Development of a new Fuzzy based Neural Network and its application in water flow control in canal

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I **KESHAV BHARDWAJ** hereby certify that the work which is being presented in the thesis entitled **Development of a new Fuzzy based Neural Network and its application in water flow control in canal** in partial fulfillment of requirements for the award of the Degree of Masters of Technology (MTECH.), submitted in the Department of Computer Science Engineering, Delhi Technological University is an authentic record of my own work under the supervision of **Asst. Prof. Nipun Bansal.**

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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Certified that **Keshav Bhardwaj (**2K22/AFI/010) has carried out their search work presented in this thesis entitled **"Development of a new Fuzzy based Neural Network and its application in water flow control in canal"** for the award of Master of Technology from Department of Computer Science Engineering, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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ABSTRACT

A novel method is being proposed in this thesis named Fuzzy Neural Network (FNN) and it used to predict the inlet to outlet key width's ratio of the PKW. In FNN, the fuzzy logic and Neural Network (NN) is used and combined for the benefits of both. Fuzzy logic is not like traditional binary system where it tells the results in 0 and 1, but the fuzzy logic deals with the degree of membership where it tell the degree of truth, just like the probability, the values of fuzzy logic lies between 0 and 1. NN is inspired by the biological neurons in humans, as biological neurons are interconnected and used to transmit information from one point to another in human brain, similarly the NN is the collection of well-connected neurons which are used to process the information in different ways, it can be used to predict the values in regressive manner, or can be used to classify in different categories and also can be used to recognize patterns and analyse those, in similar ways NN has multiple benefits. The FNN model combines the benefits of both and allows to predict the hydraulic behaviours of PKW with very high accuracy.

The dataset used in this thesis is not pre-defined, it is used collected experimentally from the laboratory. Different values were recorded for different ratios of inlet to outlet key width and then that dataset is used to test the FNN model for the prediction. The dataset includes crucial data that is essential for understanding the hydraulic performance of PKWs, including energy dissipation and discharge flow rates.

The popular metrics used for the validation of the model are RMSE and MAE. The RMSE of 0.0305 and MAE of 0.0222 showcased the FNN model's exceptional accuracy and reliability. As the values for these metrics fall in the ideal range , it depicts the accurate prediction of the model.

These findings tells that the relevance of FNN model can go beyond the predictions for PKW. It can be applied in the multiple fields of problem solving and pattern recognition. It can offer useful insights in different sectors of engineering.

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Keshav Bhardwaj

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LIST OF SYMBOLS, ABBREVIATIONS, AND NOMENCLATURE

S. NO.	Abbreviation	Explanation
1	FNN	Fuzzy Neural Network
2	PKW	Piano Key Weir
3	UK	United Kingdom
4	AI	Artificial Intelligence
5	MLPNN	Multilayer Perceptron Neural Network
6	ANFIS	Adaptive Neuro-fuzzy inference system
7	PSO	Particle Swarm Optimization
8	GA	Genetic Algorithm
9	MFO	Moth Flame Optimization
10	FA	Firefly Algorithm
11	GEP	Gene Expression Programming
12	SVR	Support Vector Regression
13	ANN	Artificial Neural Network
14	W	Width of channel of PKW
15	H_t	Total head of PKW
16	Q	Discharge flow of PKW
17	P	Height of PKW
18	E_L	Relative energy dissipation
19	W_i	Width of inlet key of PKW
20	W_o	Width of outlet key of PKW
21	ML	Machine Learning
22	e	Epsilon
23	δ	Partial Differentiation
24	α	Learning Rate
25	C_{DL}	Crest Developed Length of PKW
26	RMSE	Root Mean Square Error
27	MAE	Mean Absolute Error

CHAPTER 1: INTRODUCTION

Technology is advancing at a fast pace, and engineering problems are becoming more complicated. This calls for creative solutions that make use of artificial intelligence and machine learning. Within the field of hydraulic engineering, the safety and effectiveness of water management systems are greatly dependent on the optimisation of structures like spillways. Of them, the piano key weir (PKW) is one of the most innovative because of its improved energy dissipation and discharge efficiency. This thesis investigates the hydraulic behaviour of a particular variety, the Type A piano key weir, using a brand-new model built on a fuzzy neural network (FNN). Labyrinth weirs called piano key weirs are made to resemble a piano's keys from a plan perspective by maximising the length of the crest within a certain width. The hydraulic performance of the Type A PKW is improved by its alternating inlet and output keys. The nonlinear and dynamic nature of water flow makes optimising PKW design parameters—like the ratio of intake key width to output key width—a challenging undertaking, even with its benefits. Extensive physical modelling and empirical analysis are required in traditional approaches of optimising PKW designs, which may be resource- and time-intensive. NN is inspired by the biological neurons in humans, as biological neurons are interconnected and used to transmit information from one point to another in human brain, similarly the NN is the collection of well-connected neurons which are used to process the information in different ways, it can be used to predict the values in regressive manner, or can be used to classify in different categories and also can be used to recognize patterns and analyse those, in similar ways NN has multiple benefits. The FNN model combines the benefits of both and allows to predict the hydraulic behaviours of PKW with very high accuracy. Machine learning presents a possible substitute in this situation. The inherent uncertainties and nonlinearities of hydraulic systems may be efficiently handled by machine learning models, especially those that use fuzzy logic. Fuzzy logic allows for blending approximations and human-like reasoning into decision-making while neural networks excels at spotting patterns in vast sets of data. The aim of this study is to forecast the inlet to outlet key width ratio in PKW through the proposed FNN model. Utilizing real data from laboratory tests on PKW hydraulic activities, such as energy dissipation and discharge rates, the FNN model aims to offer accurate predictions. Handling unbalanced experimental data with the fuzzy part and utilizing NN for data analysis and prediction helps enhance predictive capabilities without extensive physical models. This not only reduces the need for detailed modelling but also boosts predictive accuracy under different hydraulic conditions. This change not only lessens the need for in-depth physical modelling but also improves the model's capacity for prediction and flexibility in response to various hydraulic circumstances. To ensure that the suggested FNN model accurately predicts the ideal design parameters, experimental data is compared to the model. This finding has implications that go beyond the particular use of PKWs. It illustrates how sophisticated machine learning methods may be used to solve challenging engineering challenges and data-drivingly optimise design parameters. The proposed model FNN provides a complete new approach for the prediction of hydraulic behaviours and it can be used later in multiple areas. This thesis is organised as follows: The next chapters provide a thorough analysis of the literature on PKWs and machine learning models, including the underlying theories and earlier studies in these fields. A thorough explanation of the experimental design and data gathering techniques utilised to compile the Type A PKWs' hydraulic behaviour data is then provided. After that, the architecture, training procedure, and specifics of the FNN model's implementation are provided. The performance of the FNN model in predicting the ideal ratio of inlet key width to outlet key width is covered in the results chapter and is backed up by a comparison with conventional techniques. The thesis ends with a review of the results, suggestions for further study, and possible uses for the suggested model.

The suggested approach and a real-world dataset were utilised to illustrate the contribution. An outline of the contribution would look something like this:

- A novel model known as the Fuzzy Neural Network (FNN) is put out; this approach has never been employed previously. By suggesting FNN, a research gap in hydraulic behaviour pattern prediction for piano key weirs will be addressed.
- The dataset used in this study is not pre-defined; rather, it was obtained experimentally and used to assess suggested approaches. Experimentation was used to obtain the dataset used in this paper. The study provides a unique dataset, which improves the validity of the data, in contrast to typical methods that rely on pre-defined datasets.

