An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction

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Abstract

Despite the massive diversity in the modeling requirements for practical hydrological applications, there remains a need to develop more reliable and intelligent expert systems used for real-time prediction purposes. The challenge in meeting the standards of an expert system is primarily due to the influence and behavior of hy drological processes that is driven by natural fluctuations over the physical scale, and the resulting variance in the underlying model input datasets. River flow forecasting is an imperative task for water resources operation and management, water demand assessments, irrigation and agriculture, early flood warning and hydropower generations. This paper aims to investigate the viability of the enhanced version of extreme learning machine (EELM) model in river flow forecasting applied in a tropical environment. Herein, we apply the complete or thogonal decomposition (COD) learning tool to tune the output-hidden layer of the ELM model's internal neu ronal system, instead of the conventional multi-resolution tool (e.g., singular value decomposition). To
https://doi.org/10.1016/j.jhydrol.2018.11.069 Received 23 August 2018; Received in revised form 4 October 2018; Accepted 4 November 2018 Abbreviations: A-ELM, AdaBoost.RT-extreme learning machine; AI, artificial intelligence; ANFIS, adaptive neuro-fuzzy inference system; ANN, artificial neural network; ARIMA, autoregressive integrated moving average; AtmP, atmospheric pressure; B-ANN, bootstrap-artificial neural network; BCSO, binary-coded swarm optimization; B-ELM, bootstrap-extreme learning machine; C-ELM, complex-extreme learning machine; Cl^{-1} , chloride; COD, complete orthogonal decomposition (COD); CRO-ELM, coral reefs optimization-extreme learning machine; DE-ELM, deferential evolution-extreme learning machine; DID, department of Irrigation and Drainage; DO, dissolved oxygen concentration; EC-SVR, evolutionary computation-based support vector machine; EDI, effective drought index; ELM, extreme learning machine; EELM, enhanced extreme learning machine; EEMD, ensemble empirical mode decomposition; EL-ANFIS, extreme learning adaptive neuro-fuzzy inference

system; EMD, empirical mode decomposition; Ens, Nash-Sutcliffe coefficient; Ensemble-ELM, ensemble-extreme learning machine; EPR, evolutionary polynomial regression; ESNs, echo state networks; ETo, evapotranspiration; Fe, iron; Fr, Froude number; FS, factor of safety; GA-ELM, genetic algorithm-extreme learning machine; GCM, general circulation model; G-ELM, geomorphology extreme learning machine; GP, genetic programming; GRNN, generalized regression neural network; HCO_3^{-1}, bicarbonate; HDSR, diffuse solar radiation; HRT, hydraulic retention time; I-ELM, integrated extreme learning machine; KELM, Kernel extreme learning machine; LST, land surface temperature; LASSO, least absolute shrinkage and selection operator; LSTM, long short-term memory network; LSSVM, least square support vector machine; MAE, mean absolute error; MARS, multivariate adaptive regression spline; MBFIPS, Multi-objective binary-coded fully informed particle swarm optimization; MC-OS-ELM, meta cognitive-online sequential-extreme learning machine; MLPNN, multi-linear perceptron neural network; MLR, multiple linear regression; MME, multi-model ensemble; NEMR, northeast monsoon rainfall; NO_2^{-1}, nitrite; NO_3^{-1}, nitrate; NO_2, nitrogen dioxide; NT, total nitrogen; O_3, ozone; OP-ELM, optimally pruned-extreme learning machine; OSELM, online sequential extreme learning machine; PCA, principal component analysis; pH, power of hydrogen; PM10, air pollution “suspended particulate matters”; PO_4^{-3}, phosphorus; R-ELM, radial basis-extreme learning machine; r, determination coefficient; RE, relative error; RF, rainfall; RH, relative humidity; RHmax, maximum relative humidity; RHmean, mean relative humidity; RHmin, minimum relative humidity; RMSE, root mean square error; RVM, relevance vector machine; SaE-ELM, self-adaptive evolutionary-extreme learning machine; SC, specific conductance; S-ELM, sigmoid-extreme learning machine; SHr, sunshine hour; SR, solar radiation; SO_4^{-2}, sulfate; SiO_2, Silicon; SO_2, sulfur dioxide; SOM-ELM, self-organizing map extreme learning machine; SOM, self-organizing-map; SST, sea surface temperature; SVD, singular value decomposition; SVD-MLR, singular value decomposition based multiple liner regression; SVM, support vector machine; SVR, support vector regression; T, weather temperature; Tavg, average ambient temperature; Tdew, dew point temperature; Tmax, maximum weather temperature; Tmean, minimum weather temperature; Tmin, mean weather temperature; TOC, total organic carbon; TP, total phosphorus; TU, turbidity; VC-OS-ELM, variable complexity-online sequential extreme learning machine; VP, vapor pressure; WBT, wet bulb temperature; WD, wind direction; WI, Willmott’s index; WNN, wavelet neural network; WS, wind speed; WT, water temperature; WT-ELM, wavelet transform-extreme learning machine; WT-GMDH, wavelet transform-group method of data handling