Neurocomputing in Surface Water Hydrology and Hydraulics: A Review of Two Decades Retrospective, Current Status and Future Prospects

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Abstract

Neurocomputing methods have contributed significantly to the advancement of modelling techniques in surface water hydrology and hydraulics in the last couple of decades, primarily due to their vast performance advantages and usage amenity. This comprehensive review considers the research progress in the past two decades, the current state-of-the-art, and future prospects of the application of neurocomputing to different aspects of hydrological sciences, i.e., quantitative surface hydrology and hydraulics. An extensive literature survey, by running over more than 800 peer-reviewed papers, outlines and concisely explores the past and recent tendencies in the application of conventional neural-based approaches and modern neurocomputing models in relevant topics of hydrological and hydraulic sciences. Apart from segregated descriptions and analyses of the main facets of surface hydrology and hydraulics, this review offers a practical summary of prevailing neurocomputing methods used in different subfields of hydrology and water engineering. Six relevant topics to modelling hydrological and hydraulic sciences are articulated and analysed, including modelling of water level in surface water bodies, flood and risk assessment, sediment transport in river systems, urban water demand prediction, modelling flow through hydro-structures, and hydraulics of sewers. This review is meant to be a mainstream guideline for researchers and practitioners whose work is associated with data mining and machine learning methods in various areas of water engineering and hydrological sciences to assist them to decide on suitable methods, network structures and modelling strategies for a given problem.

Keywords: Artificial neural networks; Machine learning; Hydroinformatics; Hydrosciences; Artificial intelligence; Soft computing

Acronym list

AI: Artificial Intelligence; **ANFIS**: Adaptive Neuro-Fuzzy Inference System; **ANN**: Artificial Neural Network; **ARIMA**: Auto Regressive Integrated Moving Average; **BSA**: Backtracking Search Algorithm; **BNN**: Bayesian Neural Network; **CART**: Classification And Regression Tree; **CCNN**: Cascade Correlation Neural Network; **CGPBANN**: Conjugate Gradient Powell-Beale Artificial Neural Network; **CHAID**: Chi-Square Automatic Interaction Detector; **CNN**: Convolutional Neural Network; **DAN2**: Dynamic Artificial Neural Network; **DBNN**: Deep Belief Neural Network; **DL**: Deep Learning; **DT**: Decision Tree; **DWT**: Discrete Wavelet Transformation; **ELM**: Extreme Learning Machine; **EMD**: Empirical Mode Decomposition; **ENN**: Elman Neural Network; **ESN**: Echo State Neural Network; **FFNN**: Feedforward Neural Network; **FIS**: Fuzzy Inference System; **FNN**: Fuzzy Neural Network; **FSP**: floodwater storage pond; **GA**: Genetic Algorithm; **GEP:** Gene-Expression Programming; **GMDH**: Group Method of Data Handling; **GRNN**: Generalized Regression Neural Network; **GRU**: Gated Recurrent Unit; **GSA**: Gravitational Search Algorithm; **HNN**: Hopfield Neural Network; **HPP**: hydropower plants; **LS-SVR**: Least Square Support Vector Regression; **LSTM**: Long Short-Term Memory; **MAE**: Mean Absolute Error; **MAPE**: Mean Absolute Percentage Error; **ML**: Machine Learning; **MLP**: Multi-Layer Perceptron; **MLR**: Multiple Linear Regression; **MNLR**: Multivariate Non-Linear Regression, **MNN**: Modular Neural Network; **MSA**: Multiplicative Season Algorithm; **NARX**: Nonlinear Autoregressive Exogenous Model; **NFNN**: Neuro-Fuzzy Neural Network; **PSO**: Particle Swarm Optimization; **RBNN**: Radial Basis Neural Network; **RDNN**: Range Dependent Neural Network; **RF**: Random Forest; **RMSE**: Root Mean Square Error; **RNN**: Recurrent Neural Network; **RPNN**: Resilient Back-Propagation Neural Network; **SSC**: Suspended Sediment Concentration; **SOM**: Self-Organizing Maps; **SRC**: Sediment Rating Curve; **SVM**: Support Vector Machine; **SVR**: Support Vector Regression; **WA**: Wavelet Transforms; **WA-ANN**: Coupled Wavelet and Artificial Neural Network; **WBNN**: Wavelet-Bootstrap-Neural Network; **WDF-ANN**: Water Demand Forecasting using Artificial Neural Networks; WLSSVR: Weighted Least Square Support Vector Regression; **WNN**: Wavelet Neural Network.

Introduction

1.1.Background

Topics associated with hydrological sciences broadly include two primary disciplines: hydrology and hydraulics, covering subjects which range, for instance, from hydrological forecasts and hydraulic modelling to water resource management and risk analyses. Soft computing and machine learning (ML), or neurocomputing in short, have been widely applied to a wide range of scientific and technological aspects in hydrological and hydraulic sciences. In this context, neurocomputing serves as a cross-cutting discipline to address modelling and solve complex and sophisticated problems that involve technical and societal aspects, data science, computer science, information and communication technologies (Makropoulos & Savic, 2019).

Hydrological sciences tools enable the emulation of various natural processes of the water cycle with mathematical models, mainly classified into three categories: *black-box* models, *conceptual* models, and *physically based* models. While conceptual and physically based models, such as the HBV model (Bergström, 1976), SWIM (Krysanova et al., 2000), and TELEMAC-MASCARET model (Hervouet, 2007) are based on many physical and topographical parameters and sometimes require expensive computational efforts, black-box models, e.g., neurocomputing models, can infer the underlying functional relationships between the historical data and the resulting sought variables, without any priori physical background. The neurocomputing methods, including methods based on machine learning, have been increasingly used in the water management field in the last decades, demonstrating their great potential and raising increasing interest in the hydrological sciences research community (Chen et al., 2018; Zounemat-Kermani et al., 2020a). Over the last two decades, machine learning methods have achieved a high level of success and have become a reliable alternative to the conventional mathematical and hard computing methods in numerous areas of application, such as robotics and image recognition (Stone and Veloso, 2000; Man et al., 2013). Given their computational efficiency and flexibility, these approaches have also been intensively applied to address various challenges related to hydrological sciences.

1.2. Theory and Methods

Neurocomputing and related neural-based models, e.g., Artificial Neural Networks (ANNs), are the fundamental and principal soft computing methods and inseparable elements of ML models, capable of learning from different types of datasets. The theoretical and technical aspects of various types of neurocomputing models have already been introduced in detail in the literature (e.g., ASCE Task Committee, 2000; Ham and Kostanic, 2000; Govindaraju and Rao, 2000; Jain et al., 2007; Ding et al., 2013; Amezquita-Sanchez et al., 2016; van Gerven and Bohte, 2017, and references therein). In brief, neurocomputing models are interconnected networks composed of different layers (input layer, hidden layer(s), and output layer), each of which consists of several processors called artificial neurons (Figure 1). In general, neurons in each layer are connected to the neurons of the previous and next layers, so that they transmit information. Each neuron receives input signals from the other ones (through synaptic weights and biases), then processes them with predetermined functions (activation functions), and finally sends the processed information as output to the connected neurons in the next layer. The activation or transfer functions convert the input signals to the output responses. Most of the conventional ANNs implement the basic impression of using artificial neurons and their connections through layers. Yet, other mathematical and statistical tools, such as fuzzy logic and wavelet transforms, can be also embedded to create combined neurocomputing models (sometimes they are referred to as hybrid neural networks), e.g., Adaptive Neuro-Fuzzy Inference System (ANFIS) and Wavelet Neural Network (WaveNet) (Keshtegar et al., 2018; Bakshi and Stephanopoulos, 1993). In most of the neurocomputing networks, the transition of the data is realised through forward transmission (*feedforward*) from the antecedent layers to the subsequent layers, such as the Multi-Layer Perceptron neural network (MLP) or the Group Method of Data Handling Network (GMDH. In other types of neurocomputing models, information can be returned to the preceding layers in a loop mechanism so that they can be stored and use new information during the processing procedure, e.g., recurrent neural networks (Figure 1a). Figure 1b depicts the internal architectures of four types of commonly-used standard neurocomputing models.

The training process of neurocomputing model is accomplished by adjusting the network parameters, such as synaptic weights and biases, of connections between the artificial neurons in the layers usually based upon a back-propagation process. Various mathematical (e.g., Levenberg–Marquardt algorithm) and heuristic (e.g., particle swarm optimization algorithm) techniques might be utilized for training the networks. Regardless of their nature, these training algorithms are designed to adjust the weights and biases in a way to minimise the network's predicting error (Barnard, 1992; Ilonen et al., 2003).

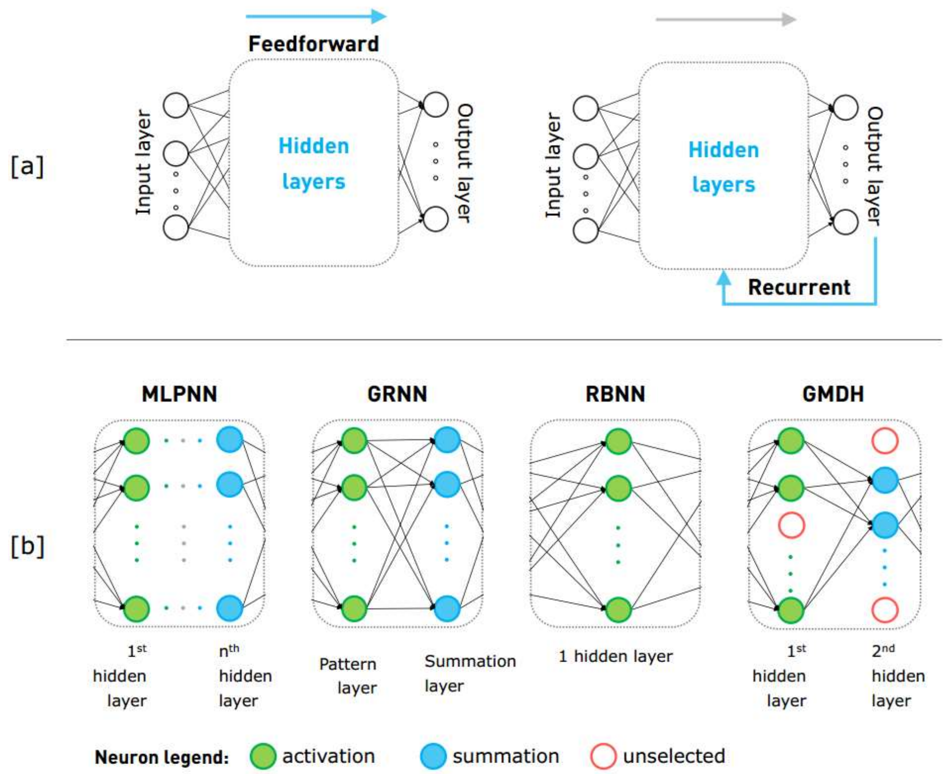

Fig 1. a) Schematic structure of neurocomputing models: *feedforward* vs. *recurrent* approaches; b) Internal architecture of different types of standard neurocomputing models (MLPNN: Multi-Layer Perceptron ANN, GRNN: Generalized Regression ANN, RBNN: Radial Basis ANN, GMDH: Group Method of Data Handling)

