Soft Computing Methods for Groundwater Level Prediction: A Survey

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Abstract--Population growth and pollution are causing groundwater depletion in developing countries like India. Monitoring groundwater levels is crucial for effective water resource management. Accurate estimation of groundwater resources is essential, but groundwater modeling is inherently non-linear and cannot be solved using traditional methods alone. Consequently, soft computing technologies such as Fuzzy Logic, Genetic Algorithms, and Artificial Neural Networks (ANN) are gaining importance in hydrological studies.

Fuzzy Logic is adept at handling imprecise and ambiguous datasets, while ANN, inspired by human learning, can learn from examples and adjust weights accordingly. Genetic Algorithms, mimicking natural evolutionary processes, offer innovative solutions. This thesis investigates the development of Fuzzy Logic (FL), ANN, and other methodologies like FPSO in predicting groundwater levels. Four models are evaluated, incorporating different combinations of groundwater recharge and discharge as inputs, with groundwater level as the output.

ANN is trained, tested, and validated using groundwater datasets to identify the most effective model for groundwater level prediction. FL works optimally with two inputs, while ANN performs better with more inputs. Fuzzy interval optimization within FL has traditionally been challenging, often relying on hit-or-miss approaches. However, Genetic Algorithms offer a solution by adjusting fuzzy interval length, with methodologies like Wang and Mendel's rule basis creation enhancing performance.

The fuzzy Genetic Algorithm method for estimating groundwater levels outperforms traditional FL methods, providing more accurate predictions. Creating fuzzy sets in FL without specialized knowledge poses a challenge, prompting the development of computational methods. This thesis proposes a methodology based on central tendency concepts to determine the appropriate number of fuzzy sets.

This approach effectively identifies intervals and fuzzy sets for fuzzy time series forecasting. Chennai's reservoir rainfall is modeled using a central tendencies-based fuzzy approach, serving as a benchmark challenge for fuzzy time series analysis. Comparative evaluations against other methods demonstrate the superiority of the proposed computational technique, yielding promising results for benchmark datasets.

I. INTRODUCTION

The depletion of surface mineral sources has resulted in a greater amount of material being extracted from open pit mines at greater depths. When mining is carried out at deeper levels, the pit of the mine eventually falls below the level at which groundwater is found. Excavation may need to be carried out below the water table as a result of the increasing depth of mining, which can result in the movement of water toward mining facilities. In addition to producing issues with the environment and worker safety, problems caused by an excessive amount of water entering the mining environment may cause the project to be delayed or hinder output. Groundwater seeping into the mining environment causes an increase in the number of equipment breakdowns, has a detrimental impact on the stability of the pit slope, leads to an increase in the usage of explosives, creates unsafe working conditions, and prevents access to portions of the mining area. Therefore, in order to solve these issues, it is required to construct a dewatering system that is effective, and the forecast of the level of groundwater can contribute greatly to the design of this system. Modeling and forecasting changes in groundwater levels can be accomplished through the application of a wide variety of contemporary and numerical techniques [1-3].

In order to simulate both the quantity and the quality of groundwater, numerical models are utilized to a significant degree. The numerical modeling of groundwater by using this model (i.e., MODFLOW) requires various input parameters; as a result, obtaining correct values for these parameters is an activity that is both time-consuming and expensive. Numerical methods have a number of drawbacks, including the fact that it can be difficult to accurately represent irregular boundaries that they do not provide optimization for unstructured meshes, that they are slow for solving large problems, and that they often result in one-dimensional physics around edges [4-5].

Soft computing techniques are a very valid alternative for estimating groundwater levels since they provide findings with high precision and use less computational time [6]. These constraints can be controlled by using soft computing techniques. The use of nonlinear algorithms in modeling and prediction of the complicated groundwater level behavior at diverse locations is one of the advantages that soft computing approaches have over numerical methods. This advantage can be seen when comparing the two.

