Journal of Hydrology 530 (2015) 829–844

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Review Paper

# Artificial intelligence based models for stream-flow forecasting: 2000–2015

Zaher Mundher Yaseen [a,*], Ahmed El-shafie [a,b], Othman Jaafar [a], Haitham Abdulmohsin Afan [a], Khamis Naba Sayl [a]

[a] Civil and Structural Engineering Department, Faculty of Engineering and Built Environment, National University of Malaysia, 43600 UKM Bangi, Selangor Darul Ehsan, Malaysia
[b] Civil Engineering Department, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia

A R T I C L E   I N F O

*Article history:*
Received 24 July 2015
Received in revised form 30 September 2015
Accepted 12 October 2015
Available online 22 October 2015
This manuscript was handled by Andras Bardossy, Editor-in-Chief, with the assistance of Fi-John Chang, Associate Editor

*Keywords:*
Artificial intelligence
Stream-flow forecasting
Fast orthogonal search
Swarm intelligence

S U M M A R Y

The use of Artificial Intelligence (AI) has increased since the middle of the 20th century as seen in its application in a wide range of engineering and science problems. The last two decades, for example, has seen a dramatic increase in the development and application of various types of AI approaches for stream-flow forecasting. Generally speaking, AI has exhibited significant progress in forecasting and modeling non-linear hydrological applications and in capturing the noise complexity in the dataset. This paper explores the state-of-the-art application of AI in stream-flow forecasting, focusing on defining the data-driven of AI, the advantages of complementary models, as well as the literature and their possible future application in modeling and forecasting stream-flow. The review also identifies the major challenges and opportunities for prospective research, including, a new scheme for modeling the inflow, a novel method for preprocessing time series frequency based on Fast Orthogonal Search (FOS) techniques, and Swarm Intelligence (SI) as an optimization approach.



**Contents**



## 1. Introduction

The phenomena and characteristic pattern of stream-flow are not easily predictable. This is due to the fact, that stream-flow is characterized by high complexity, non-stationarity, dynamism and non-linearity.

Stream-flow modeling and forecasting are very significant for water resources planning and management. Basically, stream-flow forecasting is categorized into two main temporal categories. Firstly, short-term (real-time) forecasting (e.g., hourly and daily), which is crucial for reliable operation of flood and mitigation systems. Secondly, long-term forecasting (e.g., weekly, monthly and annual), which is important in the operation and planning of reservoirs, hydro-power generation, sediment transport, irrigation management decisions, scheduling releases and many other applications. The classical black box time series models such as Auto Regressive (AR),

* Corresponding author. Tel.: +60 018 2700214.
*E-mail address:* zahermundher@gmail.com (Z.M. Yaseen).

http://dx.doi.org/10.1016/j.jhydrol.2015.10.038
0022-1694/

Moving Average (MA), Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Integrated Moving Average with exogenous input (ARIMAX), Linear Regression (LR), and Multiple Linear Regression (MLR) (Box and Jenkins, 1970; Salas, 1980; Valipour et al., 2012a,b; Valipour, 2012, 2015; Valipour et al., 2013; Wu et al., 2009a), have been applied for stream-flow forecasting since 1970. Those conventional models which are linear, are unable to capture non-stationarity and non-linearity of the hydrological application. As a result, researchers have concentrated on developing models that are capable of overcoming the drawbacks of the conventional models.

Motivation for using data-driven techniques of Artificial Intelligence (AI) for stream-flow forecasting has received considerable attention from hydrologists in the last two decades (Jothiprakash and Magar, 2012; Kentel, 2009; Terzi and Ergin, 2014; Valipour and Montazar, 2012a,b; Yaseen et al., 2015). AI has shown progress in forecasting and simulating non-linear hydrological applications and in capturing the noise complexity in dataset. The features of AI-based models have motivated researchers to develop models, which are suited for hydrological problems. According to (Luger, 2005), AI methods such as mathematical optimization as well as logic-, classification-, statistical learning- and probability-based methods, have been broadly used. In order to develop better visualization of data-driven models, it is useful to provide a classification for the modeling. In particular, four subcategories of AI have been broadly utilized in hydrological and environmental fields:

