Final Year Project Report below:

Title : Length of Hydraulic Jump Using Artificial Neural Network

Author : Boon Chun Wui

Matric No. : 4580

has been read and certified by:

(Assoc. Prof. Dr. Nabil Bessaih)
Supervisor

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LENGTH OF HYDRAULIC JUMP USING ARTIFICIAL NEURAL NETWORK

BOON CHUN WUI

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Abstract

A relatively new tool, artificial neural network (ANN), was applied to simulate the relative length of hydraulic jump of the Natural stilling basin with horizontal floor (Basin I). A set of data which was obtain from previous research were used as the input and target to train the neural networks. The trained model was used to generate the relative length of jump (L/D_2). Different combinations of variables and parameters have been tested on 2 different networks (Feedforward Backpropagation and Recurrent) to find the best result by using Regression Analysis.

Coefficient of Regression, R^2 is the indicator of how good fit of the simulated L/D_2 compare to the recommended curve. Feedforward Backpropagation Networks (R^2=0.789) and Recurrent Networks (R^2=0.825) can produce the relative length of the jump (L/D_2) with better accuracy than the recommended curve (R^2=0.782).

Abstrak

Sebagai salah satu kaedah yang baru, " Artificial Neural Network (ANN)", digunakan untuk meramal panjang sesuatu lompatan hidraulik bagi suatu kawasan tadahan semula jadi dengan dasar yang mendatar ("Basin 1"). Satu set data yang diperolehi daripada penyelidikan dahulu telah digunakan sebagai input dan sasaran untuk kalibrasian rangkaian. Model kalibrasi yang digunakan untuk menghasilkan panjang lompatan (L/D_2). Kombinasi pembolehubah dan parameter yang berbeza telah diuji melalui pengunaan 2 rangkaian berbeza (Feedforward Backpropagation dan Recurrent) untuk mendapat keputusan yang terbaik dengan menggunakan "Regression Analysis".

"Coefficient of Regression", R^2 ialah penunjuk yang menunjukkan betapa sesuainya L/D_2 yang dihasilkan berbanding dengan lengkungan yang disyorkan. Rangkaian Feedforward Backpropagation (R^2=0.789) dan Rangkaian Recurrent (R^2=0.825) dapat menghasilkan panjang lompatan relatif dengan lebih tepat berbanding dengan lengkungan yang disyorkan (R^2=0.782).

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Topic 1

Introduction

1.1 Background

The Length of hydraulic jump is defined as the distance measured from the front face of the jump to a point on the surface immediately downstream from the roller. This length has been investigated experimentally by many hydraulicians. The best known and most widely accepted curve for length of jump is that of Bokhmeteff and Matzke (curve 1 in Figure 1.1) which was determined from experiment made at Columbia University at 1936.