Without an in-depth understanding of the fundamental physical parameters, it is possible to apply innovative machine learning approaches that are based on nonlinear dependence to estimate groundwater levels and the complexity of the circumstances below the surface. In recent years, artificial intelligence methods have gained widespread use for predicting water system variables due to their high ability to learn complex mathematical relationships between output and prediction variables. This has led to the widespread adoption of artificial intelligence techniques. The artificial neural network is one of the machine learning techniques that is utilized most frequently in order to forecast the level of the groundwater (ANN). Based on the diverse architectures that they utilize, the artificial neural network (ANN) approaches that are used the most frequently are the multilayer perceptron (MLP), cascade forward (CF), radial basis function (RBF), general regression (GR), and committee machine intelligence system (CMIS). MLP was utilized for the purpose of groundwater level forecasting in Montgomery, Pennsylvania. modelled river flow in the Kotralai River in the Tiruvallur district of Tamil Nadu State using CF and MLP that has been tuned. RBF and grey relational analysis were used to make a prediction about the trihalomethane levels in tap water. have implemented the supervised intelligence committee machine method to predict the reservoir water level variation for the design and operation of dams; have assessed the effectiveness of GR neural network models in simulating the groundwater contaminant transport; have evaluated the GR neural network models in simulating the groundwater contaminant transport. Each of the models has its own characteristics, thus it is feasible to combine models that have acceptable mistakes with each other to use the properties of all these generated models for predicting. There are a variety of approaches to modeling and forecasting groundwater levels, and there are also a variety of spatial and temporal data that can have an impact on groundwater levels. Most research have employed spatial or temporal parameters individually to forecast groundwater levels using machine learning, yet both spatial and temporal parameters affect groundwater levels [7-10].

The primary objective of this study is to model and anticipate changes in groundwater level using accurate machine learning algorithms as an alternative to numerical methods such as MODFLOW. These changes will be modelled based on data that is both powerful spatially and temporally. In order to accomplish this goal, 6182 data points were utilized, which included 36 geographical characteristics and 12 temporal factors. There are a total of 2478 data points that have been utilized in the creation of various networks. In order to verify the effectiveness of the models that have been constructed, an additional 560 validation data points have been utilized. After that, four different optimal forms of Bayesian regularisation (BR), Levenberg-Marquardt (LM), resilient backpropagation (RB), and scaled conjugate gradient were utilised in the construction of four different MLP neural network models and four different CF neural network models (SCG). In addition, the methodologies of the RBF neural network and the GR neural network have been utilised to model the level of the groundwater. After the models have been developed, a CMIS is created by combining the three candidate models that provide the least amount of inaccuracy. The proposed CMIS undergoes an evaluation utilizing statistical and graphical error analysis in order to determine whether or not it is valid. The examination of the powerful CMIS approach as an alternative to numerical methods such as MODFLOW for predicting groundwater level is the novel contribution that comes from this line of research. In addition, both the relevancy factor of the data in relation to the level of the groundwater and the outlier diagnostic has been determined [11-13].

II. MATERIALS AND METHODS

Study Area: The river Kosasthalaiyar has a length of 136 kilometres (85 miles), begins its journey in Pallipattu in the district of Thiruvallur, and empties into the Bay of Bengal. The Chitoor district of Andhra Pradesh is the birthplace of the river's northern offshoot, the Nagari river, which eventually meets up with the main river in the backwaters of Poondi reservoir. Its catchment area encompasses a number of districts, including Vellore, Chitoor, North Arcot, Thiruvallur, and Chennai. It has a catchment area in the North Arcot District, which is close where it splits off near Kesavaram Anicut. This tributary is known as the Cooum River, and it goes into the city of Chennai. The main river, meanwhile, drains into the Poondi reservoir. The river begins its journey at the Poondi reservoir and continues on through the Thiruvallur District before entering the greater Chennai metropolitan area and finally emptying into the sea at Ennore Creek. There are nine check dams along the river. Tamaraipakkam and Vallur are both home to check dams that may be found across the river.

The Tamarapakkam Anicut, which is located on the other bank of the river, just downstream of the Poondi reservoir, is responsible for regulating the river's overflowing discharge. A tiny check dam known as Vallur Anicut was built near Minjur across the river in order to regulate the water levels in the area and provide irrigation to the surrounding canals. Within the metropolitan region of Chennai, it flows for a total distance of 16 kilometres (about 10 miles).

The bed width of the river varies from 150 to 250 metres, and the river's catchment area covers a total distance of 3,757 kilometres, or 2,334 miles (490 to 820 ft). The river has a discharge capacity of 110,000 cubic metres per second, which is equivalent to 3,900,000 cubic feet per second. The discharge capacity of the river during a flood is approximately 125,000 cubic metres per second, which is equivalent to 4,400,000 cubic feet per second. During the monsoon season, the river is capable of discharging flood water into the sea at a rate of up to 1,400 metres per second (or 50,000 cubic feet per second) via Ennore Creek.