CHAPTER 2: LITERATURE REVIEW

The Piano Key Weir (PKW) is a kind of spillway used in dam water control. There are height and space constraints in dam engineering; under certain circumstances, PKW is a highly effective management solution and has a non-linear design. It looks like piano keys, as the name implies, with the keys arranged in a stepped pattern to provide the desired effect. PKW has much superior discharge capacity, energy dissipation, and material utilisation in comparison to conventional linear spillways. This is a fairly modern structure that controls and monitors water flows in dams. PKW is an improved version of labyrinth weirs, which were first studied and became well-known as a more efficient and cost-effective weir (Lempérière & Ouamane, 2003). PKW is being used in a growing number of recent projects in France to increase the water release capacity of the nation's existing suction dams (Laugier et al., 2017) and as a potential dam weir on derailed constructions in Vietnam (Khanh, 2017). Reference material summarising the present status of PKW technology has been compiled since 2011 thanks to substantial information exchanged via geographical conferences (Erpicum et al., 2011; Erpicum et al., 2013; and Erpicum et al., 2017). In the UK, Algeria, South Africa, France, Switzerland, Vietnam, India, Australia, and Sri Lanka, among other countries, more than 35 PKWs have been constructed successfully (Crookston et al. 2019). The Goulours Dam in France erected the first PKWs in 2006, while the Hazelmere Dam in South Africa installed them more recently. They greatly raised the likelihood of spillway and reservoir releases. Tzaneen Dam is in the process of implementing PKW (Deventer et al., 2015; Chemaly, 2017). Interestingly, in addition to the main emphasis on using PKWs as lateral weirs for runoff release, there has been a new interest in PKW implementations for interior weir applications (Karimi et al., 2018). In the last twenty years, Singh & Kumar (2021) and Abhash & Pandey (2020) have provided comprehensive overviews of PKW geometry and hydraulic behaviour. Geometric parameters that significantly affect head-discharge efficiency and energy dissipation are weir altitude (P), relative advancement L/W ratio (crest length), (Ht/P) ratio, alveolar width (Wi/Wo), and cycle number (N) for a constant channel width (where L = overall development length, W = weir's width, Ht is cumulative head over the weir, and P is weir altitude). The style of crest, overhang lengths, upstream apex walls, and elevating the crest with a parapet wall all have an additional impact on PKW behaviour (Anderson & Tullis, 2013). Scientific theories, case studies, and original research on PKW energy loss and labyrinths have all been the subject of several investigations (Ribeiro et al., 2011; Bieri et al., 2011; and Khanh, 2013). According to Silvestri et al. (2013), residual energy in PKWs with stepped chutes was lowest at the spillway toe and grew as the spillway length and release occurred. Al-Shukur et al.'s (2018) investigation on the relationship between the PKW slope and energy loss revealed that as the slope declined, so did the percentage of energy dissipation. PKW hydraulic behaviour has been defined using computational methods that leverage AI models including MLPNN, ANFIS, PSO, GA, MFO, and FA based on geometrical parameters (Zounemat-Kermani & Mahdavi-Meymand, 2019). For hydraulic jump aspects across a rocky bed, Karbasi & Azamathulla (2016) used GEP and compared its performance with traditional AI techniques, such as SVR and ANN. Numerous studies (Rashki et al., 2019; Ghasempour et al., 2021; Emadi et al., 2022; Pandey et al., 2020, Pandey et al., 2020, Singh et al., 2022, and Birbal et al., 2021) have attempted to determine the depth to which scour may occur along dikes, weirs, and piers that are partly submerged. To advance PKW technology, we therefore need more fresh concepts and competitors. et al. (2022) have released in-depth analyses of PKWs for power dissipation and discharge measurement, emphasising the need of carrying out exhaustive computational and experimental research to fully understand PKW hydraulic properties. Important information on energy loss in free streams under rectangular sharp-crested weirs has been presented by Amin et al. (2019). They emphasise the need of carefully designing hydraulic systems to maximise efficiency and minimise adverse impacts on the environment and structure. The purpose of this research is to investigate how PKW flow and energy loss are affected by the variation in the width of the air sacs at the entry and the exit (Wi/Wo). Only the effects of the Wi/Wo ratio on the discharge capacity, coefficient, and energy dissipation in PKWs have been investigated in previous research. On the other hand, there is still a dearth of information on this subject. Thus, with a primary emphasis on Type A PKWs, this experimental study was carried out to provide thorough insights into how the Wi/Wo ratio affects hydraulic efficiency and downstream energy dissipation. The research makes use of a fuzzy neural network to improve our comprehension of this crucial PKW performance and design characteristic. (Poonia et al., 2021) concentrate on the issue of resource allocation and inadequate disaster response, which exacerbates natural catastrophes. The goal is to address problems such as inadequate communication, delayed reactions, and corruption within the relevant organisations. The author suggests a methodical approach to disaster management based on blockchain technology. Data management is the first phase, which involves a blockchain architecture that guarantees the prompt exchange of reliable and traceable information pertaining to different elements of catastrophes. The second phase, automated assistance distribution, is based on smart contracts and aims to distribute help intelligently, avoid corruption in its usage, and automate the quick transmission of emergency relief. (Kumar et al., 2021) examine and comprehend the shift in harsh conditions in order to create solutions that are long-lasting and productive. The booklet lists India's drought- and flood-prone areas so that people may lower their risk and prepare ahead of time. The author provides a sound methodology for risk assessment and increasing the resilience of critical infrastructure. The suggested method builds methods that can endure climate-related problems after first evaluating the possible effect of severe weather on vital infrastructure. (Tiwari et al., 2024) investigate the connection between water quality and climate change by concentrating on the

Narmada basin's electrical conductivity. Water quality may be predicted using AI algorithms. In order to forecast the EC levels at the Sandia station in the Narmada basin, the author creates 10 AI models. The management of the area's drinking water, irrigation, and other purposes may be done using this knowledge. Out of all the models, Model 8 performs the best, with an R2 score of 0.889. The absence of a thorough examination of the combined dependency of drought duration and its impact across Indian river basins was addressed by (Poonia et al., 2021). The lack of research is impeding the creation of successful drought mitigation plans. The author proposes to use a bivariate copula-based approach to represent the joint dependency structure of drought features. The author wants to pinpoint trends and areas in India where severe and protracted drought episodes occur. The goal of (Poonia et al., 2021) is to close the knowledge gap on the uncertainty of climate model forecasts and scenarios while evaluating CWR and CIR in the Eastern Himalayan area, particularly in Sikkim. A detailed examination of the effects of climate change on a Sikkim agricultural field is given by Das et al. (2020), with a focus on rice, wheat, and maize. They forecast crop yields under various emission scenarios and GCMs using calibrated AquaCrop simulations based on historical data. They also use possibility theory in their analysis of uncertainty using GCMs. (Jamal et al., 2024) seek to address the issue of land loss in Indian states such as West Bengal. Various materials and techniques are used in the current riverbank protection systems to assess the size and efficacy of stones under various temporal fluctuations. The author points out that not enough study has been done to determine which stone is best for preventing bank collapse. The goal of Poonia et al. (2020)'s physical model approach to assessing a riverbank's response to varying stone sizes is to meet the need for rainfall-runoff modelling in the Hoshangabad Narmada River watershed of Madhya Pradesh. Since floods often occur in this region, accurate runoff estimate is essential for effective flood control. The author proposes simulating water flow in the Hoshangabad region using ANN-based models. Various metrics are used to assess the models' performance, including their accuracy, degree of improvement over the original data, and degree of closeness to the actual data. The goal of Kantharia et al.'s (2024) study is to determine how successfully soil and precipitation data may be used to forecast the daily flow of water out of the Damanganga River. The aim of the project is to close this gap by developing a customised ANFIS model for the Damanganga basin that incorporates input variables for soil moisture at different depths. The R2 and the NSE are the two statistics we use to gauge how well the model fits the data. The Urban Heat Island (UHI) phenomenon and its effects are becoming more well known, but there aren't many comprehensive studies on the subject, particularly in areas with hot, semiarid climates like India, as Sharma et al. (2023) found. By using remote sensing and geospatial analytic techniques to investigate how surface temperatures and UHI effects change throughout the course of the year, particularly taking into account the impact of land use and water body cooling, the author's model aims to close the existing knowledge gaps on UHI impacts. In areas like South Gujarat, India, precise rainfall forecast models are essential, as Baudhanwala et al. (2024) point out. The region is seeing increasingly severe rainstorms, which has an adverse effect on the local water supply, agriculture, infrastructure, and quality of life. Four different machine learning approaches are used by the author: RF (Random Forest), DT (Decision Tree), MLR (Multiple Linear Regression), and SVR (Support Vector Regression). Based on the study, the maximum discharge coefficient indicates that the hydraulic efficiency is achieved at a width ratio between 1.25 and 1.30. Energy dissipation rises and returns become less significant beyond this range. In the end, improving civil engineering and water resource management techniques, this study underscores the usefulness of fuzzy neural networks in hydraulic engineering and provides insightful information for PKW design.