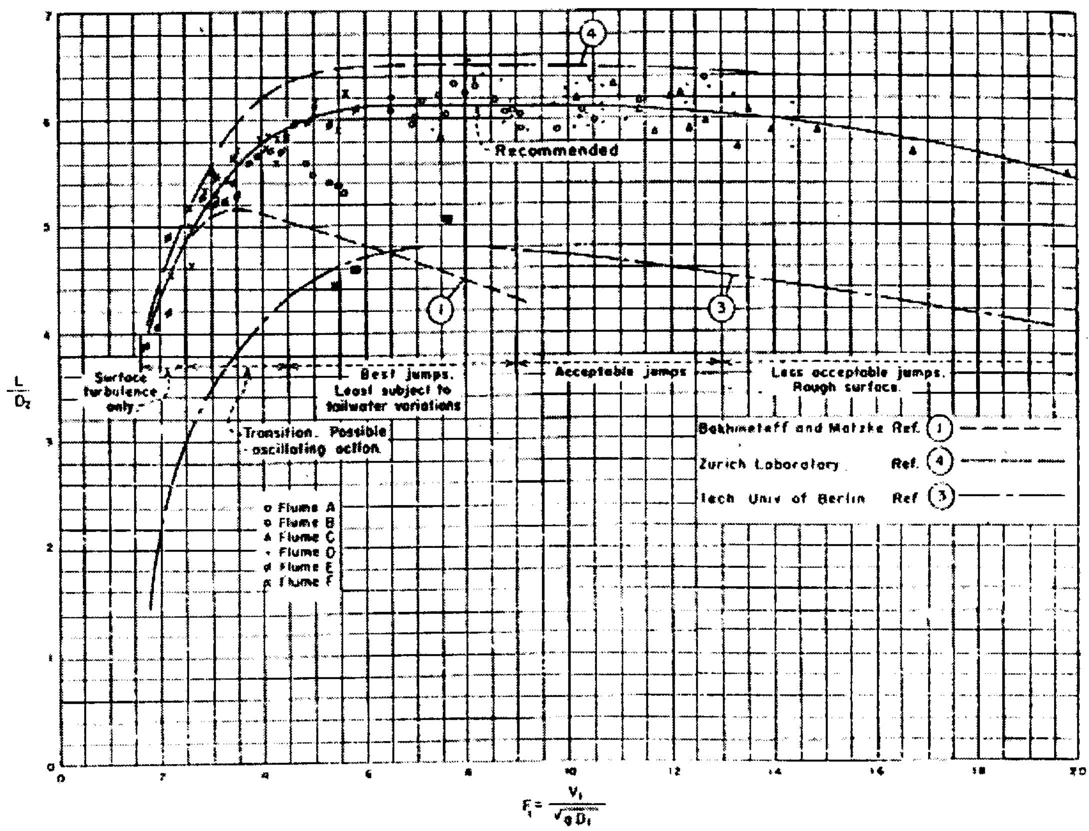


Figure 1.1 Length of jump in terms of D_2 (Basin 1)

A general investigation of the hydraulic jump on horizontal aprons (Basin 1) has been carried out. It was done in all six test flumes (A,B,C,D,E,F) which involved about 125 tests for discharges of 1 to 28 c.f.s. However, the length of jump obtained from the two smaller flumes, A and F, was consistently shorter than that observed for the larger flumes. It was found that results form Flume F, contained 3 points which are given the symbol ⊠ and fall short of the recommended curve as shown in the figure 1.1. Besides, a lot of the data (dots) are also tabulated away and quite far from the recommended line as shown in the figure

1.1. Therefore, other approach has to be used to improve the prediction of the length of jump.

1.2 Artificial Neural Networks (ANNs)

Attempts have been made to develop a technique that that can solve the problem of modeling. One such technique is known as neurocomputing, and the networks laid out with many parallel processing elements to do this neurocomputing are called artificial neural networks (ANNs). The ANNs try to mimic the functioning of the human brain, which contains billions of neurons and their interconnections. The human brain is able to rapidly recognize patterns and learn from past experiences.

The potential of ANNs as a modeling tool for stage and discharge relationship in developing a rating curve is presented in S.K.Jain and D. Chalisgaonkar (2000). Based on the efficiency of their research, this project tries to investigate capability of ANN to improve the curve for length of hydraulic jump.

1.3 Objective

The objective of this project is to produce an ANN to give the relative length of the jump (L/D_2) with better accuracy than the recommended curve shown in Figure 1.1.

Topic 2

Literature Review

2.1 Hydraulic jump

The hydraulic jump was first investigated experimentally by Bidone in 1818. This led Belanger (1828) to distinguish between subcritical and supercritical slopes, since he had observed that in steep channels hydraulic jump is frequently produced by a barrier in originally uniform flow. Thereafter, a lot of researches were made and the results were quoted by many writers. Outstanding contributors were Bresse (1860), Gibson (1913), Smetana (1934), Bakhmeteff and Matzke (1936), Nebbia (1940), Forster and Skrinde (1950) and others.

A hydraulic jump is formed whenever flow changes from supercritical flow to subcritical flow. In this transition from supercritical to subcritical flow, water surface rises abruptly, surface rollers are formed, intense mixing occurs, air is entrained, and a large amount of energy is usually dissipated. The Figure 2.1 as shown below show the hydraulic jump. The V_{in} is the velocity at initial depth, y_1 while the V_{out} is the velocity at sequent depth, y_2.

