0.242	0.352	0.357	0.419	0.309	0.584
0.405	0.283	0.245	0.367	0.348	0.389	0.334	0.553
0.558	0.295	0.253	0.506	0.511	0.542	0.482	0.518
0.132	0.126	0.180	0.200	0.168	0.227	0.134	0.500
0.142	0.149	0.185	0.202	0.165	0.236	0.131	0.515
0.246	0.257	0.300	0.080	0.197	0.107	0.300	0.612
0.135	0.092	0.069	0.159	0.144	0.105	0.126	0.452
0.182	0.102	0.077	0.136	0.148	0.128	0.136	0.582
0.224	0.155	0.085	0.125	0.167	0.199	0.170	0.683
0.273	0.180	0.057	0.144	0.214	0.276	0.185	0.982
0.152	0.221	0.228	0.134	0.153	0.177	0.141	0.592
0.131	0.217	0.226	0.172	0.170	0.127	0.116	0.551
0.129	0.215	0.215	0.194	0.177	0.104	0.110	0.531
0.139	0.208	0.197	0.210	0.182	0.092	0.116	0.529
0.161	0.180	0.160	0.222	0.187	0.095	0.141	0.570
0.189	0.133	0.111	0.212	0.209	0.136	0.185	0.667
0.280	0.297	0.092	0.169	0.276	0.266	0.234	0.906
0.196	0.282	0.191	0.129	0.128	0.263	0.173	0.586
0.157	0.266	0.190	0.182	0.133	0.192	0.143	0.547
0.136	0.235	0.187	0.214	0.139	0.129	0.117	0.571
0.183	0.122	0.190	0.206	0.141	0.082	0.123	0.671
0.242	0.203	0.214	0.166	0.144	0.104	0.178	0.759
0.247	0.117	0.078	0.306	0.270	0.194	0.241	0.316