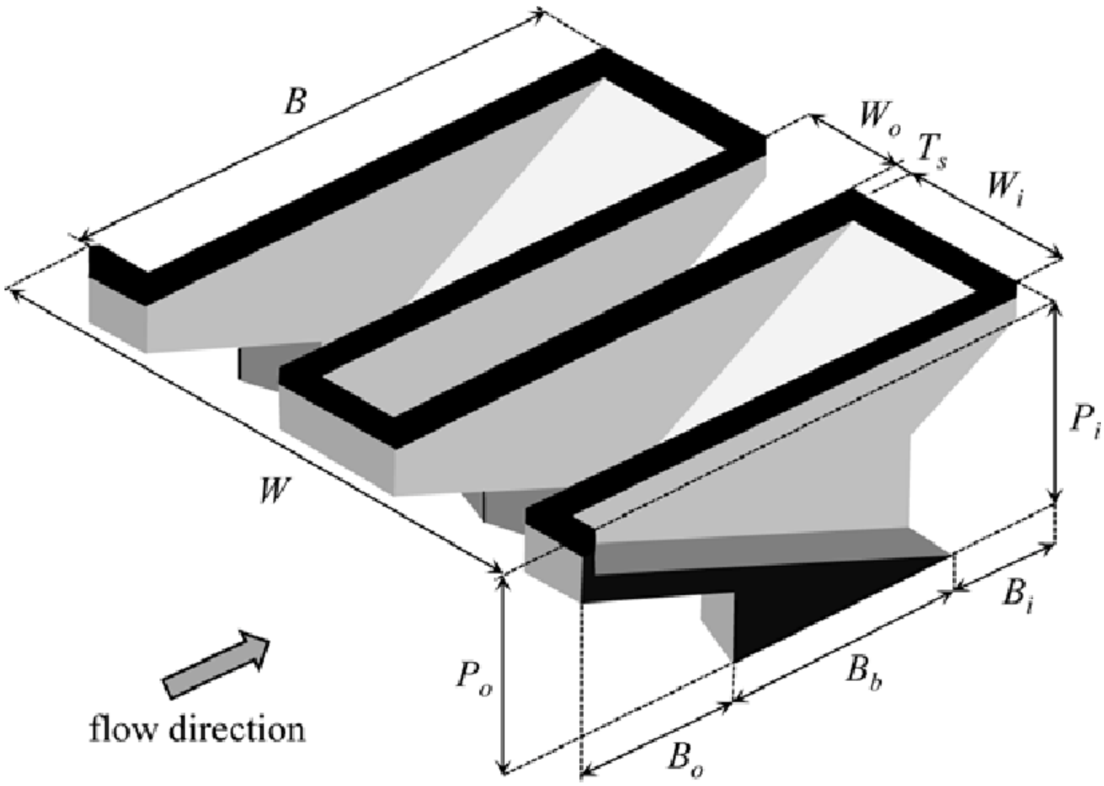


Figure 1 Schematic experimental setup plan view

CHAPTER 3: EXPERIMENTAL SETUP AND DATASET

The width ratio data from the PKW that Singh & Kumar provided in their 2023 publication is used in this research. A horizontal flume with a rectangular cross-section of 0.516 metres in width, 0.6 metres in height, and 10 metres in length was used for a variety of laboratory testing. The discharge flow rate was measured with an accuracy limit of ±0.2% using an electromagnetic flowmeter. A metal monitor gate was installed on the flume headbox to increase the upstream approach flow's homogeneity. The average flow velocity was determined using an Acoustic Doppler Velocimeter (ADV). The models, as seen in Fig. 1, were constructed from 8 mm-thick transparent acrylic sheets and assembled using chloroform. A thorough explanation of the geometrical characteristics and data collected throughout the investigation may be found in Table 1.

Table 1 indicates that W_i is the width of the input key and W_o is the width of the outlet key. Whereas W is the width of the PKW channel, H_t is the total head, Q is the discharge flow of PKW, P is the height of PKW, E_L is the relative energy dissipation, and E_1 or E_2 is the energy dissipation at a specific section.

S. No.	$\frac{W_i}{W_o}$	$\frac{L}{W}$	S_i=S_o	$H_t(m)$	$Q(L/s)$	B_i/P= B_o/P	Range of (E_L/E_1)	Range of (E_2/E_1)	No. of readings
1	1.00	5	1.08	0.0300-0.0971	10.17-50.26	0.69	0.8093-0.1930	0.1907-0.8096	18
2	1.10	5	1.08	0.0304-0.0986	10.14-50.26	0.69	0.7860-0.1785	0.2140-0.8214	18
3	1.20	5	1.08	0.0307-0.0989	10.19-50.07	0.69	0.7700-0.1731	0.2300-0.8268	18
4	1.25	5	1.08	0.0317-0.1011	10.28-50.18	0.69	0.7533-0.1734	0.2467-0.8265	18
5	1.30	5	1.08	0.0322-0.1004	10.09-50.00	0.69	0.7356-0.1655	0.2644-0.8344	18
6	1.35	5	1.08	0.0310-0.0891	10.16-50.07	0.69	0.7297-0.1501	0.2703-0.8498	18
7	1.40	5	1.08	0.0303-0.0985	10.19-50.13	0.69	0.7031-0.1435	0.2969-0.8564	18
8	1.50	5	1.08	0.0310-0.0992	10.15-50.45	0.69	0.6822-0.1411	0.3118-0.8588	18
9	2.00	5	1.08	0.0313-0.0995	10.29-49.82	0.69	0.6518-0.1342	0.3482-0.8657	18

Table 1: Sample of data collected in the present study

CHAPTER 4: METHODOLOGY

4.1 Fuzzy Logic

Fuzzy logic is a mathematical framework that allows for thinking about erroneous or imprecise information. Unlike standard binary logic, which requires variables to be either 0 or 1, true or false, fuzzy logic incorporates the notion of partial truth, where variables may have values between 0 and 1. This delicate approach to logic is particularly useful in replicating complex systems where uncertainty, ambiguity, and vagueness are common. The idea of fuzzy logic was introduced by Lotfi A. Zadeh in the 1960s. Zadeh recognized that traditional binary logic was insufficient for dealing with the intricacy of real-world situations where information is often erroneous or incomplete. He presented fuzzy logic as a strategy to bridge the gap between human thinking and the rigid binary logic applied in computers. At the heart of fuzzy logic is the idea of a fuzzy set. A fuzzy set is a collection of components with a continuum of degrees of membership. Each element in a fuzzy set is linked with a membership value, which ranges from 0 to 1. This membership value represents the degree to which the element belongs to the set. For example, in a fuzzy set representing "tall people," a person who is 6 feet tall may have a membership value of 0.8, but a person who is 5 feet 8 inches tall would have a membership value of 0.5. This enables for a more flexible and accurate depiction of categories. Fuzzy logic also encompasses the use of linguistic variables, which are variables expressed in terms of words rather than numbers. These linguistic variables are associated with fuzzy sets and may be altered using a series of rules known as fuzzy if-then rules. For instance, in a temperature management system, the language variables may be "cold," "warm," and "hot," and the rules may be stated as: "If the temperature is cold, then increase the heater output," or "If the temperature is hot, then decrease the heater output." These rules allow the machine to make decisions based on erroneous input data. One of the primary aspects of fuzzy logic is its capacity to handle uncertainty and ambiguity. This is done by the use of membership functions, which explain how each point in the input space is transformed to a membership value between 0 and 1. These functions may adopt different shapes, such as triangular, trapezoidal, or Gaussian, depending on the unique application. The choice of membership function effects the performance of the fuzzy logic system and is generally decided by trial and expert knowledge. Fuzzy logic systems usually consist of four essential components: fuzzification, rule basis, inference engine, and defuzzification.

1. Fuzzification: This step comprises changing crisp input values into fuzzy values employing membership functions. For example, if the input temperature is 18°C, it may be fuzzified into a degree of membership for the fuzzy sets "cool" and "warm."

2. Rule Base: The rule base contains a set of fuzzy if-then rules that construct the relationships between fuzzy input and output variables. These recommendations are produced from expert knowledge or empirical evidence.

3. Inference Engine: The inference engine analyses the fuzzy input values according to the rules in the rule base to produce fuzzy output values. This includes assessing the degree of match between the fuzzy inputs and the criteria of each rule.

4. Defuzzification: The final step is to turn the fuzzy output values back into crisp ones. This is done utilizing many defuzzification procedures, such as the centroid method, which calculates the centre of gravity of the aggregated fuzzy set.

To explain the usage of fuzzy logic, use the example of a fuzzy logic-based washing machine. Traditional washing machines work using predetermined cycles and settings, which may not always be best for all sorts of laundry.

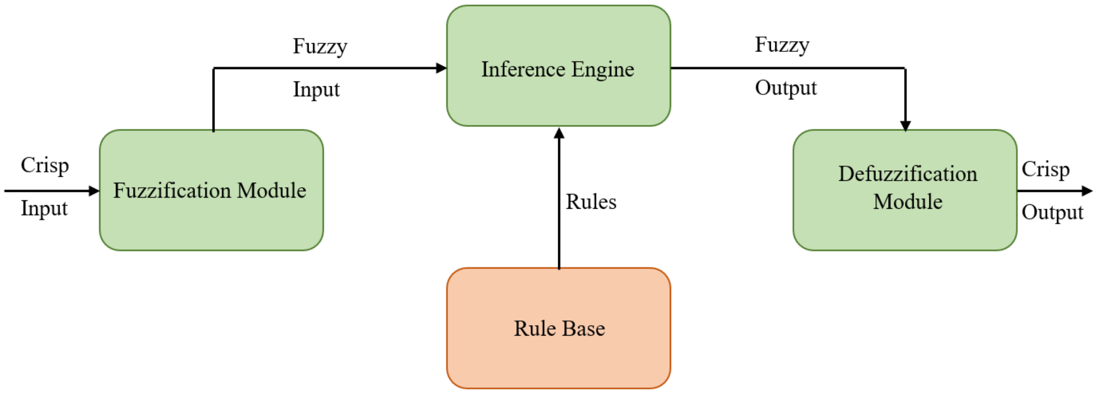


Figure 2 Fuzzy logic

A fuzzy logic-based washing machine, on the other hand, may dynamically adjust its washing cycle depending on the sort and amount of laundry, dirtiness degree, and fabric type. In this system, sensors monitor numerous factors such as the load size, water temperature, and dirt level. These measurements are then fuzzified into language variables such as "small," "medium," or "large" for load size, and "low," "medium," or "high" for dirt level. The fuzzy if-then rules might comprise statements like: "If the load size is small and the dirt level is low, then set a short wash cycle," or "If the load size is large and the dirt level is high, then set a long wash cycle with a high agitation level." The inference engine understands these rules and combines them to yield fuzzy outputs, which are then defuzzied to establish the exact parameters for the wash cycle, such as the duration, water level, and agitation intensity. This results in a more efficient and effective washing technique that is customized to the particular needs of each load of laundry. Another example of fuzzy logic in action is in the subject of driverless automobiles. Self-driving cars need to make real-time decisions based on a range of inputs, such as speed, distance to other vehicles, road conditions, and traffic signals.