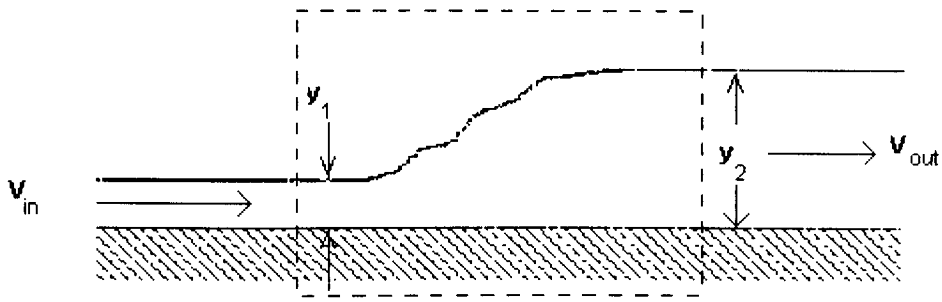


Figure 2.1 Hydraulic jump

The practical applications of hydraulic jump are many. It can be used to dissipate energy in water flowing over dams, weirs, and other hydraulic structures and thus prevent scouring. It also can be used to recover head or raise the water level on the downstream side of a measuring flume and thus maintain high water level in the channel for irrigation or water distribution systems. Sometime it is also used for mixing chemicals used for water purification and aerates water for city water supplies.

2.2 Types of jump

Hydraulic jumps on horizontal floor are of several distinct types. According to studies of the U.S Bureau of Reclamation, these types can be conveniently classified according to the Froude number F_1 of the coming flow as follows:

For $F_1 = 1$, the flow is critical, and hence no jump can form.

For $F_1 = 1$ to 1.7, the water surface shows undulations, and the jump is called an undular jump.

For $F_1 = 1.7$ to 2.5, a series of small rollers develop on the surface of the jump, but the downstream water surface remains smooth. The velocity throughout is fairly uniform, and the energy loss is low. This jump may called a weak jump.

For $F_1 = 2.5$ to 4.5, there is an oscillating jet entering the jump bottom to surface and back again with no periodicity. Each oscillation produces a large wave of irregular period which, very commonly in canals, can travel for miles doing unlimited damage to earth banks and ripraps. This jump may be called an oscillating jump.

For $F_1 = 4.5$ to 9.0, the downstream extremity of the surface roller and the point at which the high-velocity jet tends to leave the flow occur at practically the same vertical section, the action and position of this jump are least sensitive to variation in tailwater depth. The jump is well-balanced and the performance is at its best. The energy dissipation ranges from 45 to 70 %. This jump may be called a steady jump.

For F_1 = and larger, the high-velocity jet grabs intermittent slugs of water rolling down the front face of the jump, generating waves downstream, and a rough surface can prevail. The jump action is rough but effective since the energy dissipation may reach 85%. This jump may be called a strong jump.

2.3 Length of hydraulic jump

The length of the jump is the distance measured from the front face of the jump to a point on the surface immediately downstream from the roller.

The length of a jump is needed to select the apron length and height of the side walls of a stilling basin. To determine the length of a jump during laboratory investigations, it is difficult to mark the beginning and the end of a jump because of highly turbulent flow surface, formation of rollers and eddies, and air entrainment. In addition, the surface disturbances are of random nature, and the time-averaged quantities may not always give consistent results. The length of the roller may be taken to the point where the flow velocity at the top reverses and the jet continues.

The experimental data on length of jump can be plotted with the Froude number F against a dimensionless ratio L/D_1, L/D_2. The plot of F_1 vs L/D_1 is probably the best, for the resulting curve can best defined by the data. For practical purposes, however, the plot of F_1 vs L/D_2 is desirable, because the resulting curve shows regularity or a fairly flat portion for the range of well-established jumps. The Figure 2.2 shows the length of hydraulic jump.