Neurocomputing models are now known as the most popular and common ML models in simulating and predicting hydrological and hydraulic phenomena (Mosavi et al., 2018). Figure 2 presents and classifies the most common types of neurocomputing models used in hydrological and hydraulic sciences in three main categories including (i) their general structure and architecture (i.e. a *feedforward* structure or a *recurrent* structure), (ii) the learning methodology, such as the *ensemble* learning or the *individual* (*stand-alone)* learning, and (iii) the nature of the training procedure. Detailed information about the mentioned neurocomputing models given in Figure 2 can be found in the following references:

Recurrent Neural Networks (Mandic and Chambers, 2001), Gated Recurrent Unit Networks (Wang et al., 2018), Deep Learning Neural Networks (Schmidhuber, 2015), Long Short Term Memory Neural Networks (Kratzert et al., 2018), and Nonlinear Autoregressive Exogenous Networks (Zounemat-Kermani et al., 2019a). Feedforward Neural Networks (Svozil et al., 1997), Inductive ANNs (Mahdavi-Meymand & Zounemat-Kermani, 2019), Extreme Learning Machines (Alizamir et al., 2018), WaveNet (Rajaee, 2011), Adaptive Neuro-Fuzzy Inference Systems (Firat and Güngör, 2008), and Conventional ANNs (Zounemat-Kermani, 2014). Ensemble Neural-Based Models (Araghinejad et al., 2011), and Integrative Neural-Based Models (Zounemat-Kermani et al., 2020a).

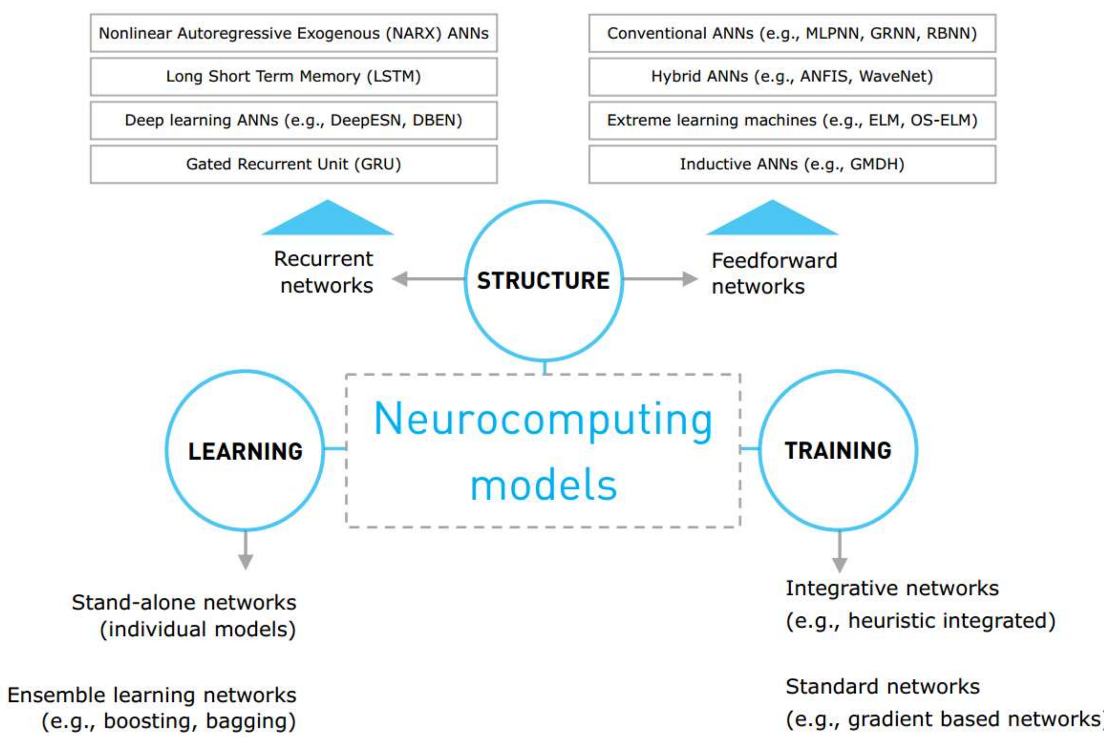

Fig 2. The illustrative diagram for different categories and types of mostly used neurocomputing models in hydrological and hydraulic sciences.

1.3. Rationale, Research Motivation, and Framework

Despite the increasing usage of neurocomputing in hydrological and hydraulic sciences, to the authors' best knowledge, a comprehensive review of the most recent applications of neurocomputing models in the relevant topics is still missing. This paper reviews peer-reviewed articles published over the last two decades (2000-2019), presenting the applications of neurocomputing models in quantitative surface water hydrological and hydraulic sciences. But it is worth noting that the current review does not include the use and application of neurocomputing in the field of surface water quality (Anmala et al., 2015; Anmala et al., 2019). The focus of this work is twofold:

- First, this study presents a comprehensive, inclusive, and general review of the application of neurocomputing in various fields of surface hydrology, hydraulics, and water engineering sciences (see Section 2).
- Second, the current study aims to analyse and categorise the state-of-the-art of different neurocomputing models in six main fields of quantitative hydrological and hydraulic sciences categorized in two facets: i) surface hydrology, and ii) hydraulics in civil and water engineering (see Section 3).

We expect this work to contribute to problem-specific guidelines and recommendations for future usage of neurocomputing models for addressing water-related modelling challenges (see Sections 4-6).

The remainder of this review is organized as follows. In section 2, we present the methods adopted to build and organize this literature review and list the specific fields of applications that we investigate to reveal the recent advances of neurocomputing models in hydrological and hydraulic sciences. The current status quo, research challenges, and specific directions associated with neurocomputing applications in each of the above fields are discussed in section 3. We make final remarks in section 4. Finally, in sections 5 and 6, research gaps, recommendations and directions for the future researches are provided.

2. General Overview and the Review Methods

The application of neurocomputing models in hydrology and hydraulics has received considerable attention during the last decades, and it is still an expanding field of research. Within the scope of this review, scientific peer-reviewed articles were retrieved by searching on Scopus (https://www.scopus.com/home.uri) for the combinations of the following keywords:

- Keywords related to the *neurocomputing* part: Neural Network/ Neural/ Neuro-/ Neural-Based/ Neurocomputing/ ELM/ NARX/ GMDH/ ANFIS/ WaveNet/ LSTM/ DBNN/ DeepESN/ GRU/ ESN/ ENN/ RNN/ CNN;
- Keywords related to the *surface hydrology* part: Water level/ flow discharge/ hydrology / flow rate/ river flow/ streamflow/ open channel flow/ compound channel/ suspended sediment/ sediment yield/ bedload/ sediment transport/ rainfall-runoff/ flood;
- Keywords related to the *hydraulics* part: urban water/ water demand/ hydraulic/ hydro-structure/ dam/ spillway/ outlet works/ waterworks/ weir/ sewer/ water treatment plant/ wastewater/ overflow/ conduit/ intake/ stilling basin/ chute.

Moreover, we distinguish between two neurocomputing categories in this paper:

- *Conventional* neurocomputing models include the feedforward, standard, and stand-alone versions of neurocomputing models, such as MLPNNs, GRNNs, etc. (see Figure 2);
- *Modern* neurocomputing models include more advanced model techniques such as integrative, recurrent, and deep learning networks as well as other complementary types of neurocomputing models.

Overall, the publication rate of papers in hydrological modelling using the conventional neurocomputing models has not been significantly increasing during the last two decades, with an average of 11 papers published per year (from 2000 to 2019). Conversely, there has been a noticeable increasing trend in the number of studies using modern neurocomputing models in different subjects related to surface hydrology since 2000 (15 papers per year, on average between 2000 and 2019, with 32 papers published in 2018 alone). Similar to the surface hydrology facet, there has been increasing attention in employing modern neurocomputing models in hydraulic sciences.

Due to the existence of a large number of reported applications of neurocomputing models to the vast areas of hydrological and hydraulic sciences (more than 800 papers since the year 2000), we summarize in this section the content of those published as *Review Articles*. Overview of these *Review Articles* and their major remarks are summarized in Table 1. This section is primarily designed to provide readers with an overall insight regarding the past and present status of neurocomputing applications in hydrological and hydraulic sciences as a general perspective. A more detailed discussion of different specific fields will be given in the next section.