Fuzzy logic assists these autos to handle the inherent ambiguity and variability of the driving environment. For instance, the automobile's control system may apply fuzzy logic to compute the ideal speed based on the distance to the vehicle ahead and the road conditions. The laws might include: "If the distance to the car ahead is close and the road is wet, then reduce speed significantly," or "If the distance to the car ahead is far and the road is dry, then maintain current speed." The fuzzy logic system examines these inputs and generates a result that balances safety and efficiency, ensuring that the vehicle changes effortlessly to changing scenarios. This capability is crucial for delivering the high degree of reliability and safety required for autonomous driving. Fuzzy logic has also found applications in various other areas, including climate control systems, financial modelling, medical diagnostics, and robotics. In climate control systems, fuzzy logic may enhance heating and cooling by considering parameters such as room temperature, humidity, and occupancy levels. Financial models apply fuzzy logic to handle the ambiguity and vagueness in market movements and investment decisions. In medical diagnosis, fuzzy logic assists in establishing conclusions based on faulty symptoms and patient history, boosting the accuracy of diagnoses and treatment regimens. In robotics, fuzzy logic helps robots to execute hard tasks and interact with their environment in a more human-like fashion. The versatility of fuzzy logic rests in its potential to accommodate human-like reasoning and deal with ambiguity, making it a valuable tool in a wide range of applications. Its combination with other computing technologies, such as neural networks, further improves its potential. Fuzzy Neural Networks (FNN), for instance, combine the approximate reasoning of fuzzy logic with the learning capabilities of neural networks, providing excellent models for sophisticated problem-solving. These hybrid systems are particularly useful in cases when accurate mathematical models are difficult to develop or when the system must adapt to changing conditions.

4.2 Neural Network

Neural networks, a subtype of machine learning, have emerged as a pioneering technology in the realm of artificial intelligence. Inspired by the human brain's structure and function, neural networks consist of connected nodes, or neurons, that interact collectively to solve challenging problems. This section delves at the design, functioning, and different forms of neural networks, presenting a complete understanding of this remarkable technology. At the hub of a neural network is the neuron, a computer unit that accepts inputs and provides an output. Each neuron receives one or more inputs, which are later blended using a weighted sum. This sum is delivered via an activation function to form the neuron's output. The activation function introduces non-linearity into the network, enabling it to model intricate interactions between inputs and outputs. Common activation functions include the sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU). A neural network normally consists of three layers: the input layer, hidden layers, and the output layer. The input layer receives the original data, which is later transmitted by one or more hidden layers. These hidden layers are where most of the computation occurs, as they convert the inputs into meaningful patterns. Finally, the output layer produces the network's predictions or classifications based on the processed data. Training a neural network requires adjusting the weights of the connections between neurons to lower the inaccuracy in the network's predictions. This technique is carried out using an algorithm called backpropagation, which is a supervised learning approach. During backpropagation, the network's output is compared to the actual target values, and the error is communicated backward through the network. The weights are then updated using a gradient descent approach, which minimizes the error by modifying the weights in the direction of the steepest decline in error. One of the important components of neural networks is their potential to learn from data. This learning capability is what enables neural networks to accomplish tasks such as image recognition, natural language processing, and game playing with astounding accuracy. The training technique frequently entails feeding vast amounts of labelled data into the network, allowing it to detect patterns and make predictions based on new, unknown data.

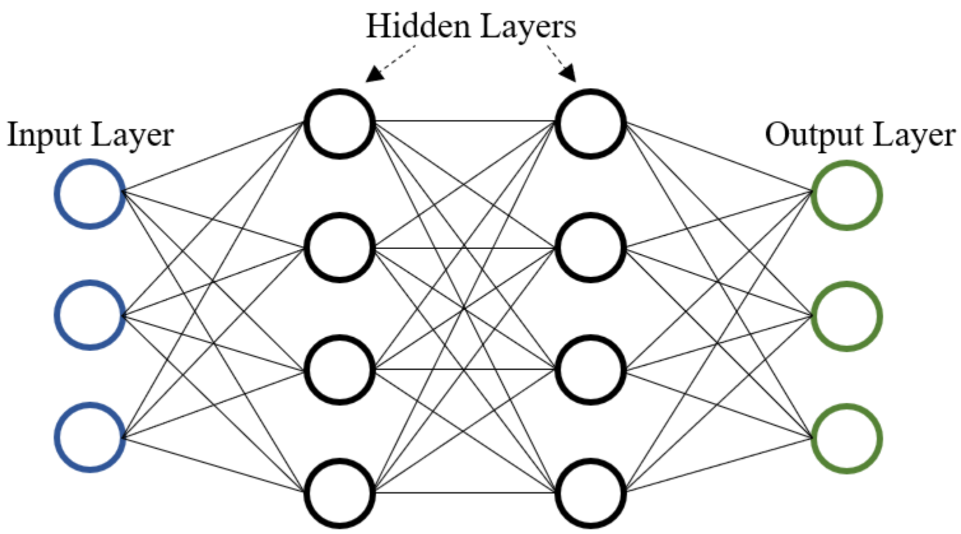


Figure 3 Neural Network

There are numerous sorts of neural networks, each created for particular activities and goals. The most basic form is the feedforward neural network, where the data goes in one manner from the input layer to the output layer. These networks are well-suited for applications such as picture classification and regression analysis. Convolutional neural networks (CNNs) are a special form of feedforward network built for processing grid-like input, such as photos. CNNs utilize convolutional layers, which apply filters to the input data to distinguish properties such as edges, textures, and shapes. These features are then applied to classify the input data. CNNs have been particularly successful in picture recognition tasks, reaching state-of-the-art performance in various benchmarks. Recurrent neural networks (RNNs) are meant to handle sequential data, such as time series or spoken language. Unlike feedforward networks, RNNs have connections that loop back on themselves, allowing them to preserve a recall of earlier inputs. This makes RNNs well-suited for applications such as language modelling, speech recognition, and machine translation. However, conventional RNNs suffer from issues such as vanishing gradients, which may make training difficult. Long short-term memory (LSTM) networks and gated recurrent units (GRUs) are variations of RNNs that alleviate these challenges by integrating gating mechanisms to regulate the flow of information. Another notable kind of neural network is the generative adversarial network (GAN), which consists of two networks: a generator and a discriminator. The generator generates synthetic data samples, while the discriminator attempts to discern between genuine and false samples. The two networks are trained simultaneously in a process that may be likened to a game, with the generator growing its ability to create realistic samples and the discriminator raising its capacity to recognize fakes. GANs have been used to make realistic graphics, create art, and even develop innovative pharmaceutical molecules. Autoencoders are another sort of neural network employed for unsupervised learning applications such as dimensionality reduction and anomaly detection. An autoencoder consists of an encoder that compresses the input data into a lower-dimensional representation and a decoder that reconstructs the original data from this representation. By training the network to minimize the reconstruction error, autoencoders may learn significant features that describe the fundamental structure of the data. Despite their incredible capacities, neural networks are not without restrictions. One of the primary difficulties is the necessity for enormous amounts of labeled data for training. Collecting and categorizing such data may be time-consuming and expensive. Additionally, neural networks may be computationally demanding, necessitating extensive processing power and memory, especially for deep networks with many layers. Another challenge is the interpretability of neural networks. Unlike standard machine learning models, which often expose apparent and intelligible linkages between inputs and outputs, neural networks behave as "black boxes," making it hard to fathom how they arrive at their predictions. This lack of transparency may be detrimental in areas where explain ability is crucial, such as in healthcare or finance. Overfitting is another key issue in neural networks. When a network is too intricate or trained for too long on a restricted dataset, it may learn to recall the training data rather than generalize from it. This results in poor performance on new, unexplored data. Regularization approaches such as dropout, where randomly picked neurons are removed during training, and early stopping, where training is halted anytime performance on a validation set starts to deteriorate, are widely applied to minimize overfitting. Recent achievements in neural network research have focused on overcoming these difficulties and enhancing the capabilities of neural networks. Transfer learning, where a pre-trained network is fine-tuned on a new job, has emerged as a potential approach for utilizing existing knowledge and minimizing the requirement for massive datasets. Additionally, improvements in technology, such as the advent of specialized processors like GPUs and TPUs, have considerably sped neural network training and inference. Neural networks have also experienced considerable improvements in architectural design. Techniques such as batch normalization, which normalizes the inputs to each layer, and residual connections, which enable gradients to flow more freely across deep networks, have facilitated the training of significantly deeper and more powerful networks. Architectures like the Transformer, which focuses on self-attention processes to handle sequential input, have revolutionized natural language processing, resulting to the introduction of models such as BERT and GPT that attain outstanding performance on multiple language tasks.