The historic Korattur anicut, which can be found in Jamin Korattur in the Tiruvallur district, is a canal that is essential to the process of regulating the flow of water to the Chembarambakkam reservoir. The dam was constructed in 1876 on a section of the Cooum river that had not been contaminated, and it now directs water that is in excess to the Chembarambakkam reservoir.

The Water Resources Department (WRD) launched the tendering process in 2011 as part of the Irrigated Agriculture Modernisation and Waterbodies Restoration and Management (IAMWARM) project, with the goal of revitalising approximately 200 lakes that are located within the Kosasthalaiyar river sub-basin. The department is also considering building groynes as a means of preventing the creation of sand bars close to the mouth of the river.

At a projected cost of 300 million and located approximately 30 kilometres (19 miles) from Chennai, the Water Resources Department (WRD) planned in May 2012 to construct a check dam across the river near Bandikavanur village in Tiruvallur district. This location is approximately 19 miles from Chennai. The Bandikavanur check dam, which is going to be built about 500 metres (1,600 feet) upstream of the Karanodai bridge on the Chennai–Kolkata National Highway, is going to be built at a height of 6.3 metres (21 feet) across the nearly 300-meter (980-foot) wide river. It will be constructed on the Chennai–Kolkata National Highway. Within a radius of ten kilometres from the check dam, the water table would be refilled (6 mi).

In 2018, plans called for the construction of two additional check dams across the river. One of them will be situated in the region that is downstream of the Karanodai bridge, between Pudhukuppam and Kudiraipallam. At a total cost of 99 million Indian Rupees (INR), the dam will be constructed such that it spans the river at a width of roughly 335 metres and a height of 1.2 metres. In total, this will be the sixth check-dam that has been constructed across the river. Another one will be constructed at Bandikavanur, which is around 30 kilometres away from Chennai. This will assist in the recharging of groundwater within a ten-kilometer radius.

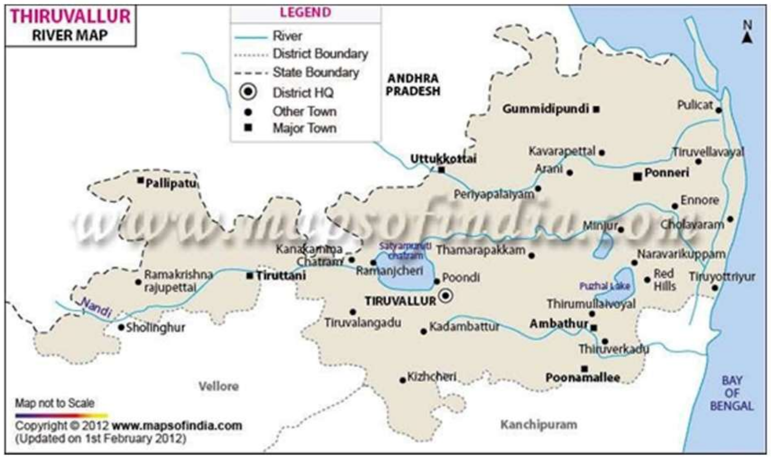

Figure 1: Location map of Kotralai River in the Tiruvallur district

Models:

Artificial Neural Network (ANN): According to Patel et al research's from 2022, the computational method known as ANN was inspired by the human brain in a biological sense. This model looks to represent the brain in two stages: (a) knowledge is received by the network from its surroundings as the result of a learning method, and (b) interneuron connection strengths are employed to collect the knowledge that has been obtained (Haykin 2004) [16]. The design process for an ANN consists of the following five stages: choosing inputs, deciding on a suitable architecture, constructing a neural network, carrying out a training and testing procedure, and finally assessing the created model (Sahoo and Jha 2013) [17]. In this study, the artificial neural network (ANN) known as the multilayer perceptron (MLP), which is the type of ANN that is employed in hydrological research the most, was implemented (McGarry et al., 1999) [18]. The MLP architecture, in its most basic form, is composed of three layers: input, hidden, and output. In order to get the ideal model structure, it is necessary to determine the number of layers and, as a direct result of that, the number of neurons that are present in each layer. The ANN model that was used only had one hidden layer since, according to the findings of earlier research, this was sufficient for GWL prediction.