Table 1. An overview of the application of neurocomputing models in hydrological and hydraulic sciences based on the published *Review Articles* between the 2000 and 2019

Researcher(s)	Category/ Bibliography period	Application	Discussed topics
Maier & Dandy, 2000	Water resources (1994-1998)	Rainfall, Water quality, Water level	This research states some guidelines for the process of choosing suitable factors, such as principles for optimising network geometry, in setting up neural networks for issues related to water resources.
Dawson & Wilby, 2001	Surface-water hydrology	Rainfall-runoff	This study surveys some of the traditional neurocomputing methods for rainfall–runoff

	(1992-2000)		modelling. Advisable information is also given on data preparation and the fundamentals of constructing neural networks in hydrological sciences.
Maier et al., 2010	Water resources (1999-2007)	Water quantity	This study reviews researches in using neurocomputing models for predicting water resources in river systems. In addition, information is given in establishing ANN models.
Kumar et al., 2011	Hydrometeorology (2000-2010)	Evapotranspiration	This study discusses the potential of neurocomputing in evapotranspiration modelling. The characteristics of neural networks from different aspects are also explored.
Nourani et al., 2014	Surface-water hydrology Hydrometeorology Hydrogeology (2003-2013)	Precipitation, River flow, Rainfall-runoff, Sediment transport, Groundwater	This study reviews papers related to artificial intelligence models, including neural networks and the wavelet transform used in surface hydrology and hydrogeology.
Ghalehkhondabi et al., 2017	Hydraulics (2005-2015)	Water demand	This study focuses on soft computing methods, including neural networks, fuzzy logic, and Support Vector Machines for water consumption forecasting.
Fahimi et al., 2017	Surface-water hydrology Hydrometeorology Hydrogeology (1998-2015)	River flow, Flood, Rainfall-runoff, Evaporation, Water level	The application of different types of neurocomputing models in water resources and hydrology are reviewed and discussed.
Mosavi et al., 2018	Surface-water hydrology (2008-2017)	Flood	This paper demonstrates the state of the art of machine learning models, such as ANN in flood prediction. Machine Learning methods are evaluated in terms of robustness, effectiveness, accuracy, and computational efficiency.
Rajaee et al., 2019	Hydrogeology (2001-2018)	Groundwater	Artificial Intelligence methods are reviewed and surveyed for groundwater level modelling and forecasting. The application

			of some neurocomputing models in groundwater modelling is discussed in detail.
Yaseen et al., 2019	Surface-water hydrology (2014-2019)	River flow	This paper presents a comprehensive review of Extreme Learning Machine models and their application in river flow forecasting.

According to the review articles as summarised in Table 1 for existing research in using neurocomputing in hydrological and hydraulic sciences, it is apparent that the majority of the neurocomputing models have been developed and applied to surface water hydrology problems, in particular, river flow modelling. In conclusion, considering the state-of-the-art of neurocomputing applications in hydrological and hydraulic sciences, it emerges that there has been a tremendous interest in using modern types of neurocomputing models rather than the traditional versions.

Figure 3 depicts the general trends of using neurocomputing models in hydrological and hydraulic sciences. As can be seen in Figure 3, four separate chronological stages might be recognized in terms of the number of published papers during the last two decades (2000-2019). Based on past trends, we might expect the commencement of a new stage of using neurocomputing in hydrological and hydraulic sciences roughly in a five-year period. The main reason for this may be related to the emerging of new neurocomputing technologies and their applications in a period of five years.

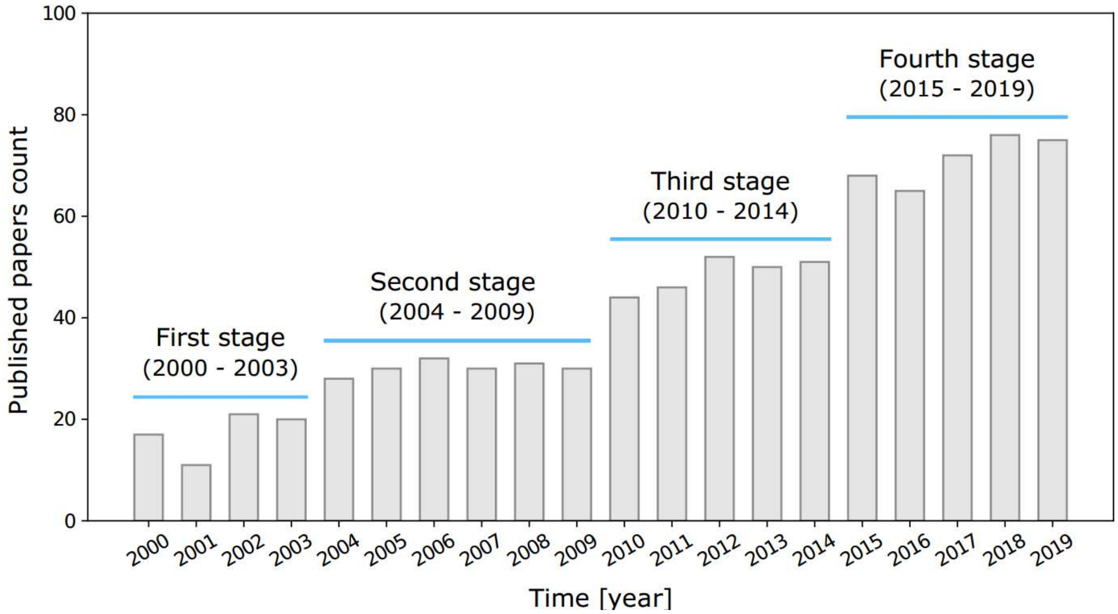

Fig. 3. Illustration of the four chronological stages of using neurocomputing models in hydrological and hydraulic sciences during the past two decades (2000-2019).

3. Applications of Neurocomputing in Hydrology and Hydraulics

Surface water hydrology and hydraulics includes a vast variety of subjects related to water engineering, water resources management, hydrology, hydrogeology, hydrometeorology, hydraulics, sanitary engineering, and river engineering. In this review, the focus is laid on six different aspects of hydrosciences, i.e., three hydrological topics, and three hydraulic topics. The three topics in surface hydrology are:

- Topic 1: Prediction of water level in surface water bodies
- Topic 2: Flood modelling, mapping, and risk assessment
- Topic 3: Modelling sediment transport in river systems

The following three topics are associated with the hydraulic facet of the current study:

- Topic 4: Urban water demand prediction
- Topic 5: Modelling flows through hydraulic structures

- Topic 6: Flow and sediment modelling in sewers

Each topic is reviewed and discussed in the following subsections.

3.1 Topic 1: Prediction of Water Level in Surface Water Bodies

The hydrodynamics in surface water bodies, for instance, free-surface wetlands, lakes, reservoirs, rivers, and oceans, are governed by nonlinear processes and often predicted through numerical simulations using deterministic models. Large sets of physical and topographical data and complex hydrological conditions are needed to set up such models, besides the high computational time. The neurocomputing approaches have been emergently used by many researchers for predicting water level and hydrodynamics in surface water bodies because of their capability to detect the nonlinear relationships existing in historical data series of water level and discharge in a catchment, and their much cheaper computational cost.

Complex natural and anthropogenic processes are continued to create impacts on the surface water bodies on Earth; information about water levels is important for understanding the impacts and informing decision-making for many aspects of engineering interventions and management. First, prediction of water level is crucial for optimizing water resources management and, thus, planning multiple water uses such as hydropower plants (HPP), irrigation agriculture and water supply (e.g., Chang and Chang, 2006), as well as to assess flood risk and develop flood control/mitigation strategies (e.g., Chang et al., 2014; Yu et al., 2006). Furthermore, water level predictions are required for river and ocean navigation (Hou et al., 2014; Ma et al., 2018) – especially concerning cargo capacity calculations, journey duration, planning of arrival times at ports and harbours – and for designing hydraulic structures (offshore, dams, weirs). Extensive research has been also conducted to monitor and understand the effects of climate, evaporation, and HPP on water level fluctuations, and to assess their various impacts on sediments, water quality parameters and related processes, such as sediment drying (e.g., Keitel et al., 2015) and transport of nutrients (e.g., Matta et al., 2018).

While recognising the importance in measuring/predicting water level fluctuations, this acquisition of information must be achieved with a suitable lead time for various applications. For example, for flood control operations and peak mitigation, the interest lies in the short-term forecast (i.e., minutes, hours); while for navigation planning or for water quality assessments, it is more relevant to the mid-term or long-term forecast (i.e., days or even months).

As an example of the early studies, See & Openshaw (2000) applied different soft computing approaches and developed a complex hybrid system for river level forecasting. The dataset was taken from the River Ouse in northern England, choosing a prediction horizon of 6 h. Self-Organizing Maps (SOM) was used as a pre-classifier to develop individual MLPs, which have been linked using a fuzzy logic model and genetic algorithm optimization (GA). While the hybrid system demonstrated its suitability for flood forecasting and high-water level detection, the fuzzy model was still not able to reproduce the lower levels and, thus, required further experimentation.

Coulibaly (2010) explored to use of the Reservoir Computing method, namely Echo State Network (ESN), to predict monthly averaged water levels for up to 10 months ahead in four Great Lakes in the USA. The author compared the results with other two approaches (the Bayesian Neural Network, BNN, and the classical Recurrent Neural Network, RNN) and found out that the ESN performed well for up to 6 months ahead while the RNN gave better results than the ESN for longer lead times (8–12 months ahead). On the other hand, ESN could be further improved by including additional factors such as evaporation and precipitation. It was also less computationally demanding and demonstrated higher usage efficiency. Panda et al. (2010) compared a physically-based hydrodynamic model, i.e., MIKE 11HD, and a Feedforward Neural Network (FFNN) trained with the Levenberg-Marquardt algorithm to predict water levels in the River branch Kushabhadra, Bay of Bengal, India. The previous five-time lags of the hourly water level data at the upstream gauges were used as input to determine the downstream gauge level at the current time. FFNN showed superior performance, and the time to peak and the peak values were much closer to the measurements than those predicted by the computationally more expensive MIKE 11HD model.

Chang et al. (2014) compared one static and two dynamic RNN type of models for water level prediction in flood control and mitigation in urban areas. Respectively, they set up a FFNN, an Elman Neural Network (ENN), and a Nonlinear Autoregressive Exogenous (NARX) neural network model to predict in the short-term (10-60 min) the multi-step-ahead water levels in a floodwater storage pond (FSP) in the Yu-Cheng Pumping Station located in Taipei City, Taiwan. Their results demonstrated that the FFNN, depending only on 'static' observed data, was inferior to the ENN and the NARX, which incorporated the observed data with time delay units through recursive inner connections from the hidden layer or from the output layer, respectively. Nevertheless, better performance was achieved by the NARX under the scenario of including not only the rainfall data of the neighbouring gauges as inputs, but also the current FSP water level.

The study presented in Ma et al. (2019) investigated the capability of FFNN and Long Short-Term Memory (LSTM) in predicting water levels at critical gauges of the Rhine River Basin (Germany), in order to support inland navigation logistics planning. The basic idea was to predict hourly and daily water levels at a specific gauge for up to 10 days ahead, only considering the historical data measurements at the same gauge and the upstream gauges. The LSTM model outperformed the FFNN on the longer term predictions (from 2 up to 10 days), and the greatest improvement was obtained when the hydrological model chain hindcasts of the German Federal Institute of Hydrology (BfG) from 2008 until 2015 were included as an additional predictor to the inputs. Table 2 summarizes the researches related to the water level prediction using neurocomputing models.