4.3 The FNN Model

The fuzzification layer, the production layer, the hidden layers of the neural network, and the output layer comprise the four main layers of the suggested model. Because each layer is carefully crafted to take use of the advantages of both fuzzy logic and neural networks, the model is able to properly manage the inherent uncertainties and nonlinearities in hydraulic data. The input variables are converted into fuzzy sets at the fuzzification layer, which is the first layer of the model. Membership functions, which measure the extent to which each input belongs to a fuzzy set, are used to accomplish this transition. Depending on the kind of input data and the needs of the particular application, membership functions might be triangular, trapezoidal, or Gaussian. The membership functions used in this investigation are shown in Figure 4.

$$A_1 = \begin{cases} 1 & x \leq b_1 \\ \frac{x-a_1}{b_1-a_1} & b_1 < x < a_1 \\ 0 & x \geq a_1 \end{cases} \qquad A_2 = \begin{cases} 1 - \frac{(x-a_2)}{0.5*b_2} & |x - a_2| < 0.5 * b_2 \\ 0 & |x - a_2| \geq 0.5 * b_2 \end{cases}$$

$$A_3 = \begin{cases} 0 & x \leq a_3 \\ \frac{x-a_3}{b_3-a_3} & a_3 < x < b_3 \\ 1 & x \geq b_3 \end{cases}$$

Figure 4 Trapezoidal membership function

The production layer comes after the fuzzification layer and uses the fuzzified inputs to create fuzzy rules. The links between the input variables and the intended result are captured in these rules, which are based on expert knowledge and empirical observations. The production layer efficiently converts the fuzzy sets received as input into a rule base that controls the behaviour of the model. The production layer's fuzzy outputs are used as inputs by the neural network's hidden layers. These hidden layers are made up of several linked neurons, each of which performs an activation function after a weighted sum of its inputs. The model's ability to learn and generalise from the data is dependent on important design characteristics, including the architecture and number of hidden layers. To reduce the inaccuracy in the model's predictions, the weights of the connections between neurons are adjusted throughout the training phase. The backpropagation algorithm, a supervised learning method, is used to do this. Iteratively updating the weights based on the gradient of the loss function with respect to the weights is how this is done. The mean squared error between the actual and predicted values, which measures the difference between the model's predictions and the actual results, is often used as the loss function in this situation. The output layer, the last layer of the neural network, has only one neuron in it. The final prediction of the model is generated by this neuron by averaging the outputs from the last hidden layer. An important factor in the construction of effective hydraulic structures is the output, which shows the expected ideal ratio of the PKW's intake to outlet key widths. Since the output layer's objective is to provide a continuous value rather than a categorical label, a linear activation function is usually used. The model's ability to provide an accurate and comprehensible prediction is ensured by its single output neuron, which allows for easy validation by comparison with actual data.

CHAPTER 5: RESULTS

The experimental dataset is gathered, pre-processed, and fed into the FNN model. Data validation is accomplished by dividing the data into two groups: training and testing data. The two datasets are split 4:1 and selected at random. By adjusting the hyperparameters, the model is trained using the training data. The testing data is then used to verify the model. This approach makes it possible to evaluate the model's performance in a balanced manner.

Data Set	H_t **v/s** Q	H_t/P **v/s** C_{DL}	H_t/P **v/s** E_L	H_t/P **v/s** E_2/E_1	**Average**
RMSE	0.0582	0.0206	0.0216	0.0216	0.0305
MAE	0.0383	0.0150	0.0183	0.0174	0.0222

Table 2 Performance evaluation of predicted parameters by FNN model for training and testing dataset

RMSE and MAE are the metrics used to assess the model. The average error, which provides a clear indication of the model's performance, is what MAE informs us about. Significant mistakes are given greater weight by RMSE, making it a more sensitive metric for assessing how accurate the forecasts are. RMSE and MAE values are tabulated in Table 2 and shown visually in Fig 5.

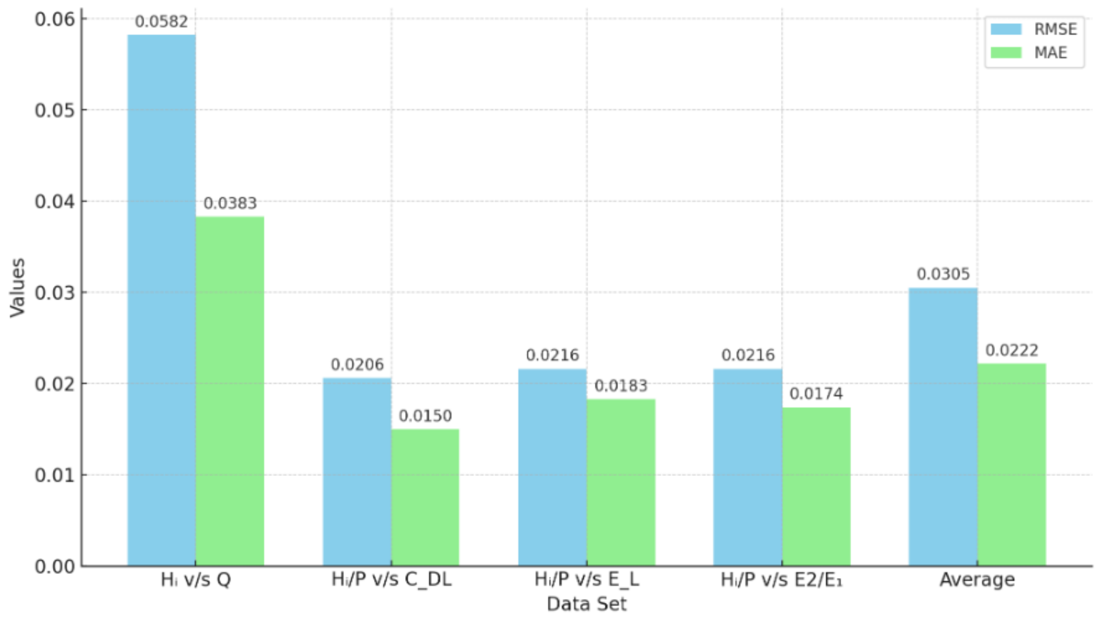
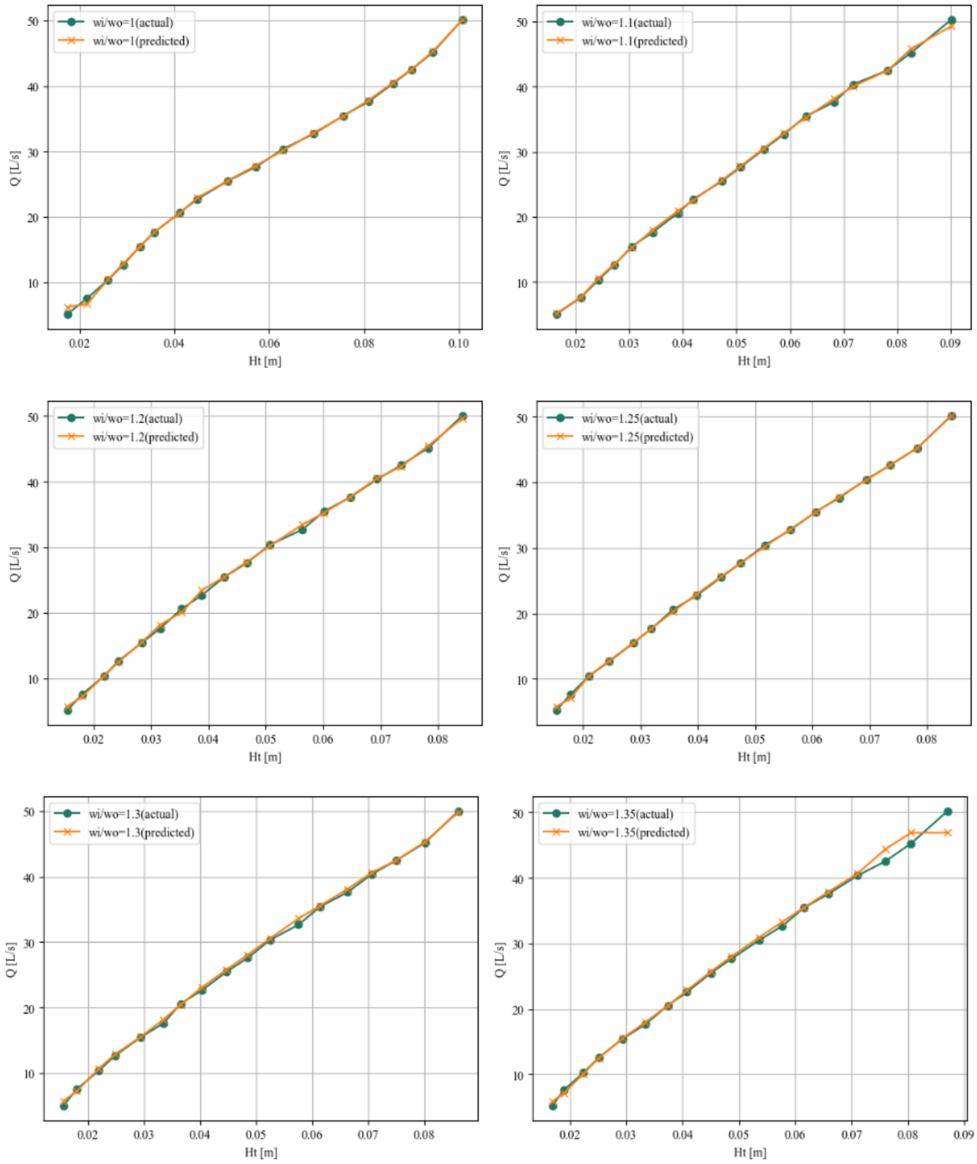