In a coastal aquifer, Krishna et al. (2008) tested and compared a number of different training methods for the purpose of GWL prediction. They came to the conclusion that when compared to the Bayesian regularisation and the scaled conjugate gradient, the Levenberg-Marquardt (LM) algorithm was the most effective learning algorithm. The current investigation made use of the LM, which is currently the quickest and most well-known method for GWL prediction (Adamowski and Karapataki 2010; Khaki et al., 2015) [18]. In this particular research project, the AI-based models were developed using the MATLAB® (Mathworks 2017b) software. Figure 2 provides an overview of the AI-based model architecture in its entirety.

Distributed processing systems make extensive use of artificial neural networks (ANNs), which are useful forms of computer intelligence that are modeled after the information processing systems utilized by humans. Interconnections and processing elements are the two primary components that make up each ANN. Interconnections, also known as weights, are responsible for making connections between neurons, whereas the processing components, which can be neurons or nodes, are the ones responsible for processing information [19]. MLP is still one of the most dominating structures of the ANN and also the structure with the most extended reach, despite the fact that the ANN has a wide variety of structures. The MLP is a universal function approximation that is utilized in the process of developing mathematical models through the utilization of regression analysis. This approximation is demonstrated by Cybenko's theorem (1989). The network is able to learn certain features concealed within the collected data samples through training on observation data, and it can even generalize what it has learnt from its training. MLP networks have a multilayered structure, with the first layer containing the data that will be used to train the model, the last layer containing the data that will be output by the model, and the layers in between the training data and the output data being referred to as hidden layers [20]. The number of input variables is the same as the number of neurons in the input layer.

The number of outputs is typically the same as the output parameter. The hidden layers are responsible for the internal appearance of the link between the model inputs and the output that is intended. The value of each neuron in the hidden layer, also known as the output layer, is calculated by adding the values of all of the neurons in the layer below it and multiplying that total by a weight that is specific to that neuron. After that, this value is added to the bias, and the resulting total is passed from an activation function. The topology of the MLP neural network that was utilized in this investigation may be seen in Figure 2, which presents the network with two hidden layers [21-22].

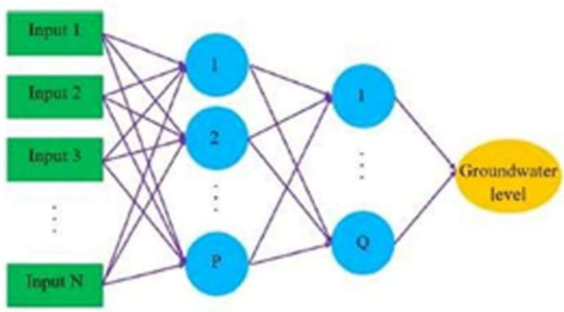

Figure 2: Schematic image of the MLP neural network structure

Fuzzy Logic (FL): The inherent uncertainty that exists between defined sets in mathematical representation can be circumvented using FL models (Zadeh 1965) [23]. Three fundamental operations are included in the construction of a fuzzy controller: fuzzification, inference, and defuzzification (Bai et al., 2006) [24]. The crisp dataset is converted into the fuzzy dataset, also known as the membership function, during the fuzzification stage (MF). In order to produce a fuzzy result, the fuzzy inference process (also known as FIS) combines fuzzy if-then rules with MFs. The FISs Mamdani, Sugeno, and Tsukamoto, which are among the most helpful ones in the field of water resources, differ from one another in terms of aggregation and defuzzification. A fuzzy rule base is utilized as the foundation for the defuzzification process, which then produces crisp results from the fuzzy outputs. For the purpose of this investigation, the genfis-2 programme was used to create the FL model. This programme generates a Sugeno-type FIS structure by the application of subtractive clustering and calls for clustering radius as input parameters. The clustering radius for genfis-2 fuzzy logic was researched using trial and error to optimize the FIS structure. The results of this investigation show that the clustering radius can range anywhere from 0.2 to 0.9. The number of clusters and the rules for the fuzzy inference system are both determined by this parameter. The model contains fewer clusters and rules as a result of the decreased radius number (Chiu 1994). As a result, the fuzzy model structure can be optimized by selecting the optimal number of clusters [25].