Table 2. Summary of the reviewed studies in applying various types of neurocomputing models for predicting water level in surface water bodies.

Author(s) / Year	Model	Motivation	Remarks
See & Openshaw, 2000	MLP, SOM, NF	Hourly river level predictions up to 6 h ahead in the Ouse River, northern England	A hybrid forecasting system was developed for potential flood forecasting and warning systems, using a SOM prior to training and a fuzzy logic model integrated with a standard MLP based on current river levels and their changes. The system better predicted the high water levels than the lower water levels.
Makarynskyy et al., 2004	FFNN	Hourly prediction of sea-level variations up to 24 h ahead, and forecast of half-daily, daily, 5-daily and 10-daily mean sea levels (three steps ahead)	Saliency analysis was adopted as an optimization method to find the best network architecture. The forecasts of the third time step ahead were less accurate compared to the previous steps.
Khan & Coulibaly, 2006	MLP, SVM	Averaged monthly water level predictions up to 12 months ahead in Lake Erie, USA	SVM could be more advantageous than MLP, due to its higher generalization capacity and smaller number of free parameters used, but the training of a large dataset was computationally more expensive.
Coulibaly, 2010	BNN, ESN, RNN	Averaged monthly water level predictions up to 10 months ahead of the Great Lakes, USA	ESN outperformed the BNN and RNN benchmark models and was demonstrated to be computationally more efficient. ESN could be further improved by including additional independent input variables.
Panda et al., 2010	FFNN	Hourly water level predictions in the River branch Kushabhadra, Bay of Bengal, India	The authors compared the physically based hydrodynamic model MIKE 11HD and a FFNN, where FFNN outperformed MIKE11HD in predicting the flood peaks.
Chang et al., 2014	ENN, FFNN, NARX	Real-time water levels in the floodwater storage pond (FSP) of a sewer-	Three different ANN types (static and dynamic) were compared to predict short-term (10-60 min) FSP water

		pumping system in Taipei City, Taiwan	levels for urban flood control. The NARX model (dynamic) outperformed the others.
Seo & Kim, 2016	ANN, ANFIS	Daily river stage of two streamflow gauging stations in South Korea	The hybrid models (an integration of the Wavelet Packet decomposition and data-driven models, WPANN and WPANFIS) might overcome certain issues of ANN and ANFIS when dealing with nonstationary data.
Ghorbani et al., 2017	MLP	Water level predictions on a monthly time scale in Lake Egirdir, Turkey	Firefly Algorithm (FFA) – i.e., heuristic optimization tool – was integrated with the Multilayer Perceptron (MLP-FFA). The further inclusion of a significative hydrometeorological variable yielded more accurate predictions.
Kaloop et al., 2017	ANFIS, WNN	Hourly water level change (WLC) predictions for one month at three tide gauges in Canada	A WLC hourly prediction model for maritime applications based on a short period (approx. 2 months) of water level measurements was developed using the ANFIS approach, which outperformed the existent WNN models.
Sung et al., 2017	FFNN	Hourly water level predictions up to 3 h ahead in a tributary of the Han River, South Korea	The predictions were satisfactory only up to 2 h ahead. In general, when the water levels at the main river gauging stations were integrated into the input data, the model gained higher accuracy.
Liang et al., 2018	LSTM, SVM	Daily water level predictions of Dongting Lake, China	Grey Relational Analysis (GRA) was adopted to select the input data of the LSTM model, which delivered better results than the SVM (benchmark).
Ma et al., 2019	FFNN, LSTM	Daily water levels up to 10 days ahead in the Rhine River Basin, Germany	The LSTM model showed its capability to predict daily water levels for up to 10 days ahead in some critical gauges of the Rhine.

Analysing the findings from the reviewed papers implies that some novel neurocomputing models such as LSTM and ESN are able to overcome the vanishing gradient problem that is typical to RNN (Coulibaly, 2010; Liang et al., 2018). Generally, including hydrological records and/or using hybrid models (e.g., physically based models in combination with neurocomputing approaches and/or optimization methods) can significantly improve water level predictions, compared with the conventional neurocomputing models (See & Openshaw, 2000; Ma et al., 2019).

3.2 Topic 2: Flood Modelling, Mapping, and Risk Assessment

Flooding is one of the most common natural hazards across the world. According to the EM-DAT international disaster database (CRED 2018), flooding is responsible for over one-third of global economic loss and two-thirds of the people affected by all types of natural hazards. Managing flood risk is, therefore, an important task for both relevant governments and non-governmental organisations across the globe.

Flood prediction and forecasting are essential to facilitate risk assessment and increase the preparedness to subsequently mitigate damages from flooding. Flood prediction is usually performed using physically based models, data-driven approaches, or a combination of the two. A physically based modelling approach usually employs a catchment-scale hydrological models to predict rainfall-induced runoff, a 1D hydraulic model for flood routing and a 2D hydraulic model to simulate inundation. It is a well-established approach that has been widely used, e.g., in the UK Flood Forecasting Centre (Robson et al. 2017).

The data-driven approaches, which usually require much less computational resources, are suited for real-time operational flood forecasting as an alternative to the physically-based models. Neurocomputing models are among the most popular methods for data-driven flood forecasting, which have traditionally been widely used for predicting runoff hydrograph, and a comprehensive review can be found in Mosavi et al. (2018).

Herein, the application of neurocomputing models in real-time flood forecasting is firstly reviewed. Chang et al. (2010) developed a Clustering-based Hybrid Inundation Model (CHIM) for forecasting flood inundation depths. In their model, the flood inundation information (including locations and depths) simulated by HEC-1 and SWMM models were categorised into clusters using a *k*-means clustering. Then FFNN was employed to predict the inundation depth for each cluster. For the test case in Central Taiwan, the model was much faster than a physically based flood forecasting model and was able to generate a 1-h-ahead flood inundation map within a few seconds with the Mean Absolute Error (MAE) for peak flood depths predicted as small as 0.06 m. Another reported method for flood inundation prediction using neurocomputing combined NARX neural network with SOM (Chang et al., 2014). Rather than dividing flood inundation information into clusters, the hybrid SOM-NARX method firstly used SOM to organise the flood inundation maps into a two-dimensional matrix, with each matrix associated with a total inundated volume. Subsequently, the inundated volume predicted by NARX was used to find the most likely inundation map from the matrix. The hybrid SOM-NARX method was shown to outperform the CHIM. Recently, this method was further improved by replacing NARX with a Recurrent NARX model (Chang et al. 2018). Kia et al. (2012) applied FFNN to predict flow hydrographs from elevation, topographic slope, flow accumulation, geology, land use, soil, and rainfall data. Then the inundation area was generated based on river cross-sections. Although the aforementioned studies are promising, they cannot provide results as accurate and as rich in information as a physically based model does. For instance, no neurocomputing or even general machine learning-based models have been reported to be able to predict flood depths at a high temporal resolution (minutes), or flood velocity maps.

In the past two decades, neurocomputing models have also been used for deriving spatial information for flood prediction and risk management, including long-term prediction of flood risk, e.g., flood susceptibility mapping. Tien Bui et al. (2016) proposed an integrative model based on metaheuristic algorithms and Neuro-Fuzzy (NF) model (namely MONF). Their model took a number of independent factors, including elevation, slope, curvature, stream power index, topographic wetness index, distance to river, normalized difference vegetation index, lithology, stream density, and rainfall as the input vectors, to predict a flood susceptibility map as the output. The model showed high accuracy and efficiency for both of the training and the validation datasets. Their study also showed that the vegetation index had the highest predictive power for flood susceptibility. Their method outperformed Random Forest (RF), SVM, and Adaptive Neuro-Fuzzy Inference System (ANFIS). In Razavi Termeh et al. (2018), three different ensemble-ANFIS models, as well as RF and SVM, were applied and compared for mapping flood susceptibility. In their models, the ensembles were constructed by training multiple models using the same method. They found that ensemble-ANFIS with Particle Swarm Optimization (PSO) gave more accurate results than others. Shafizadeh-Moghadam et al. (2018) used an ensemble of multiple types of models in which Feedforward Back Propagation (FFBP) ANN is one of the individual models. They suggested that the ensemble produced more stable and generalised results with higher predicting ability. However, they also suggested that there was no guarantee that an ensemble of models could always outperform an individual model. The method generally required a large amount of spatial information, e.g., topography, vegetation type, and lithology about the catchment under consideration. Obtaining these datasets over an entire catchment has been a challenging task, but with the advances of remote sensing, such a task is becoming increasingly feasible. A summary of the papers being reviewed in this section is given in Table 3 with the focus on the latest published papers.

For flood prediction, mapping, and risk assessment, the strength of neurocomputing lies in its high computational efficiency (given the model has already been trained), and therefore enables real-time flood forecasting with moderate or low computational demand. The drawback of the existing neurocomputing models is their incompetence to capture the dynamic features of the flooding process and its reliance on large existing hydrometric datasets. A promising way forward lies in the combination of ANN-based models with physically based models to overcome these issues.

Table 3. Summary of the reviewed studies involving the application of various types of neurocomputing models for flood prediction and risk assessment.

Author(s) / Year	Model	Motivation	Remarks
Chang et al., 2001	RBNN	Flood forecasting	The model was applied to successfully forecast flooding three hours ahead with reasonable accuracy.
Dawson et al., 2006	MLP	Flood estimation	The results indicated that neural networks were able to estimate flood statistics for ungauged catchment.
Chang et al., 2010	FFNN	Flood inundation forecasting	The ANN model could generate flood inundation maps within a few seconds with a MAE as small as 0.06 m.
Kia et al., 2012	FFNN	Flood inundation simulation	A combined system of GIS tools and neural networks was used for creating flood inundation maps.
Chang et al., 2014	SOM, NARX	Flood inundation nowcasting	The SOM was applied for the first time in this context, and promising results were obtained for nowcasting flood inundation.
Bui et al., 2016	Integrative NF	Flood susceptibility mapping	Metaheuristic optimization could improve the performance of the neuro-fuzzy model.
Razavi Termeh et al., 2018	ANFIS	Flood susceptibility mapping	Ensemble ANFIS generally performed better than an individual (non-ensemble) approach.
Shafizadeh-Moghadam et al., 2018	FFNN	Flood susceptibility mapping	Ensemble methods had greater generalisation ability and higher predicting capability.
Chang et al., 2018	SOM, NARX	Flood inundation forecasting	The recurrent NARX model produced better results than the SOM model.
Sarker et al., 2019	CNN	Flood mapping	The applied convolutional network provided promising results in mapping flood areas from Landsat images across Australia.