Figure 5 RMSE and MAE values

When evaluating the developed length, one finds the PKW (PKW) discharge coefficient within the range of 0.24 < Ht/P < 0.79. One essential feature of any flow measuring arrangement is the stage-discharge relationship. As shown in Fig. 6, it is represented as a curve that plots discharge against the head for all W_i/W_o values between 1.0 and 2.0. As shown in Figure 4, the performance metrics of the Fuzzy Neural Network (FNN) model show an RMSE (Root Mean Square Error) value of 0.0582 and a MAE (Mean Absolute Error) value of 0.0383. These metrics are essential markers of how well the model predict the provided data. Table 2 shows that the mean absolute difference between the predicted and actual values is 0.0383, and the average magnitude of prediction errors is 0.0582. These measures play a crucial role in evaluating the model's accuracy and dependability in studies, therefore advancing a thorough comprehension of its predictive powers.



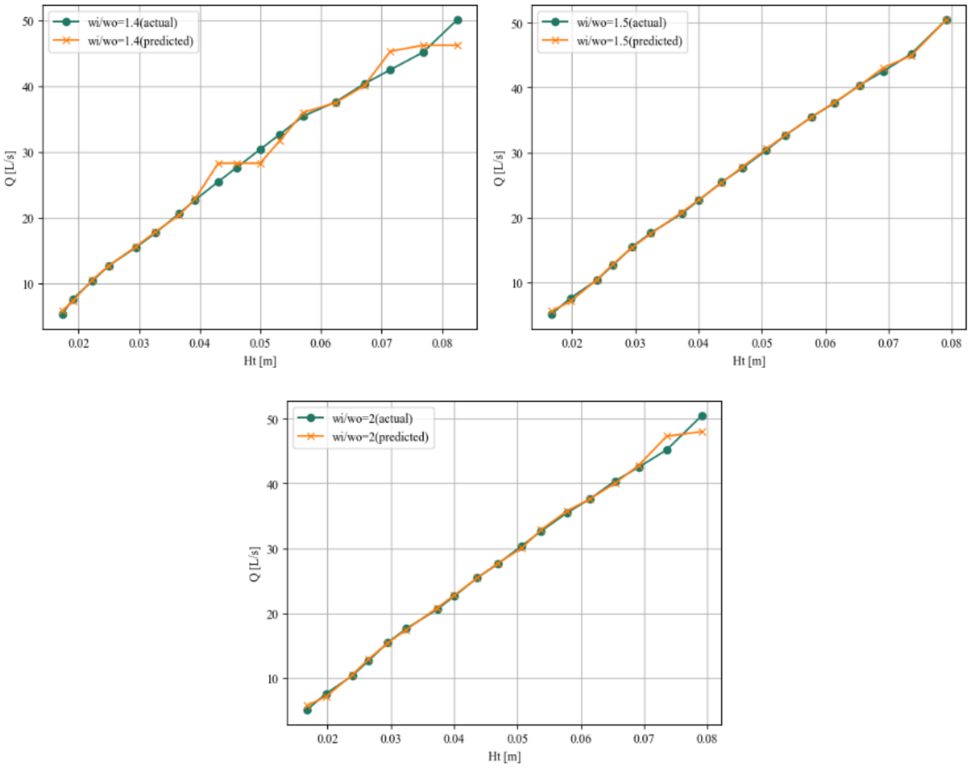
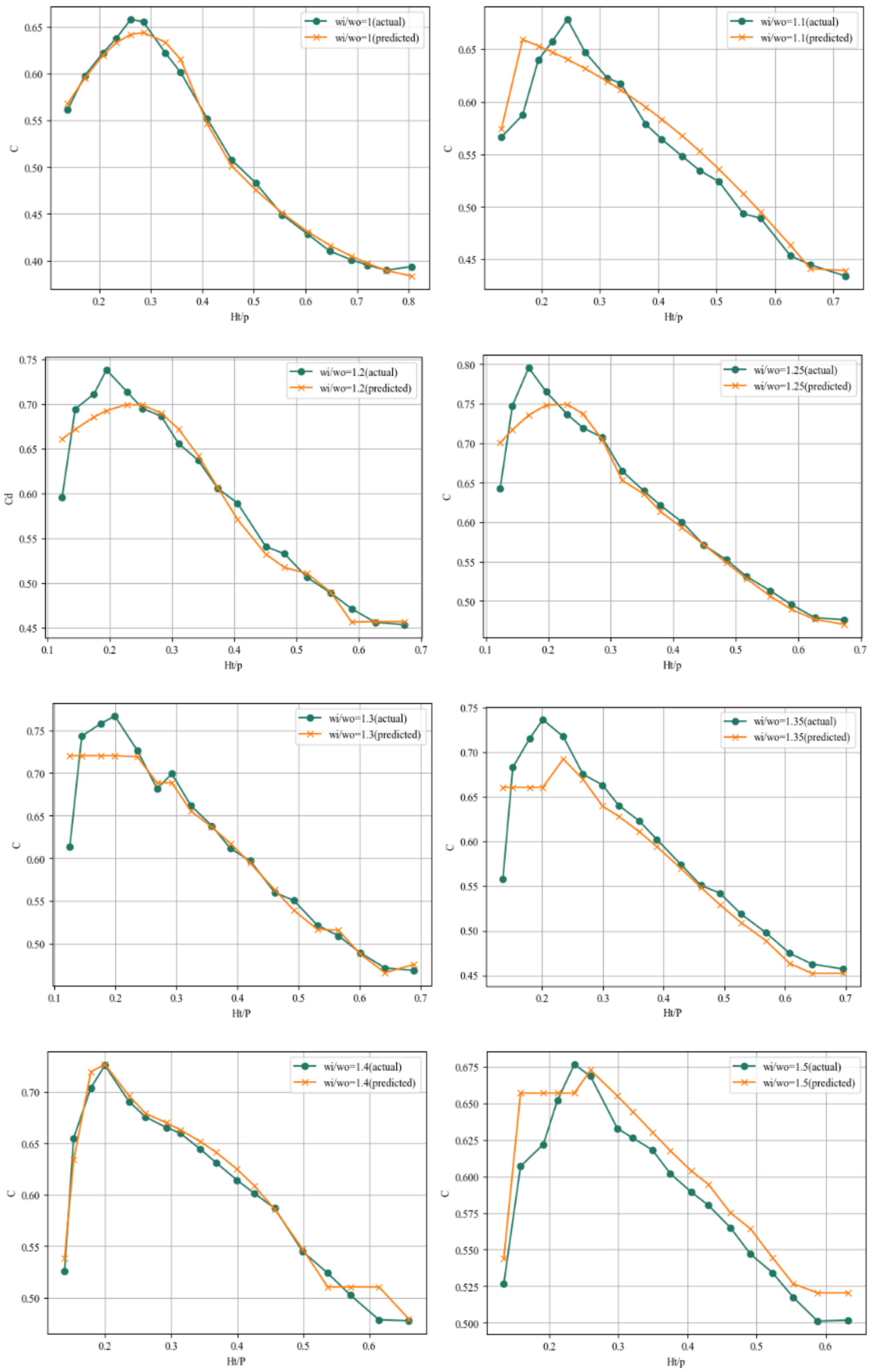


Figure 6 Stage-discharge curve Q [L/s] v/s H_t [m]

We outline the findings in Fig. 7, which shows C_{DL} as a function of H_t/P, and take into consideration the greatest C_{DL} values that indicate peak discharge efficiency to determine the ideal W_i/W_o proportion range. Fig. 7 amply demonstrates that the highest increases in discharge efficiency are obtained with W_i/W_o ratios of 1.25 and 1.3. W_i/W_o values of 1, 1.1, 1.2, 1.25, 1.3, 1.35, 1.4, 1.5, and 2 occur in close succession with them. This finding emphasises that the W_i/W_o range of 1.25 to 1.3 is where the best discharge performance is located. As can be seen from the figures, the model's predictions for the ratio of widths and parameters nearly always coincide. As a result, the model shows to be useful in predicting the hydraulic behaviours resulting from changes in the inlet and outlet keys' width.