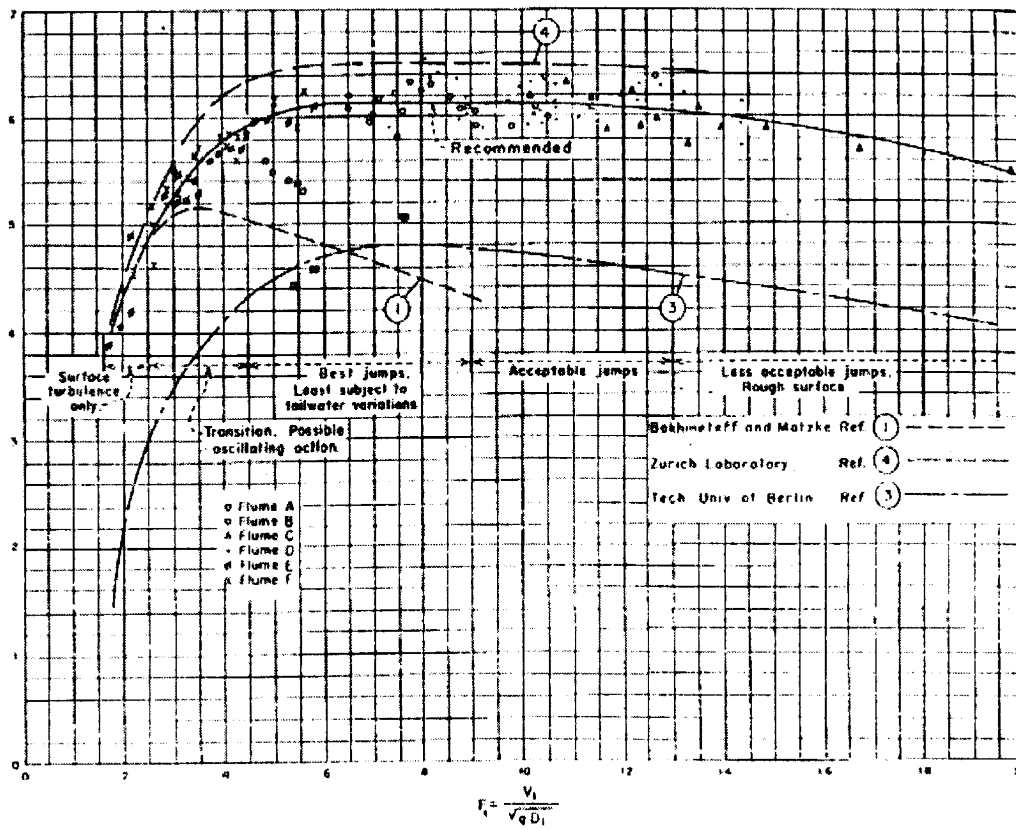


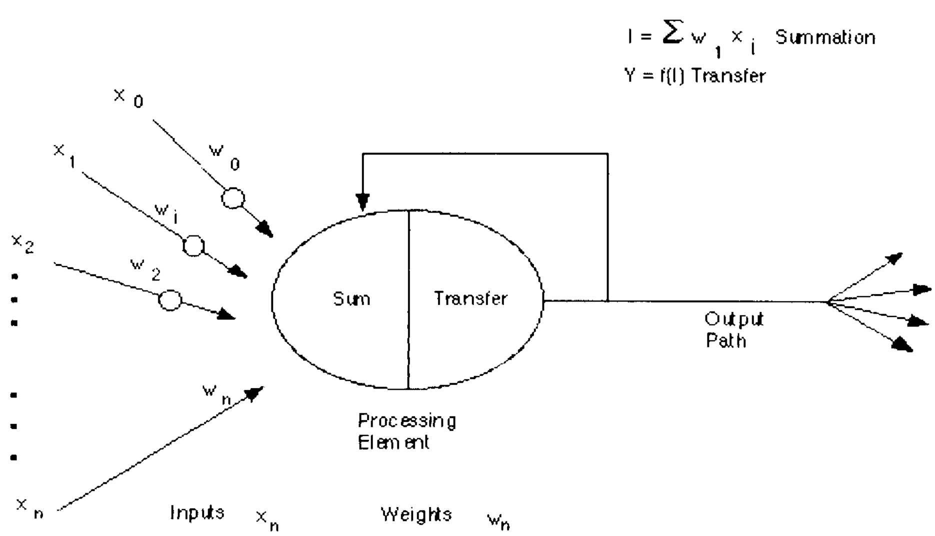
Figure 2.2 Length of jump in terms of sequent depth D_2 of jumps.