3.3 Topic 3: Modelling Sediment Transport in River Systems

Sediment behaviour is complex, dynamic and non-stationary as well as not uniformly related to the streamflow behaviour (Chien & Wan 1999; van Rijn et al., 2001). Fast moving flow can pick up sediments by turbulence and carry them in suspension. The suspended sediments may sink and deposit on the riverbed when moving flow becomes slow. Suspended sediment concentration (SSC) is often closely related to the dynamics of streamflow. However, this relationship is seldom unequivocal and can vary by several orders of magnitude due to such factors as hysteresis, seasonality, e.g., during a storm event the stream can carry much more sediment than it carries during a low flow period. As there is no unique mathematical relation between the SSC and the streamflow, predictive simulation of SSC remains a challenge (e.g., Zhou 2011, Goll 2017, Banda 2018, Zhao 2019).

SSC is of paramount importance in waterway engineering as the amount of deposited sediment and time frame determine when dredging is required to ensure sufficient water depth for shipping or reservoir operation (Vollmer & Goelz 2006, Zhang 2018). Furthermore, suspended sediment may strongly affect water quality when polluted sediments are remobilised through dredging activities, as is the case for Upper Rhine in Germany (Goll 2017, Zhang 2018). Simplified approaches for the current practical applications are based on the classical sediment rating curve (SRC) method, which determines a functional relation for SSC and the streamflow based on measurements. A fast estimation of SSC depending on the measured streamflow is possible with the SRC. However, SRC has a limited capability to capture nonlinear processes with regard to streamflow and other hydrologic processes (Melesse et al., 2011; Rajaee, 2011; Rajaee et al., 2009). For complex river systems, neurocomputing models have proven their suitability. Being a data-driven approach, neurocomputing modelling offers an effective way to handle non-uniform data from dynamic and nonlinear systems (Alp and Cigizoglu, 2007; Nourani et al., 2014). The neurocomputing models may be considered as an alternative when the physically based models show poor accuracy or demand a high computational cost (Wieprecht et al., 2013).

There has been a lot of researches on neurocomputing models for predicting sediment concentration, including assessments of the model accuracies (see Table 4). In the study of Nagy et al. (2002), a FFNN model was developed to determine sediment concentration in rivers, and better results were obtained for 80 datasets compared with several commonly applied sediment discharge formulas. Rajaee et al. (2009) investigated several neurocomputing (e.g., FFNN & NeuroFuzzy, NF), Multiple Linear MLR, and SRC models for predicting time series of sediment concentration in two different rivers. Their results showed the superiority of FFNN and NF models compared with the MLR and SRC methods in reproducing sediment concentration measurements. Melesse et al. (2011) studied FFNN, Auto-Regressive Integrated Moving Average (ARIMA), MNLR (Multivariate Non-Linear Regression), and MLR models to compute daily suspended sediment loads for three major rivers in the USA (Mississippi, Missouri and the Rio Grande). They found that FFNN produced better predictions in most of the cases compared with MLR, MNLR, and ARIMA.

Rajaee (2011) suggested a Wavelet-ANN (WNN) model for predicting daily suspended sediment load (SSL) in the Yadkin River in the USA, which decomposed each time series into discrete wave transforms for use as inputs in the ANN. In comparing the accuracy of WNN with MLR and SRC models, WNN performed the best, and furthermore, it could satisfactorily reproduce hysteresis phenomena. Liu et al. (2013) concluded that the WNN model outperforms the conventional models, such as MLP and SRC, in short-term (one-day) forecasting of nonlinear and non-stationary SSC time series. Zounemat-Kermani et al. (2016) predicted the daily sediment concentration based on an eight-year data series from hydro-metric stations in Delaware, Arkansas, and Idaho in the USA using MLP models. Their results demonstrated better performance of MLP models incorporated with the Broyden-Fletcher-Goldfarb-Shanno training algorithm and recommended this as a suitable option for modelling hydrological processes. Joshi et al. (2016) applied FFNN to model stage-discharge suspended sediment relationships for melt runoff from the Himalayan Gangotri glacier, India in the ablation season (May-September). Their results revealed the suitability of FFNN to estimate daily sediment concentration in glacier melt runoff. Zhang (2018) applied FFNN and appropriate WNN models to forecast long-term daily sediment concentration based on predicted discharges. Khosravi et al. (2018) applied several novel data mining methods, including standard and hybrid models in predicting river sedimentation. It was reported that the hybrid models provide reliable and robust predictions.

Table 4. Summary of the reviewed studies in applying various types of neurocomputing models for modelling suspended sediment transport in rivers.

Author(s) / Year	Model	Motivation	Remarks
Nagy et al., 2002	FFNN	Prediction of SSC in rivers	The FFNN performed better than discharge formulas.
Cigizoglu and Alp, 2006	GRNN, FFNN	Daily discharge (Q) and SSC prediction	GRNN and FFNN were superior compared to the traditional sediment rating curve formula.
Cigizoglu and Kisi, 2006	FFNN, RDNN, LR	Daily Q and SSC applied prediction	RDNN provided the better results, and was superior to the conventional FFNN.
Rajaee et al., 2009	FFNN, NF	Time series of daily Q and SSC in 2 rivers	FFNN and NF performed better than MLR and SRC in reproducing SSC measurements.
Melesse et al., 2011	MLP	Daily and weekly predictions of SSL in 3 US rivers	MLP outperformed MLR, MNLR, and ARIMA in most cases. Daily predictions were better than weekly.
Rajaee, 2011	WNN, FFNN,	Daily SSL modelling in the US river	WNN performed more favourably than FFNN, MLR, and SRC.
Liu et al., 2013	WNN, FFNN,	Highly nonlinear and non-stationary SSC time series one day ahead prediction	WNN performed better than FFNN and the traditional sediment rating curve method.

Nourani et al., 2014	WNN,	SSL modelling	WNN was suitable to handle non-uniform data from dynamic and nonlinear hydrological systems.
Zounemat-Kermani, 2016	MLP, PSO-MLP, ANFIS	SSC dynamics in streamflow	All of the applied neurocomputing models performed better than the statistical models.
Joshi et al., 2016	FFNN	Stage discharge suspended sediment relationships for melt runoff	FFNN was suitable for the estimation of daily SSC.
Kisi &Zounemat-Kermani, 2016	MLP, ANFIS	Suspended sediment modelling	ANFIS model was superior to the MLP.
Kumar et al., 2016	FFNN, RBNN	Daily SSC	ANN and LS-SVR methods were better than the other models, such as MLR.
Zounemat-Kermani et al., 2016	MLP	Forecast/estimate daily SSC	MLP and SVR performed better than MLR and SRC.
Zounemat-Kermani et al., 2018	FFNN, RBNN, ANFIS, WNN	Estimating incipient motion velocity of bed sediments	WNN followed by integrative GA-ANFIS, gave the better results.
Zhang, 2018	FFNN, WANN	Prediction of daily SSC	FFNN performed better than WNN and SRC.
Khan et al., 2019	MLP	Prediction of SSC in rivers	The simple ANN models successfully predicted the SSC values.

In the last two decades, neurocomputing models have been applied and extended to simulate and predict sediment transport in rivers. When compared to 1D, 2D, or 3D physically based numerical models that solve the shallow water flow and sediment transport equations, neurocomputing models are considerably more efficient from the computational point of view (Zhang 2018). Besides, many further studies have demonstrated that neurocomputing models perform better in predicting daily sediment transport compared to other mathematical methods (e.g., Cigizoglu and Alp, 2006; Cigizoglu and Kisi, 2006; Kumar et al., 2016; Liu et al., 2013). Among the common neurocomputing methods considered here, the FFNN, WNN, and MLP have been widely applied in modelling sediment transport, and shown their superiority in comparison to the traditional and statistical models, such as SRC, MLR or ARIMA.

3.4 Topic 4: Urban Water Demand Prediction

Accurate prediction of water demand in urban settings is the key to inform optimal planning and management decisions in water distribution systems, improve utilities' operations, and support the design of demand-side management programs (Donkor et al., 2012). Several types of models have been tested in the literature to capture existing relationships between water demand and its potential determinants, including natural and climatic factors, socio-demographic factors, and responses to water demand management strategies (for recent comprehensive reviews, see House-Peters & Chang, 2011; Donkor et al., 2012; Cominola et al., 2015). In the last two decades, neurocomputing models (e.g., FFNN, RBNN, MLP, CNN) have been increasingly adopted to develop forecasting models of water demand, mainly because of their ability to capture the nonlinear relationship between water demand and the aforementioned determinants, as well as because they require fewer assumptions than other parametric and more conventional methods based on regression techniques or time series analysis (Ghalehkhondabi et al., 2017; House-Peters & Chang, 2011).

Several studies in the literature (see Table 5) have demonstrated the suitability of various types and architectures of neural-based methods to accurately forecast urban water demand across different spatiotemporal scales. Most of these studies focus on predicting water demand at the city scale and in the short- or medium-term, with a temporal resolutions that spans from hourly (e.g., Herrera et al., 2010; Coelho & Andrade-Campos, 2019) or daily (e.g., Adamowski et al., 2012; Al-Zahrani & Abo-Monasar, 2015) to weekly and monthly (e.g., Jain et al., 2001; Firat et al., 2009; Firat et al., 2010), often with an emphasis on peak demand during summer months (Bougadis et al., 2005; Adamowski, 2008; Adamowski & Karapataki, 2010). Only a few examples focused on long-term forecasting (Li & Huicheng, 2010).