Moreover, $W_i/W_o = 1.25$ obtains a much greater discharge efficiency than $W_i/W_o = 1.3$ for $H_t/P < 0.35$, according to the results in Fig 7. On the other hand, $W_i/W_o = 1.3$ outperforms $W_i/W_o = 1.25$ in terms of discharge efficiency over the interval $0.35 < H_t/P < 0.44$. Among the configurations with the maximum discharge capacity in the range of $0.44 < H_t/P < 0.81$, $W_i/W_o = 1.4$ is particularly noteworthy. PKW configurations with W_i/W_o values of 1.25 and 1.3, in particular, show an impressive 7–17% rise in efficiency over $W_i/W_o = 1.0$ and an estimated 8–13% gain over $W_i/W_o = 2.0$. It is noteworthy that the Fuzzy Neural Network (FNN) model performs very well in terms of accuracy, as shown by Figure 5's RMSE of 0.0206 and MAE of 0.0150.


wi/wo=1(actual)
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C
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wi/wo=1.2(actual)
wi/wo=1.2(predicted)
Cd
Ht/p
wi/wo=1.25(actual)
wi/wo=1.25(predicted)
C
Ht/p
wi/wo=1.3(actual)
wi/wo=1.3(predicted)
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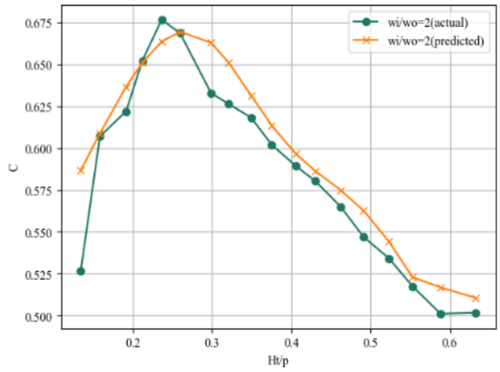
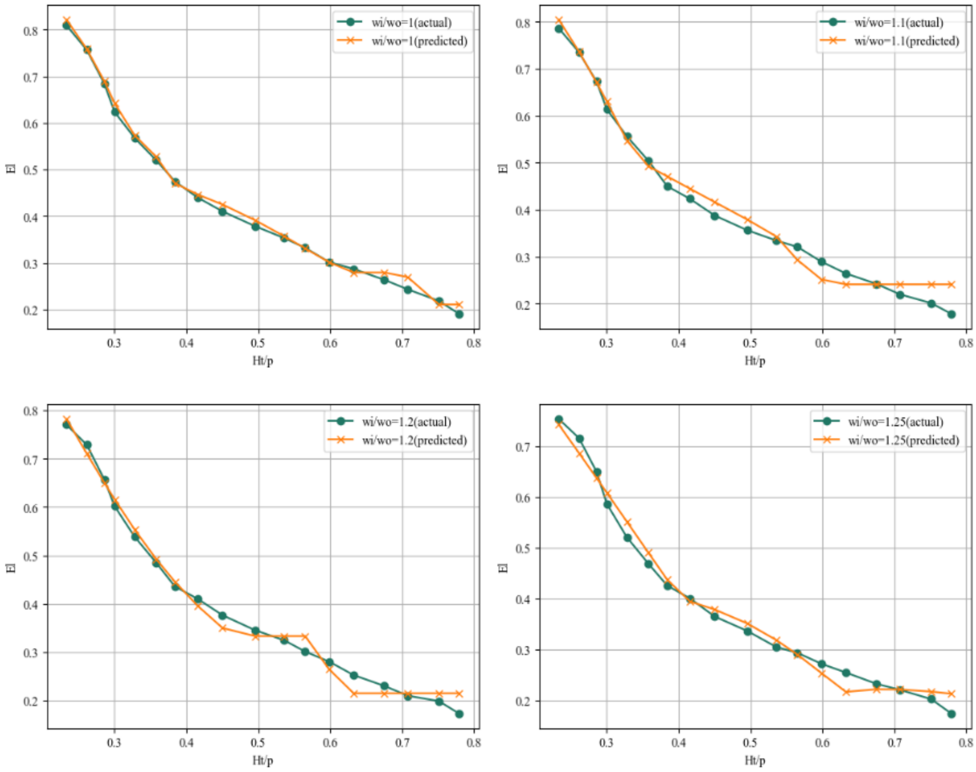


Figure 7 Discharge Coefficient variation curve C_{DL} v/s H_t/P

The FNN models demonstrated steady trends in relative energy dissipation, and their results were very accurately measured and confirmed against prior research. In this study, we observed that, for all PKW models, energy dissipation rates are often greater when H_t/P is smaller than 0.42. This finding contradicts other studies that found less energy dissipation at these levels. On the other hand, when H_t/P values were higher than 0.55 and fell between $0.42 < H_t/P < 0.55$, the relative energy dissipation rate, or $E_L = (E_1\text{-}E_2)/E_1$, exhibited a more intricate and mixed pattern. The relative energy dissipation [$E_L = (E_1\text{-}E_2)/E_1$] fluctuation at the base of PKWs as a function of the upstream head ratio (H_t/P) is shown in Figures 8 and 9.



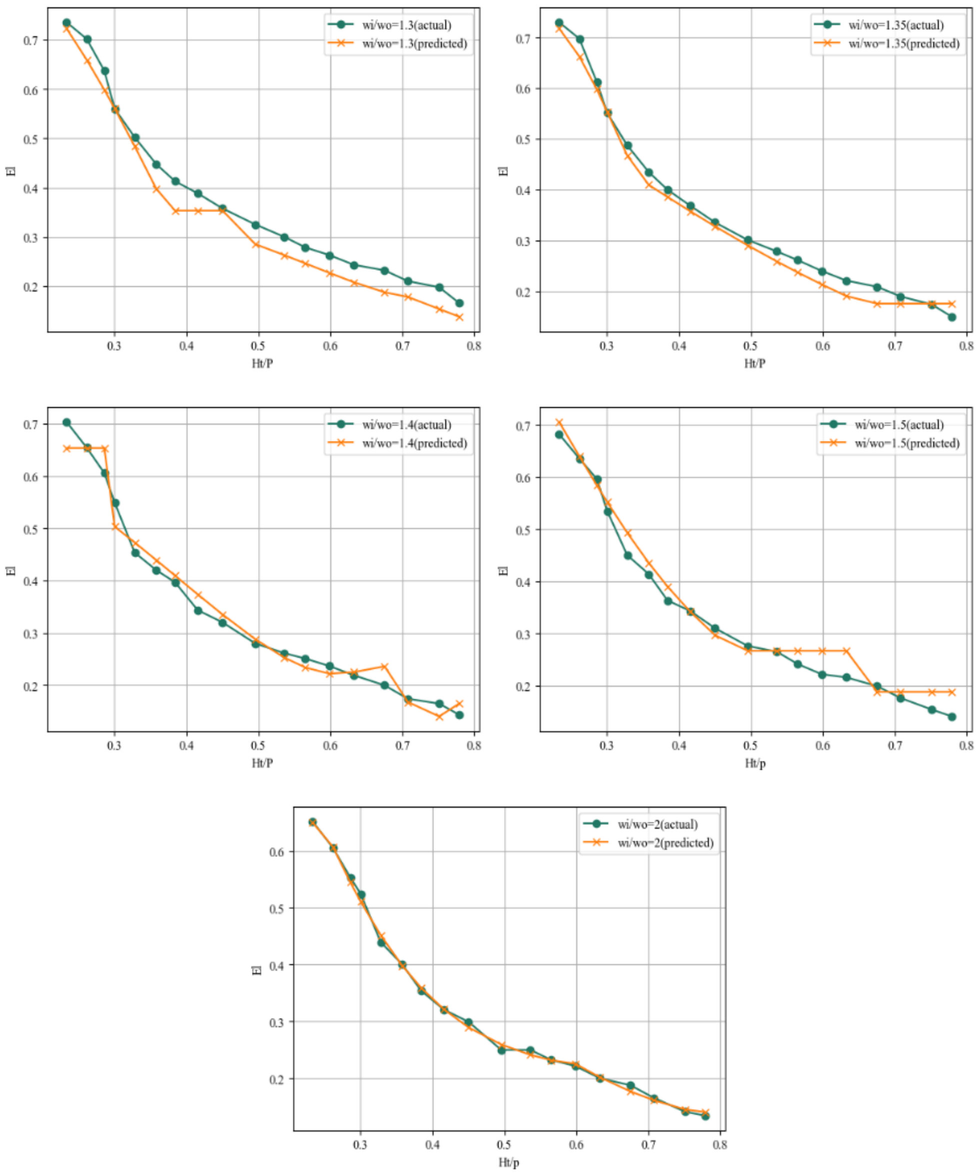
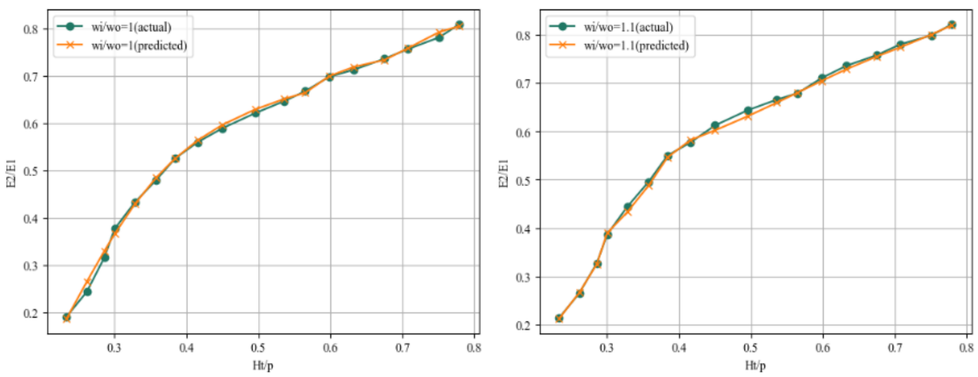


