CHAPTER 2

LITERATURE SURVEY

[1] Developing mathematical models using Artificial Neural Networks

Artificial Neural Networks (ANNs) are efficient mathematical modeling systems with efficient parallel processing, enabling them to mimic the biological neural network using inter-connected neuron units. Among all ML methods, ANNs are the most popular learning algorithms, known to be versatile and efficient in modeling complex flood processes with a high fault tolerance and accurate approximation. In comparison to traditional statistical models, the ANN approach was used for prediction with greater accuracy. ANNs were already successfully used for numerous flood prediction applications, e.g., stream-flow forecasting, river flow, rainfall–runoff, precipitation–runoff modeling etc. Despite the advantages of ANNs, there are a number drawbacks associated with using ANNs in flood modeling, e.g., network architecture, data handling, and physical interpretation of the modeled system. A major drawback when using ANNs is the relatively low accuracy, the urge to iterate parameter tuning, and the slow response to gradient-based learning processes. Artificial neural networks require processors with parallel processing power, in accordance with their structure. For this reason, the realization of the equipment is dependent. This is the most important problem of ANN. When ANN produces a probing solution, it does not give a clue as to why and how. This reduces trust in the network. Further drawbacks associated with ANNs include precipitation prediction and peak-value prediction.

[2] Training the network using Multilayer Perceptron (MLP)

The vast majority of ANN models for flood prediction are often trained with a back-propagation neural network. Simplicity, nonlinear activation, and a high number of layers are characteristics of the MLP. Due to these characteristics, the model was widely used in flood prediction and other complex hydrogeological models. In an assessment of ANN classes used in flood modeling, MLP models were reported to be more efficient with better generalization ability. Nevertheless, the MLP is generally found to be more difficult to optimize. Back-percolation learning algorithms are used to individually calculate the propagation error in hidden network nodes for a more advanced modeling approach. The output values of a perceptron can take on only one of two values (0 or 1) due to the hard-limit transfer function.

Perceptrons can only classify linearly separable sets of vectors. If the vectors are not linearly separable, learning will never reach a point where all vectors are classified properly.

[3] Predictive modeling using Decision Trees (DT)

The machine learning method of DT is one of the contributors in predictive modeling with a wide application in flood simulation. DT uses a tree of decisions from branches to the target values of leaves. In classification trees, the final variables in a DT contain a discrete set of values where leaves represent class labels and branches represent conjunctions of features labels. When the target variable in a DT has continuous values and an ensemble of trees is involved, it is called a regression tree. DTs are classified as fast algorithms; they became very popular in ensemble forms to model and predict floods. The classification and regression tree, which is a popular type of DT used in ML, was successfully applied to flood modeling. Further DT algorithms popular in flood prediction include reduced-error pruning trees, Naïve Bayes trees, chi-squared automatic interaction detectors, logistic model trees, alternating decision trees etc. Despite this there are many drawbacks to using DTs. A small change in the data can cause a large change in the structure of the decision tree causing instability. For a DT sometimes calculation can go far more complex compared to other algorithms. And it takes a lot of time to train a model.

[4] Extracting Information from Sources with Wavelet Neural Networks

Wavelet transform (WT) is a mathematical tool which can be used to extract information from various data sources by analyzing local variations in time series. Wavelet transforms supports the reliable decomposition of an original time series to improve data quality. The accuracy of prediction is improved through discrete WT (DWT), which decomposes the original data into bands, leading to an improvement of flood prediction lead times. DWT decomposes the initial data set into individual resolution levels for extracting better-quality data for model building. DWTs, due to their beneficial characteristics, are widely used in flood time-series prediction. In flood modeling, DWTs were widely applied in, e.g., rainfall–runoff, daily stream-flow, and reservoir inflow. Furthermore, hybrid models of DWTs, e.g., wavelet-based neural networks, which combine WT, feed-forward neural network, and wavelet-based regression models, which integrate WT and multiple linear regressions, were used in time-series predictions of floods.

[5] Adaptive Neuro - Fuzzy Inference System (ANFIS)

The fuzzy logic is a qualitative modeling scheme with a soft computing technique using natural language. Fuzzy logic is a simplified mathematical model, which works on incorporating expert knowledge into a fuzzy inference system (FIS). An FIS further mimics human learning through an approximation function with less complexity, which provides great potential for nonlinear modeling of extreme hydrological events, particularly floods. Adaptive neuro-FIS, or so-called ANFIS, is a more advanced form of neuro-fuzzy based on the T–S FIS, first coined. Today, ANFIS is known to be one of the most reliable estimators for complex systems. ANFIS technology, through combining ANN and fuzzy logic, provides higher capability for learning. This hybrid ML method corresponds to a set of advanced fuzzy rules suitable for modeling flood nonlinear functions. But it comes with some drawbacks. The computational cost of ANFIS is high due to complex structure and gradient learning. This is a significant bottleneck to applications with large inputs. Moreover, in terms of interpretability, ANFIS with grid partitioning produces a large number of rules which indeed cannot be easily understood by model users. Hence, interpretability is highly compromised, even though, the large number of rules contribute to improvement in model accuracy. Additionally, the trade-off between interpretability and accuracy is considered as crucial problem.

[6] Reducing Expected Errors with the help of Support Vector Machine

Hearst Et Al proposed and classified the support vector (SV) as a nonlinear search algorithm using statistical learning theory. Later, the Support Vector Machine (SVM) was introduced as a class of SV, used to minimize over-fitting and reduce the expected error of learning machines. SVM is greatly popular in flood modeling; it is a supervised learning machine which works based on the statistical learning theory and the structural risk minimization rule. The training algorithm of SVM builds models that assign new non-probabilistic binary linear classifiers, which minimize the empirical classification error and maximize the geometric margin via inverse problem solving. SVM is used to predict a quantity forward in time based on training from past data. A common disadvantage of non-parametric techniques such as SVMs is the lack of transparency of results. It is neither a linear combination of single financial ratios nor has it another simple functional form. The weights of the financial ratios are not constant.

[7] Ensemble Prediction Systems (EPSs)

A multitude of ML modeling options was introduced for flood modeling with a strong background. Thus, there is an emerging strategy to shift from a single model of prediction to an ensemble of models suitable for a specific application, cost, and dataset. ML ensembles consist of a finite set of alternative models, which typically allow more flexibility than the alternatives. Ensemble ML methods have a long tradition in flood prediction. In recent years, ensemble prediction systems (EPSs) were proposed as efficient prediction systems to provide an ensemble of N forecasts. In EPS, N is the number of independent realizations of a model probability distribution. EPS models generally use multiple ML algorithms to provide higher performance using an automated assessment and weighting system. The advantage of EPS is the timely and automated management and performance evaluation of the ensemble algorithms. Therefore, the performance of EPS, for flood modeling in particular, can be improved. The disadvantages of this approach are that it relies heavily on observed stream-flow data and requires regular updates with new data. Another drawback of the method is that the uncertainty is not captured equally across the water level spectrum.