The numerical results obtained in the state-of-the-art studies demonstrate that different types of neural-based models can provide more accurate forecasts than benchmark linear or nonlinear methods on specific case studies. For instance, the outcomes of a recent study by Mouatadid & Adamowski (2017) demonstrated that Extreme Learning Machines outperformed MLR, FFMLP, and SVM could accurately forecast daily urban water demand for the city of Montreal (Canada). Furthermore, the performance of neurocomputing methods can be enhanced by coupling neural networks with wavelet denoising (Campisi-Pinto et al. (2012) combined FFNN with wavelet denoising to reduce the variance of the model input dataset) or methods that aid the search for optimal input variables and network settings (e.g., GSA and BSA in Zubaidi et al. (2018); DWT and MSA in Altunkaynak & Nigussie (2017)). These promising insights are supported by the numerical outcomes of comparative studies that rigorously assessed the performance of neural-based methods against benchmark methods (e.g., Msiza et al., 2007; Adamowski & Karapataki, 2010; Odan & Reis, 2012; Pacchin et al., 2019). In addition to that, a few studies attempted to develop comprehensive models that are able to forecast urban water demand across different temporal scales and lead times (Ghiassi et al., 2008, Tiwari & Adamowski, 2013), showing that accuracy levels well above 90% can be reached.

While such results overall support the use of neurocomputing methods to forecast urban water demand, some challenges and opportunities for further research can still be listed. First, most of the findings from the reviewed studies can be considered as case-specific and are hard to generalize to other applications. For instance, while there is consensus on the influence of maximum temperatures on water demand, there is no full agreement on which weather-related variables best inform neural-based model predictions (e.g., rainfall amount *vs.* rainfall occurrence; Adamowski, 2008). Secondly, several other socio-demographic factors constitute potential drivers/determinants of water demand. Yet, it is still unclear which of these determinants influence water demand at different spatial and temporal scales, and gathering some of them is not under the control of water utilities (Donkor et al., 2012). Accurate short-term water demand forecast at the urban scale can be obtained even with the inclusion of lagged historical demand (Babel & Shinde, 2011), but socio-demographics become relevant when household-scale models are developed (Liu et al., 2003). More in general, the identification of optimal neural-based model predictor set would prevent developing unnecessarily complex models that include redundant or non-informative variables likely to cause a decrease in the model performance (Coelho & Andrade-Campos, 2019). Thirdly, while different ANN architectures have been demonstrated to compete and outperform more classical statistical methods (Ghalehkhondabi et al., 2017), hybrid approaches, i.e., combined methods such as the MSA-MLP (Altunkaynak & Nigussie, 2017), GSA-FFNN (Zubaidi et al., 2018) and CNN with LSTM (Hu et al., 2019) are recently gaining interest and opening up opportunities for further investigation, with applications to both short-term and long-term (extended lead time) urban water demand forecasting.

In addition, the digitalization of the water sector and the deployment of smart meter technologies are opening up new opportunities for the development of fine-scale descriptive and predictive demand models (Cominola et al., 2015, 2019). Bennett et al. (2013) demonstrated that neural-based methods, such as FFNN, BPNN and other ANN architectures, could forecast the household water demand at the end-use level, with data from over 200 households in Southeast Queensland (Australia). The Hidden Layer Sigmoid Activation Linearly Activation Output FFNN model developed by Bennett et al. (2013) accounted for socio-economic, demographic, and appliance efficiency variables. Finally, further testing of neurocomputing water demand forecasting methods in water distribution network optimization approaches (e.g., Salomons et al., 2007) is needed to assess their usability in such integrated models and account for the effect of their uncertainties. Table 5 reports and summarizes the reviewed studies that applied various types and architectures of neurocomputing methods to develop models for predicting urban water demand.

Table 5. Summary of the reviewed studies in applying various types of neurocomputing models for predicting urban water demand at various spatial and temporal scales.

Author(s) / Year	Model	Motivation	Remarks
Jain et al., 2001	FFNN	Short-term forecasting of weekly water demand for the Indian Institute of Technology (Kanpur) with ANNs	The best ANN outperformed seven benchmark models based on regression and time series analysis. Water demand was found to be mainly influenced by maximum air temperature and rainfall occurrence.
Liu et al., 2003	FFNN (embedded in the WDF-ANN model)	Forecasting of the average daily domestic water demand	The WDF-ANN model showed R^2 and correlation coefficient between observed and forecasted water demands higher than 0.9.
Bougadis et al., 2005	FFNN	Short-term forecasting of weekly peak water demand for the city of Ottawa (Canada)	ANN outperformed regression and time-series methods, with R^2 reaching values up to 0.8. The effect of rainfall amount was found to be more significant than the rainfall occurrence.
Msiza et al., 2007	MLP, RBNN	Comparing the performance of ANN and SVM models to forecast urban water demand	Different ANN and SVM models are compared. The best ANN-based method was demonstrated to outperform the best SVM-based method.
Adamowski, 2008	FFNN	Forecasting of peak daily summer water demand	ANN performed marginally better than MLR and time series analysis techniques.
Ghiassi et al., 2008	DAN2	Urban water demand forecasting	The DAN2 model reached a MAPE lower than 1% for monthly, weekly, and daily forecasts. MAPE slightly increased to 2-3% for hourly forecasts. Weather information improved hourly forecasts.
Firat et al., 2009	GRNN, FFNN, RBNN	Forecasting monthly water consumption	The GRNN model with the monthly water bill, population, and monthly average temperature input outperformed the other methods.

Adamowski and Karapataki, 2010	MLP, RPNN,	Comparing the performance of different types of ANN and MLP models to forecast peak weekly water demand	The Levenberg Marquardt neural-based models outperformed standard MLP, and it provided the best solutions, with R^2 higher than 0.9. The effect of rainfall occurrence was found to be more significant than the rainfall amount.
Firat et al., 2010	GRNN, CCNN, FFNN	Forecast monthly water consumption time series	Tests on data from the city of Izmir (Turkey) demonstrated that CCNN provided the best solutions.
Herrera et al., 2010	FFNN	Predicting the hourly urban water demand	Support vector regression was the best performing models, followed by multivariate adaptive regression splines, projection pursuit regression, and random forests. FFNN performance was lower than that of the above models.
Li and Huicheng, 2010	NFNN	Forecasting urban annual water demand in Dalian (China)	NFNNs were combined with MLR models. The combined model predicted annual water demand with a relative error lower than 10%.
Babel and Shinde, 2011	MLP	Identifying the main explanatory variables to predict daily and monthly water demands	High prediction accuracies (threshold static metric higher than 98%) were found for short-term prediction, by using one lag of the historic daily demand as the only ANN input.
Adamowski et al., 2012	MLP, WA-ANN	Comparing the performance of different predictive models to forecast daily urban demand for an urban area in Montreal (Canada)	WA-ANN outperformed other benchmark methods, as assessed with multiple metrics: R^2, Nash–Sutcliffe model efficiency coefficient, RMSE, and relative RMSE.
Campisi-Pinto et al., 2012	FFNN (coupled with wavelet-denoising)	Forecasting urban monthly water demand for the municipality of Syracuse (Italy)	The performance and generalization of FFNN were improved when a first-level wavelet decomposition was applied to reduce the variance of the input dataset.
Odan and Reis, 2012	MLP-BP, DAN2, two hybrid NN coupling MLP-BP and DAN2 with FS	Identifying the best model to forecast hourly water demand for the water system of Araraquara (São Paulo, Brazil)	DAN2 models outperformed MLP-BP models. The hybrid model coupling DAN2 with FS achieved the best performance (lowest mean absolute error) for 1- and 24-hour ahead forecasts.
Bennett et al., 2013	FFNN, RBNN	Building a water end-use demand forecasting model at the household scale	Moderate forecast accuracies (R^2 in the range 0.33-0.60) were obtained for all end uses, except for bath

			demand, by means of Hidden Layer Sigmoid Activation Linearly Activation Output FFNN.
Tiwari and Adamowski, 2013	WBNN	Forecasting daily, weekly, and monthly urban water demand for the city of Montreal (Canada)	WBNN performed better than several other benchmark methods across different time resolutions and lead times.
Al-Zahrani and Abo-Monasar, 2015	GRNN (combined with time series models)	Forecasting daily water demand for the city of Al-Khobar (Saudi Arabia)	With an R^2 close to 0.9, the combined model performed better than time series models or GRNN models alone.
Altunkaynak and Nigussie, 2017	MLP (coupled with DWT and MSA)	Forecasting urban monthly water demand of Instanbul (Turkey) with extended lead time	Stand-alone MLP could not predict monthly water consumption for a lead time longer than 1 month. The combined MSA-MLP outperformed stand-alone MLP and coupled DWT-MLP.
Mouatadid and Adamowski, 2017	ELM, MLR, FFMLP, SVM	Comparing the performance of different linear and non-linear methods to forecast daily urban water demand for the city of Montreal (Canada)	ELM achieved the best performance (R^2 and RMSE) for urban water demand forecasting with 1- and 3-day lead time.
Zubaidi et al., 2018	FFNN (coupled with GSA and BSA)	Short-term forecasting of urban water demand considering weather variables	The model coupling GSA with FFNN achieved better forecasting performance than the BSA-FFNN model.
Coelho and Andrade-Campos, 2019	FFNN	Short-term forecasting of hourly water demand for a water network in Portugal	Models based on FFNN overall performed better than benchmark naïve and exponential smoothing models when external predictors (e.g., anthropic and weather variables) were included.
Hu et al., 2019	CNN combined with Bidirectional LSTM	Short-term forecasting of daily urban water demand	The hybrid model combining CNN with Bidirectional LSTM provided more accurate forecasts, compared to the single models.
Pacchin et al., 2019	MLP	Comparing the performance of different predictive models to forecast hourly urban water demand	Data-driven and pattern-based techniques achieved similar short-term forecasting accuracy in calibration. Models based on moving-window techniques showed better accuracy in validation.

3.5 Topic 5: Modelling Flow through Hydraulic Structures

Hydraulic structures are known as works and structures that are associated with any water bodies (submerged or partially submerged) including the rivers, coastal regions and estuaries, which may be constructed to retain, convey, or disrupt the natural flow of water. Accordingly, hydraulic structures can be classified into several categories, including water retaining structures (e.g., dams), water conveying structures (e.g., channels, spillways, flumes) and other special-purpose hydro-structures (e.g., fishways, water intakes, irrigation canals) depending on their purpose and impact on the natural streamflow (Chen, 2015).