The Adaptive Network Based Fuzzy Inference Systems (ANFIS): bThe Adaptive Network Based Fuzzy Inference Systems (ANFIS) first was proposed by Jang (1993). It is a sophisticated multi-layer adaptive network-based fuzzy inference system and able to simulate and analysis the relationship between the input and output data through a learning to find out the optimal distribution of membership function. The fuzzy inference system (FIS) represents a knowledge representation technique where each fuzzy rule defines a local behavior of the system. ANFIS exhibits a high performance for prediction (Yilmaz and Kaynar 2011) [26-27].

Suppose a typical ANFIS architecture has two fuzzy if–then rules. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules may be described as:

$$Rule\ 1: If\ x\ is\ A_1\ and\ y\ is\ B_1, then\ f_1 = p_1x + qp_1y + r_1, \quad (1)$$

$$Rule\ 2: If\ x\ is\ A_2\ and\ y\ is\ B_2, then\ f_1 = p_2x + qp_2y + r_2$$
(2)

An ANFIS commonly consists of five layers of neurons to accomplish the tuning process of the fuzzy modeling system. The five layers are as follows:

Layer 1: The membership grades are produced in first layer, the fuzzy layer.

$$o_i^1 = \mu_{A_i}(x_1), \mu_{B_i}(x_2) \quad (3)$$

Where *X1* and *X2*are the inputs, and Oi^1 is the output.

Layer2: weights are generated in layer 2, the production layer, by

$$o_i^2 = w_i = \prod_{j-1}^{m} (\mu_{A_i}(x_1), \mu_{B_i}(x_2)) = and\ method\ (\mu_{A_i}(x_1), \mu_{B_i}(x_2)) = \mu_{A_i}(x_1).\mu_{B_i}(x_2))$$
(4)

Where *Wi* is the output and represents firing strength of a fuzzy control rule. Layer3: The firing strength is normalized in layer 3, the normalized layer.

$$o_i^3 = \overline{w_i} = w_i / w_1 + w_2 \quad (5)$$

Where $\overline{W_i}$ is normalized firing strength.

Layer4: The consequent parameters are measured in layer 4, the defuzzy layer

$$o_i^4 = y_i = \overline{w_i} f = \overline{w_i}\ (p_i x_1 + q_i x_2 + r_i) \quad (6)$$

Where f is a linear function of input variables and $\{p_i, q_i, r_i\}$ are the coefficients of the linear combination.

In layer 5, the output of the whole network is produced

$$o_i^5 = \sum_i \overline{w_i} f_i = \sum_i \overline{w_i} f \Big/ \sum_i \overline{w_i} \quad (7)$$

Least Square Support Vector Machine (LSSVM): Vapnik is credited with the development of the fundamental concepts underlying SVM as well as its theory (1998). Because it is based on the process of structural risk minimization rather than the experimental risk minimization that is used by the ANN, the broad overview capability of the SVM is seen as being superior to that of the ANN. The most important step in the SVM model is the selection of support vectors, which helps to maintain the framework of the model and defines the weights of the vectors. Vapnik included a comprehensive mathematical outline of the SVM in his proposal (1998). The SVM model served as the foundation for the development of Suykens and Vandewalle's (1999) LSSVM model. It is a reliable method for tackling issues involving function estimation, nonlinear classification, and density estimation. One of the linear programming issues is solved by the LSSVM algorithm by changing the inequality constraints imposed by the SVM method to equality constraints (Kumar and Kar 2009; Kisi 2013). In addition to this, the LSSVM model produces results that are superior to those produced by the SVM when applied to performing fast training (Gu et al., 2010).

In order to tackle the issue of dual optimization that plagues SVMs, a number of different strategies have been proposed. Sequential Minimal Optimization is the name given to the more modern learning algorithm for SVMs (SMO). SMO makes use of an analytical QP phase (Platt 1999), and as a simplistic approach, an SMO algorithm is able to rapidly address the SVM problem without the need to use a quadratic optimizer and without the requirement of any additional matrix space, both of which were applied in this work.