1. Classifiers and machine-learning approaches: the most commonly used classifiers are Artificial Neural Networks (ANNs) (Haykin, 1994), decision tree and kernel methods such as the Support Vector Machine (SVM) (Vapnik, 1995). ANNs are categorized into (i) supervised (e.g., Feed Forward Back Propagation (FFBP), Radial Basis Function (RBF), multilayer perceptron (MLP), and generalized regression neural network (GRNN). (ii) unsupervised (e.g., Self-Organizing Map (SOM)).
2. Fuzzy sets: Fuzzy logic approach (Zadeh, 1965), which distinguishes itself by accounting for the uncertainties in the modeling variables.
3. Evolutionary computation (EC): Considered as the most well-established class of optimization techniques that includes evolutionary algorithms such as Evolution Strategies (Schwefel, 1981), Genetic-Programming (GP) (Koza, 1992), Gene-Expression Programming (GEP) Genetic-Algorithms (GA) (Holland, 1975) and swarm intelligence algorithms such as Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 1995) or Ant Colony Optimization (ACO) (Dorigo et al., 1996).
4. Wavelet conjunction models: Wavelet transformation is a signal processing tool which is capable of analyzing the non-stationarity dataset as well as provide a time-scale localization of a process, (Grossmann et al., 1984). There are two types of the mother wavelet; the Discrete Wavelet Transforms (DWT) and Continuous Wavelet Transforms (CWT) wavelet signal process.

In the field of hydrologic research, the most widely employed of AI approaches are ANN, SVM, Fuzzy set, EC and Wavelet-Artificial Intelligence (W-AI) models. (Table 1) exhibits numerous successful hydrological processes (e.g., sediment transport, water quality, groundwater modeling, precipitation, water level forecasting, evapotranspiration, evaporation, flood and draught) using data driven models (e.g., ANN, SVM, Fuzzy, EC and W-AI models).

The major contributions of the current review paper are to comprehensively categorize Artificial Intelligence approaches and recite their advanced implementation in stream-flow modeling and forecasting alongside with their advantages. In turn, this evaluation will offer fresh ideas with respect to future research. This comprehensive assessment concentrates on the utilization of ANN, SVM, Fuzzy logic, EC and W-AI in stream-flow modeling and forecasting. The review focuses on articles from high-impact factor journals, which have been collected based on a 16-year timeframe (i.e., from 2000 to 2015). As there are several useful books and papers introducing the data-driven of AI, this review paper will not explore the mathematical theory behind data-driven of AI. Only the main concepts will be presented. There will be a recommended literature for more information regarding each method. Details of the selected articles, including, AI techniques, authors, methods, input variables, and time scale are tabulated in (Table 2). Discussion of the basic theory behind every data-driven of AI for stream-flow models and reviewing the most developed researches, are presented in (Section 2). An evaluation and assessments of the reviewed researches are in (Section 3). Recommendations for future research are presented in (Section 4). Summary and conclusions are exhibited in the last sections of the paper.

## 2. Artificial intelligence based model for stream-flow forecasting

### 2.1. Artificial neural network modeling in stream-flow

An ANN is a massively parallel-distributed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1994). ANNs are technologically advanced as a generalization of

**Table 1**
Examples of AI approaches in hydrological application.

| Hydrological applications | ANN | SVM | Fuzzy set | EC | W-AI models |
|---|---|---|---|---|---|
| Sediment modeling | Afan et al. (2014) | Kakaei Lafdani et al. (2013) | Wieprecht et al. (2013) | Altunkaynak (2009) | Liu et al. (2013) |
| Water quality modeling | Singh et al. (2011) | Liu and Lu (2014) | Patki et al. (2013) | Eslamian and Lavaei (2009) | Najah et al. (2012) |
| Groundwater modeling | Mohanty et al. (2013) | Yoon et al. (2011) | He et al. (2008) | Ketabchi and Ataie-Ashtiani (2015) | Moosavi et al. (2013) |
| Precipitation | Dahamsheh and Aksoy (2013) | Chen et al. (2010) | Jeong et al. (2012) | Kashid and Maity (2012) | Kisi and Cimen (2012) |
| Water level forecasting | Chang et al. (2014a,b) | Hipni et al. (2013) | Alvisi and Franchini (2011) | Kisi et al. (2014) | Wei (2012) |
| Evapotranspiration | Kisi (2008) | Tabari et al. (2013) | Shiri et al. (2013) | Abdullah et al. (2015) | Evrendilek (2014) |
| Evaporation | Nourani and Sayyah Fard (2012) | Tezel and Buyukyildiz (2015) | Shiri et al. (2011) | Guven and Kişi (2011) | Abghari et al. (2012) |
| Flood | Chang et al. (2014a,b) | Wu et al. (2009a,b) | Lohani et al. (2014) | Sivapragasam et al. (2008) | Sahay and Srivastava (2014) |
| Drought | Dehghani et al. (2014) | Ganguli and Reddy (2013) | Bacanli et al. (2009) | Song and Singh (2010) | Belayneh et al. (2014) |