The proper design, control, and rehabilitation processes of hydraulic structures necessitate accurate and rapid simulations of flows. These can be carried out either via hard computing procedures (e.g., numerical models) or soft computing techniques (e.g., neurocomputing). In this section, the application and suitability of different types and configurations of neurocomputing models to simulate flow through hydraulic structures are investigated. Zeng and Huai (2009) used a three-layer MLPNN model to predict the friction factors in open channel flow, considering the Reynolds number and the relative roughness as input parameters. The MLP-simulated results were compared with the results obtained from empirical formulae. Comparison of results showed that the MLPNN model was more accurate in predicting the nonlinear relationship between the friction factor and effective input parameters. Sahu et al. (2011) made an attempt to predict the total flowrate in compound channels using an MLPNN model. Comparison of the estimated discharges obtained using different models demonstrated the superiority of MLP over the conventional models (e.g., the coherence method and the exchange discharge method).

In another study, Zounemat-Kermani and Scholz (2013) employed ANFIS and MLPNN to study the volume of air required in low-level outlet works of dams. ML methods were utilized to estimate the discharge of vent air in different gate openings for embankment dams. The results indicated that the fuzzy rule-based neural network model performed better than the standard MLP and MLR models. More recently, Zounemat-Kermani et al. (2019) examined the precision of three ML models (namely, Gene-Expression Programming (GEP), Chi-square Automatic Interaction Detector (CHAID), and Support Vector Machine (SVM)) and two types of neural networks (Bayesian Neural Network (BNN) and MLPNN) for the estimation of flow rate over triangular arced labyrinth weirs. The findings of the study showed that the MLP managed to estimate the flow rate over the weir with the highest accuracy based on statistical measures. Mahdavi-Meymand et al. (2019) investigated and challenged the capability of standard and integrated versions of different types of neurocomputing models, including ANFIS, Wavelet Neural Network (WNN), MLPNN, and RBNN to estimate the spillway aerator air demand in dams. Analysis of the model outputs revealed that ANFIS integrated with a genetic algorithm achieved the best performance.

To sum up, Table 6 provides a summary of studies for predicting flow through hydraulic structures using various types of neurocomputing. According to the findings of the studies being reviewed, neurocomputing models have been successfully exploited in simulating flow through hydraulic structures and started to play an important role in the current engineering research and practice.

Table 6. Summary of the reviewed studies applying various types of neurocomputing models for modelling flow through hydraulic structures.

Author(s) / Year	Model	Motivation	Remarks
Zeng & Huai, 2009	MLP	Prediction of the friction factor in open channel flow	The adopted MLP model successfully predicted the friction and other influencing factors.

Bonakdari et al., 2011	MLP	Investigation of the flow patterns and velocity profiles in curved open channels	The velocities in some sections were estimated and the results were compared with numerical predictions.
Sahu et al., 2011	MLP	Discharge estimation compound channels	The adopted MLP model produced better results than several conventional models.
Kamanbedast, 2012	MLP	Investigation of discharge coefficient for morning glory spillways	MLP provided promising results in predicting the discharge through spillway.
Zounemat-Kermani & Scholz, 2013	ANIFS, MLP	Studying of air demand in low-level outlet works of dams	The ANFIS and MLP models performed better than the applied empirical relations.
Parsaie and Haghibi, 2015	MLP	Estimating the discharge coefficient over side weirs.	The MLPs outperformed the traditional models and improved the accuracy of discharge estimation.
Hosseini et al., 2016	ANFIS	Estimation of the discharge coefficient of the labyrinth spillway	The construction cost obtained from the integrative ANFISs were up to 20% lower in comparison to a real benchmark design.
Parsaie et al., 2018	MLP, GMDH	Estimation of energy dissipation of flow over stepped spillways	The GMDH gave better results than the MLP models.
Zounemat-Kermani et al., 2019b	MLP, BNN	Discharge prediction over triangular arced labyrinth weir	The MLP was superior to the BNN model and successfully estimated the flow rate over the weir.
Mahdavi-Meymand et al., 2019	MLP, RBNN, WNN, ANFIS	Estimating the spillway aerator air demand in dams	The integrated ANFIS produced more accurate results.

3.6 Topic 6: Flow and Sediment Modelling in Sewers

In the recent years, different mathematical and numerical approaches have been used for modelling flow and sediment transport in sewer networks and sewage collection systems. However, the majority of the applied models and simulation techniques are known as deterministic hard computing techniques (Cataño-Lopera et al., 2017). Such models and techniques require detailed information on the hydraulic characteristics of the flow/sediment as well as the knowledge of the sewer network geometries, some of which are difficult to acquire or are simply unavailable (Zounemat-Kermani et al., 2020b). In this respect, a number of studies have been conducted to apply soft computing methods such as neurocomputing for predicting flow or sediment transport in sewers (e.g., short-term predictions of wastewater). Consistent with the topic of this study, some of the most pertinent studies using neurocomputing in modelling flow and sediment transport in sewers are reviewed as follows.

El-Din & Smith (2002) presented a feedforward MLPNN for short-term prediction of wastewater outflow rate of a sewer network entering a wastewater treatment plant. The established MLP used observed rainfall data as inputs and produced promising results. It was demonstrated that the MLP model could be integrated with a real-time control algorithm for minimizing the total pollution from the wastewater treatment plant.

Fernando et al. (2006) employed a FFNN model to forecast the incidents of wastewater overflows in a combined sewerage system. Their results showed that the proposed model provided promising results in forecasting sewer overflow rates. One of the main findings was that precise forecasting of overflow rates was highly dependent on the antecedent real-time flow rate data measured at the overflow structure. In other words, the FFNN model failed in producing satisfactory results without having access to the past records of flow rates. Mounce et al. (2014) assessed the potential of MLPs in predicting the hydraulic performance of combined sewer overflows as an alternative method to hydraulic models. The applied MLP models were capable of predicting the depth of sewer overflows with less than 5% error in more than one hour ahead. They concluded that neural networks are useful alternatives to fully physically based models, removing manual modelling overheads, and geometric data requirements for model calibration.

Ebtehaj et al. (2016) applied three neurocomputing models, i.e., Radial Basis Neural Network (RBNN), integrative Particle Swarm Optimization RBNN (PSO-RBNN) and hybrid RBNN (combined with decision trees, DT), to predict sediment transport in sewer collectors. It appeared that the hybrid DT-RBNN predicted more accurate results than the other two RBNN methods. Zhang et al. (2018) evaluated different neurocomputing models, including MLP, Gated Recurrent Unit (GRU), LSTM and WNN, for predicting the water level of a combined sewer overflow structure. Comparison of the predicted results indicated that the LSTM and GRU presented superior capabilities for time series prediction. It was also found that the conventional MLP neural network could only provide reasonable short-term predictions (just one- and two-step ahead). However, the WNN model managed to improve predictions of multiple steps ahead. Overall, the LSTM and GRU outperformed WNN and MLP and produced satisfactory results for multi-step-ahead prediction. The LSTM model showed slightly better performance than GRU, but the GRU model presented certain advantages, such as quicker learning process and simpler architecture. Safari (2019) investigated bedload sediment transport in sewer pipes with clean bed and non-deposition condition using Generalized Regression Neural Network (GRNN). Results from the model performance indicators showed that GRNN outperformed conventional regression models. Table 7 summarizes the key researches related to the application of neurocomputing models in predicting flow rate and sediment transport in sewer systems.

Table 7. Summary of the reviewed studies involving the application of various types of neurocomputing models for modelling flow and sediment in sewers.

Author(s) / Year	Model	Motivation	Remarks
El-Din & Smith, 2002	MLP	Prediction of wastewater inflow incorporating rainfall events	The MLP model was found to be efficient in providing accurate predictions of inflow.
Fernando et al., 2006	MLP	Forecasting the occurrences of wastewater and sewer overflows	Accurate forecasting of overflow rates could be achieved by MLP when records of real-time overflow were available.
Azamathulla et al., 2012	ANFIS	Prediction of sediment transport in sewer pipes	The ANFIS model gave acceptable results in comparison to the existing empirical models.

Ebtehaj and Bonakdari, 2013	MLP	Prediction of sediment transport in sewer pipes	Compared with other empirical formulations, the MLP provided more accurate results.
Mounce et al., 2014	MLP	Predicting combined sewer overflows	The trained MLP model provided a fair prediction of the depth of combined sewer overflows.
Ebtehaj et al., 2016	RBNN, DT-RFNN, PSO-RBNN	Predicting sediment transport in sewer pipes	The hybrid DT-RBNN (a combination of neural network and decision tree) produced more accurate results than the other models.
Najafzadeh & Bonakdari, 2016	GMDH, PSO-GMDH	Predicting the threshold deposition velocity in storm sewer systems	Compared to the GMDH, the integrated PSO-GMDH model provided more accurate predictions.
Wolfs and Willems, 2017	MLP	Modelling sewer water quantity simulations	ANN models were suited to capture complex flow dynamics.
Zhang et al., 2018a	LSTM, MLP, WNN, GRU	Predicting water level of combined sewer overflow	In contrast to the conventional neurocomputing models, both LSTM and GRU presented accurate predictions.
Ebtehaj et al., 2018	Hybrid MLP, RBF	Sediment transport prediction in clean sewer collectors	The Hybrid MLP outperformed the standard RBF model.
Zhang et al., 2018b	ENN, LSTM, NARX	Forecasting overflow in sewers	The recurrent LSTM model was superior to the other neurocomputing models.
Safari, 2019	GRNN	Modelling sediment transport in sewer pipes	GRNN model outperformed the conventional regression models.
Al-Ani and Al-Obaidi, 2019	MLPNN	Prediction of sediment accumulation for trunk sewer	MLPNN model found to be practical and gave better results compared to the MLR model.
Zaji and Bonakdari, 2019	RBNN	Modelling the discharge and velocity field in sewer structures	The RBF method performed significantly better than the multiple nonlinear regression model.

As indicated in Table 7 (by closely looking at the chronological order of the studies as listed), there is a clear increasing trend in the application of neurocomputing approaches in modelling sewer systems in the last five years. Majority of studies focus on predicting flow or sediment transport in sewers based on the hydraulics of flow and geometries of structures. These researches have effectively demonstrated the competence of neurocomputing approaches in modelling the hydraulics of sewer networks.