The final result of the LSSVM model is highly dependent on the appropriate selection of the kernel function as well as the accurate adjustment of the C and parameters. Because of its superior performance in GWL prediction based on the dataset that was used in the study region, the polynomial kernel function was chosen for the LSSVM model that was employed in the current investigation. It was determined through a process of trial and error which parameters of the SVM model produced the best results (Suryanarayana et al., 2014). Support Vector Machines (LIBSVM) library codes were supplied by Chang and Lin, and they were responsible for applying the LSSVM modeling methodologies used in this investigation (2011).

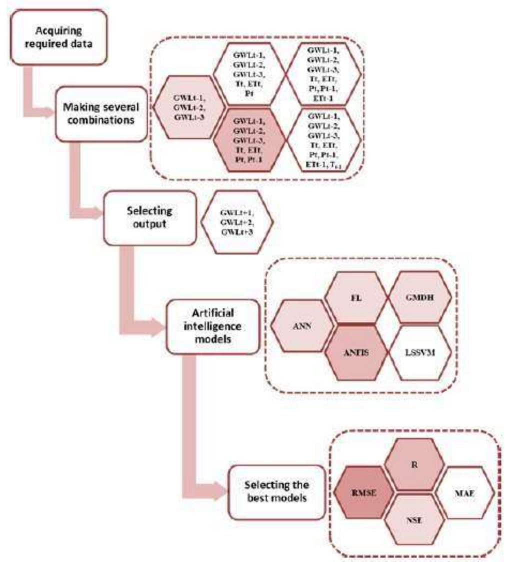

Figure 3: Methodological framework of the proposed groundwater models Figure 3 explains the methodology of groundwater models.

III. EFFICIENCY CRITERIA

Various standards can be used to evaluate the performance of AI-based models. In this investigation, a number of statistical measures, such as the correlation coefficient (R), Nash–Sutcliffe efficiency (NSE), mean absolute error (MAE), and root means squared error (RMSE), were applied to evaluate the efficacy of the techniques (RMSE). The model's capacity for estimating will improve in direct proportion to the degree to which R and NSE approach the value of one, and the reverse is also true. Values of MAE and RMSE that are closer to zero suggest that the model is operating more efficiently.

To determine the error related to the model output, various statistical measures can be used to compare the effectiveness of the developed models. The performance of the trained model is compared in terms of statistical measurement of precision. During this research, the average absolute relative error (AARE, %), average relative error (ARE, %), root mean square error (RMSE), and standard deviation (SD) are taken under consideration to check the efficiency of the models as predictive tools. The mentioned parameters are expressed as

$$\mathrm{AARE} = \frac{100}{N}\sum_{i=1}^{N}\frac{|\mu_{r_{\exp.i}} - \mu_{r_{\mathrm{pred}.i}}|}{\mu_{r_{\exp.i}}} \tag{8}$$

$$\mathrm{ARE} = \frac{100}{N}\sum_{i=1}^{N}\frac{\mu_{r_{\exp.i}} - \mu_{r_{\mathrm{pred}.i}}}{\mu_{r_{\exp.i}}} \tag{9}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mu_{r_{\exp.i}} - \mu_{r_{\mathrm{pred}.i}})^2} \tag{10}$$

$$\mathrm{SD} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{\mu_{r_{\exp.i}} - \mu_{r_{\mathrm{pred}.i}}}{\mu_{r_{\exp.i}}}\right)^2} \tag{11}$$

- **Advantages of groundwater level prediction using machine learning**

- Machine-learning tools have the potential to improve groundwater prediction, thus enabling resource planners.
- Anticipate water quality in unsampled areas or depth zones.
- Design targeted monitoring programs.
- Inform groundwater protection strategies.
- Evaluate the sustainability of groundwater.

IV. CONCLUSION

An example of a renewable resource is groundwater, which refers to water that permeates through rocks and soil, accumulating beneath the surface. Effective management of these resources is crucial to preserving groundwater supplies. However, challenges arise when mathematical modeling struggles to address the uncertainty inherent in the data due to numerous influencing factors. Soft computing techniques offer a versatile solution to tackle such uncertainty and simulate complex issues across various engineering domains.

The primary objective of my thesis research is to explore recent advancements in conventional soft computing methodologies and assess their applicability in forecasting groundwater levels. This investigation aims to validate the efficacy of these developments in accurately predicting groundwater levels, thereby contributing to improved resource management strategies.

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