Figure 8 Energy dissipation curve [E_L v/s H_t/P]



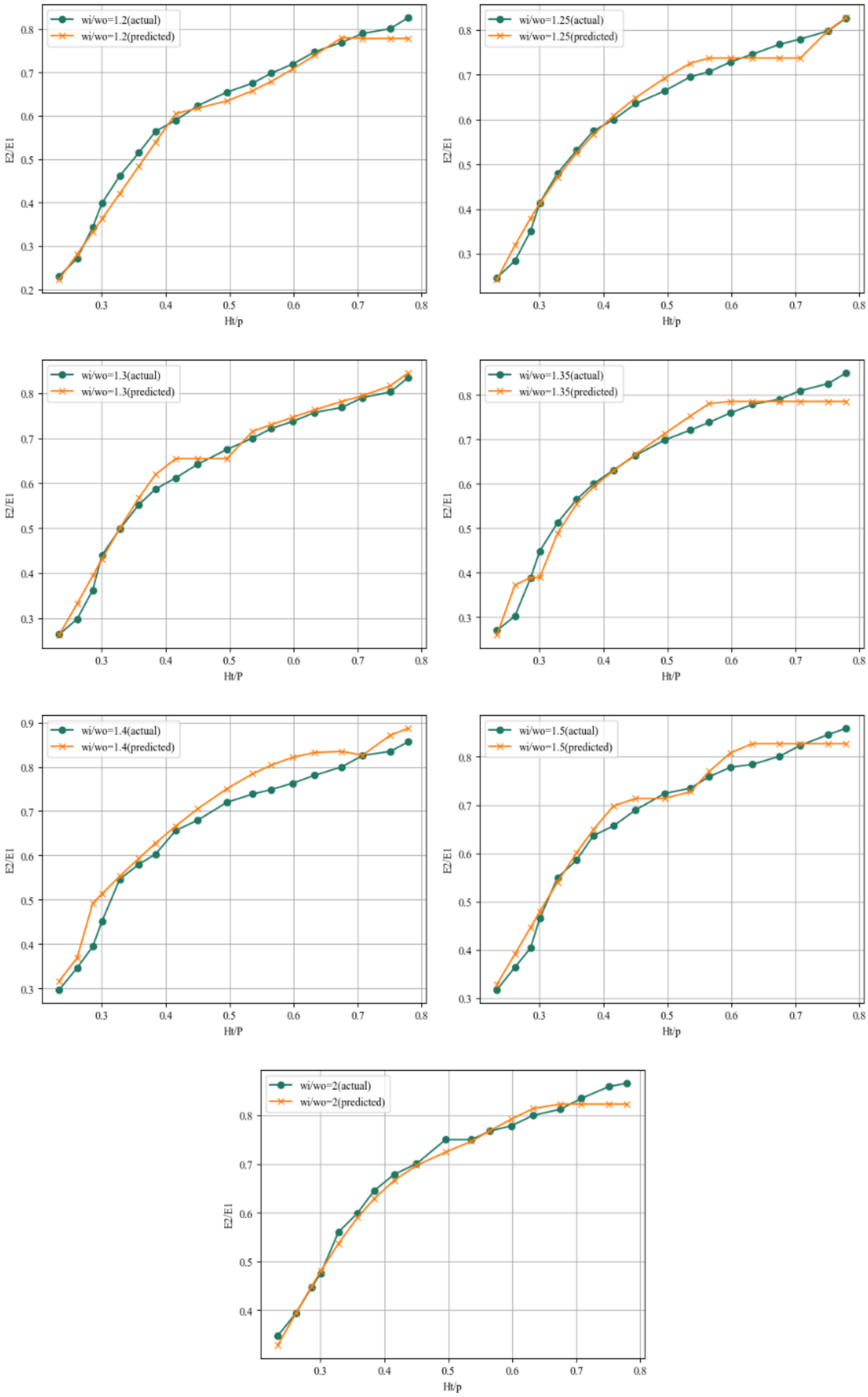


Figure 9 Residual energy curve [E_2/E_1 v/s H_t/P]

CHAPTER 6: CONCLUSION

To precisely calculate the optimal inlet-to-outlet key width ratio of PKW and the impact of various width ratios on energy dissipation, Singh and Kumar (2023) employed experimental data to create the Fuzzy Neural Network (FNN) algorithm-based model in this study. The proposed model for predicting the width ratio of the key indicates that the strategies established a highly nonlinear link between the width ratio and input parameters, with promising prediction outcomes. Three hydraulic behaviours are measured by this procedure: discharge flow over the piano key weir, coefficient of discharge along the crest length (C_{DL}), and relative energy dissipation (E_L). The highest efficiency is obtained at a width ratio (W_i/W_o) of around 1.2755–1.28, with an efficiency boost of 7–17% over W_i/W_o = 1 and 8–13% over W_i/W_o = 2.0. The energy losses over the weir decrease as the W_i/W_o ratio increases, with the highest relative energy dissipation corresponding to the lowest width ratio (i.e., E_L = 0.8093 or 80.93%, the corresponding W_i/W_o = 1) and the lowest energy loss corresponding to the highest width ratio (i.e., E_L = 0.5818 or 58.18%, the related W_i/W_o = 2.0). This implies that with W_i/W_o = 2.0, there is 12–23% less energy dissipation across the weir compared to W_i/W_o = 1. The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) figures are computed to assess the algorithm's performance. More investigation is needed into forecasting and other soft computing techniques. Furthermore, taking scaling effects into account makes it possible to carry out an experimental investigation or a CFD simulation.

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Prediction of inlet to outlet width ratio of type-A Piano Key Weir using Fuzzy Neural Network (FNN)

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ABSTRACT

In this paper, a novel method, named Fuzzy Neural Networks (FNN), is proposed to predict the width of the inlet to outlet key of the Piano Key Weir (PKW) and understand the hydraulic behaviours according to it. Fuzzy logic is a mathematical logic that does not stick to a binary system, i.e., 0 or 1, and calculates things by degree of membership. A Neural Network (NN) is a connection of digital neurons, a concept inspired by biological neurons. The proposed model combines these technologies, allowing the complete network to predict the outputs accurately. The dataset used in this study is collected experimentally, and as it's not a conventional dataset, the authenticity of this study also increases. The model's performance is evaluated by the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE); both values are 0.0305 and 0.0222, respectively. According to the dataset, these scores tell the model's reliability as it is in the ideal range. The FNN approach can be used in multiple fields to predict patterns or solve problems. This study demonstrates the model in a real-life scenario. As it performs very well, this model can be widely used to predict hydraulic behaviours soon.

Keywords: *Fuzzy Neural Network (FNN), Hydraulic behaviours, inlet to outlet key width ratio (W_i/W_o), Root Mean Square Error (RMSE), Mean Absolute Error (MAE).*

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