4. Summary and Conclusion Remarks

4.1. General Findings

This study is focused on critically analysing and classifying the state-of-the-art applications of neurocomputing approaches in modelling surface water hydrology and hydraulics, published as peer-reviewed articles over the last two decades (2000-2019). The main concluding remarks are provided as follows:

(1) In the past two decades, neural-based and neurocomputing models have been proven to be flexible and promising tools for modelling a variety of problems in hydrological and hydraulic sciences. In addition, in comparison with the traditional statistical models, stochastic methods, and empirical formulations, these models have great potential in providing more accurate and reliable predictions.

(2) Although they are capable of identifying the relationship between the input and output (target) variables using a black-box strategy, neurocomputing models cannot provide a straightforward and explicit function for articulating the physical essences behind the modelling process. On the other hand, other types of machine learning models such as Gene Expression Programming (GEP) and Regression Trees (RT) do not suffer from this specific issue and may be considered as alternative options in certain cases.

(3) Approaches to developing neurocomputing models differ substantially in relation to a number of factors, such as input vector decomposition, selection of network type, adoption of network architecture and choice of proper learning scheme. Existing works in the literature indicate that the use of decomposition techniques such as wavelet methods improves the performance of the adopted neurocomputing models, especially for sophisticated and high-dimensional hydroscience applications, such as flood modelling.

(4) Fuzzy-based neurocomputing models, e.g., NFNN and ANFIS, demonstrate great potential in capturing the nonlinearity of complex hydrosystems dynamics.

(5) Employing a recurrent structure for the network (namely RNN), for example, NARX, and LSTM, improves the performance of feedforward models in predicting time series of hydrological problems. RNN facilitates time delay units through feedback connections, being computationally more efficient and biologically more plausible than feedforward structures.

(6) Most of the works being reviewed suggest that integrating meta-heuristic and nature-based optimization algorithms may enhance the accuracy of the training process of the standard neurocomputing models. However, the use of these optimization algorithms increases the computation cost.

(7) Regarding the application of different neurocomputing approaches in different problems of hydrological and hydraulic sciences, it can be concluded that modern neurocomputing models, such as Extreme Learning Machine, Deep Learning models, integrative networks, and Wavelet Neural Network, are likely to perform better than the conventional models, such as Multi-layer Perceptron and Generalized Regression Neural Network. However, it is not possible to distinguish one particular type of modern neural network-based models as a prominent candidate for all different applications.

4.2. Findings Related to Surface Water Hydrology and Hydraulics

Besides the overall review of the pertaining literature, six topics within the surface water hydrology and hydraulic sciences were appraised and evaluated in detail from the neurocomputing perspective. Specific findings and concluding remarks are given as follows:

(1) The selection of a specific neurocomputing approach for time-dependent problems in hydrology (e.g., water level prediction, flood modelling, and sediment transportation) is highly dependent on the scope of the study. Commonly, traditional FFNNs can

perform well in the short-term predictions and should be preferred in such cases for their easy implementation, while RNN and WNN models are in general more suitable for longer-term-predictions.

(2) Multi-dimensional physically based numerical models for complex hydrological and hydraulic phenomena, such as sediment transport in rivers and sewers, need many physical parameters (e.g., settling velocities, initial grain size distributions, critical shear stresses for erosion and deposition) which are ideally determined through laboratory experiments requiring substantial time and effort, especially for fractional sediment transport. Meanwhile the overall accuracy of these models is still limited in many cases. Neurocomputing provides a reliable alternative with fewer required inputs and CPU time to predict the nonlinear and non-unique behaviour of sediment transport, without necessity of investigating in detail the nature of all physical processes involved and their interactions.

(3) Neurocomputing models have proven to be superior with regard to the prediction of daily suspended transport when compared with other mathematical models. This is due to the fact that, in these models, the value of the dependent variable computed in the previous time step(s) can be used as an (additional) input for the current time step, contributing to a better simulation of hysteresis phenomena. In addition, neurocomputing can provide more reasonable predictions for extremely high or low values (Zhu et al., 2007), because specific algorithms using distributed neurons and nonlinear transforms are involved.

(4) Some studies showed that the neurocomputing models can detect water level peaks better than a hydrodynamic model (e.g., Panda et al., 2010). While in other applications, the lower or higher peaks were under- or overestimated (as in See and Openshaw, 2000) or slightly delayed (as in Ma et al., 2019).

(5) The review of the methods for urban water demand prediction suggests that a variety of neural-based models constitute viable alternatives to other linear or nonlinear models, often achieving better performances as measured by heterogeneous error metrics. Their flexibility and computational efficiency make them suitable for identifying the underlying dependencies between water demand and potential drivers/determinants (Cominola et al., 2018), which can vary for different case studies or spatiotemporal scales.

(6) The application of physically based models for predicting water level in rivers, flooding, wastewater overflows, and flow rate in sewers requires accurate physical data, such as topography and bathymetry, and usually demands high computational costs. Neurocomputing methods can effectively overcome these drawbacks and can predict water level and flow rate at a much lower computational cost without the necessity of knowing any physical information about the study area, provided that historical hydrological data series are available.

(7) In general, the inclusion of historical re-forecast modelling information, a smart pre-processing of input and output data, the integration of different neurocomputing methods and/or the combination of neurocomputing methods with physically based models can improve model performance. Specifically, for water level prediction along a gauged stream, including the historical data at the target gauge can increase the accuracy of the results and it is usually recommended. This is also valid with regard to the supervision of the model training, e.g., considering time delays units through recursive inner connection (Chang et al., 2014).

(8) In modelling surface water hydrology (e.g., water level prediction) and hydraulic (e.g., flow over hydraulic structures) problems, data pre-processing plays an important role in detecting the most relevant variables for the problem under consideration (e.g., feature selection analysis, also to avoid redundant information); in some cases, the inclusion of

additional predictor(s) such as precipitation, temperature, slope, in the input dataset can lead to a higher accuracy and better performance of the model(s).

5. Research Gaps, Lacunae, and Limitations

Neurocomputing methods usually require long historical data series and high-quality data to deliver good results. Also, being black box models, inner physical relations cannot be explicitly identified, and this could be the limitation for some applications. In other words, one major limitation of neurocomputing models is their need for long time series data for training and testing. It is evident from the literature review that for hydrological and hydraulic simulations with long series of data, neurocomputing works very well. However, this type of models is much less competent in applications without sufficient data. For instance, few studies have addressed neurocomputing for estimating flood dynamics and sediment concentrations in poorly gauged or ungauged catchments.

In sediment transport modelling, there are only very few studies about long-term forecasts. Many studies are focused on exploring the capability of models based on a historical re-forecast, i.e., they first prepare the input combinations using the entire data series and later divide them into calibration and validation data sets to set up and test the models. As a consequence, the resulting input used to forecast the value at a particular moment is computed using information from the 'future'; such information is clearly not available in the realistic forecasting process (Zhang et al, 2015b, Zhang, 2018). Therefore, the historical re-forecast modelling can be used to compare capabilities of models or one-step advance predictions, but is not suitable for long-term predictions. Development of neurocomputing methods in operational hydrodynamics and morphodynamics forecasting has gained particular interest over the past years. But there are yet few neurocomputing models that are able to support long-term prediction with acceptable accuracy. Some of the recurrent neural networks such as ESN and LSTM (e.g., Coulibaly, 2010;

Ma et al., 2019) have been shown to be promising, but further research in this direction is still needed.

Related to the application of neurocomputing for water demand prediction, existing limitations are primarily linked to the generalisation of the developed models and the accuracy of the results, rather than the model implementation. For instance, the models presented in the literature have been mostly trained and validated on specific case studies, targeting the prediction of water demand at different spatial and temporal scales, forecast horizons, and considering a variety of different predictors. The obtained results are, thus, often hard to cross-compare and seldom valid for a different setting. Future comparative studies should perform sensitivity analysis and assessment of the portability of state-of-the-art models to different case studies, along with their robustness with respect to uncertainties in the input set, sampling resolution of their input/output variables, required forecast horizon, and model parameterization.

6. Recommendations and Future Directions

In the retrospectives of most published researches related to the application of neurocomputing models in hydrological and hydraulic sciences (see Tables 1 to 7), two interesting facts related to their historical trends may be highlighted. Firstly, unlike the use of neurocomputing models for hydrological predictions, their application to predicting flow through hydraulic structures does not have a long history and it is mostly limited to the last decade. Secondly, the majority of the published works have used the prevailing and conventional version of neurocomputing models, namely MLPNN, for various applications. Hence, there is still a wide scope for researchers to pursue this specific topic using novel neurocomputing models, such as deep learning and integrative models. In general, a robust supervision of neurocomputing models is essential to support their successful application to tackle hydrological- and hydraulic-related challenges, e.g. through data pre-processing using SVM, feature-selection and/or optimization algorithms. From this review, the following recommendations may be made for future research in terms of developing or applying neurocomputing models for different types of hydroscience problems:

(1) Substantial researches have been reported in the development and application of neurocomputing models in hydrological and hydraulic sciences. A number of different machine learning approaches have been used and achieved different level of success, such as tree-based and vector-based models. Conducting a comprehensive survey on the susceptibility of soft computing models (e.g., machine learning models) versus hard computing models (e.g., numerical methods) in hydrological sciences is highly encouraged.

(2) Although this paper provides a detailed review of the application of neurocomputing in six different topics in hydrological and hydraulic sciences, it is inevitable that some related subjects have to be excluded, which should be included in the future studies, e.g., groundwater modelling, irrigation systems, water quality simulation, precipitation forecast, evaporation estimation, and rainfall-runoff processes.

(3) A forward step in developing and deploying neurocomputing models is to integrate these models into physically and geospatial-based models. In that case, both the pre-processing and post-processing parts of the models can be directly linked to the geographic information system (GIS) in the information layer.

(4) Hybridization and integration of neurocomputing models and other types of soft computing concepts should be considered for enriching the original neurocomputing simulation models and overcoming the restrictions of the individual models. Several studies have been carried out to develop hybrid neurocomputing models in the recent years, and this has led to some novel combined models showing improved performance for different types of problems. It is worth noting that, in some cases, combining

different soft computing methods would not necessarily enhance the performance of the resulting hybrid models; more research effort is needed to develop more efficient and accurate hybrid models in the future.

(5) Limited studies have been recorded in the application of DL models, such as ESN and CNN models to predict water level fluctuations in rivers, flooding, sediment transport, flow through the hydraulic structures, and flow rate in sewer systems as well as assessing water quality; further research in this direction is also encouraged.

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