2.4 Artificial Neural Networks (ANN)

Artificial Neural Network is a system loosely modeled on the human brain. The field goes by many names, such as connectionism, parallel distributed processing, neuro-computing, natural intelligent systems, machine learning algorithms, and artificial neural networks. It is an attempt to simulate within specialized hardware or sophisticated software, the multiple layers of simple processing elements called neurons. Each neuron is linked to certain of its neighbors with varying coefficients of connectivity that represent the strengths of these connections. Learning is accomplished by adjusting these strengths to cause the overall network to output appropriate results.

2.5 The Artificial Neuron

The basic unit of neural networks, the artificial neurons, simulates the four basic functions of natural neurons. Artificial neurons are much simpler than the biological neuron; the figure below shows the basics of an artificial neuron.



2.3 Artificial Neuron

Note that various inputs to the network are represented by the mathematical symbol, x(n). Each of these inputs are multiplied by a connection weight, these weights are represented by w(n). In the simplest case, these products are simply summed, fed through a transfer function to generate a result, and then output.

Even though all artificial neural networks are constructed from this basic building block the fundamentals may vary in these building blocks and there are differences.

2.6 Layers

Biologically, neural networks are constructed in a three dimensional way from microscopic components. These neurons seem capable of nearly unrestricted interconnections. This is not true in any man-made network. Artificial neural networks are the simple clustering of the primitive artificial neurons. This clustering occurs by creating layers, which are then connected to one another. How these layers connect may also vary. Basically, all artificial neural networks have a similar structure of topology. Some of the neurons interface the real world to receive its inputs and other neurons provide the real world with the network's outputs. All the rest of the neurons are hidden form view.

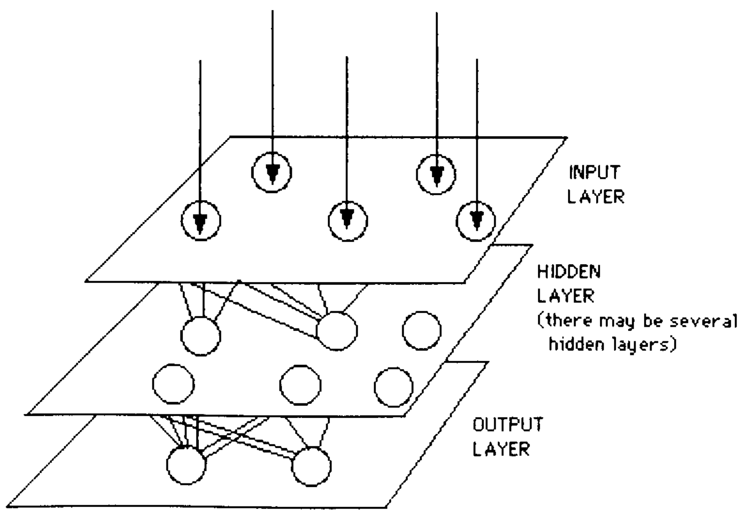


Figure 2.4 Different layers in Neuron Network

As the 2.4 above shows, the neurons are grouped into layers The input layer consist of neurons that receive input form the external environment. The output layer consists of neurons that communicate the output of the system to the user or external environment. There are usually a number of hidden !ayers between these two layers; the 2.4 above shows a simple structure with only one hidden layer.

When the input layer receives the input its neurons produce output, which becomes input to the other layers of the system. The process continues until a certain condition is satisfied or until the output layer is invoked and fires their output to the external environment.

To determine the number of hidden neurons the network should have to perform its best, one are often left out to the method trial and error. If increase the hidden number of neurons too much it will be over fitted that is the net will have problem to generalize. The training set of data will be memorized, making the network useless on new data sets.

2.7 Communication and types of connections

Neurons are connected via a network of paths carrying the output of one neuron as input to another neuron. These paths is normally unidirectional, there might however be a two-way connection between two neurons, because there may be an another path in reverse direction. A neuron receives input from many neurons, but produce a single output, which is communicated to other neurons.

The neuron in a layer may communicate with each other, or they may not have any connections. The neurons of one layer are always connected to the neurons of at least another layer.

2.8 Inter-layer connections

There are different types of connections used between layers, these connections between layers are called inter-layer connections.