ISSN: 2350-0328

International Journal of AdvancedResearch in Science, Engineering and Technology

Vol. 5, Issue 11, November 2018

Sensitivity Analysis on Daily Stream flow Forecasting

S. Bahrami*, E. P. Wigand

*Department of Hydrological Science, College of Science, University of Nevada, Reno
Department of Geography, University of Nevada, Reno

ABSTRACT: The most forecasting methods still reproduce substantial uncertainty that increases with time and confines the predictability of observed events beyond a few weeks of lead time. Sensitivity analysis (SA) refers to the determination of the contributions every uncertain input data to the uncertainty in the outputs and is a fundamental approach to identify the most significant and sensitive parameters. It helps us understand complex hydrological models particularly for time-consuming distributed flood and stream flow forecasting models based on complicated theory with numerous parameters.SA is increasingly being used in environmental modelling for a variety of purposes, including uncertainty assessment, model calibration, diagnostic evaluation, dominant control analysis, and robust decision-making. The complex SA approaches are enabled by the continuous growth of computing capabilities, a better understanding of physical processes and their interactions throughout all compartments of the system, and the availability and use of more and better observation data which is scarce in ungauged region. This paper aims at delivering an introduction to SA for non-specialist readers, as well as practical advice with best practice examples from the literature. Moreover, as an example, two powerful forecasting engines called Nonlinear Echo State Network (NESN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are tested. It is shown that NESN is a powerful tool in streamflow forecasting which serves as a robust engine and does not need complex SA and precise observational data input. The SA is conducted under different climatic conditions. The simulation results demonstrate the efficiency of the NESN. The simulation results of the NESN compare favourably with ANFIS.

KEY WORDS: Forecasting, nonlinear echo state network using multivariable polynomial (NESN-MP), streamflow, Sensitivity Analysis.

I.INTRODUCTION

The most hydrological models suffer from uncertainties regarding input data, initial or boundary conditions, forcing data and model structure. These uncertainties may be caused by bad data entry along with poor knowledge of hydrological process mechanism. Therefore, the model uncertainty is an important issue when developing a modelling system [1]. A useful task to overcome these uncertainties and enhance the model accuracy is to set the values of the model parameters in which the simulation data closely meet observation data.The common approach to achieve this purpose generally called Sensitivity Analysis (SA). SA investigates how the variation in the output of a numerical model can be attributed to variations of its input [2-4]. Within this broad definition, the level of complexity and purposes of SA vary quite significantly depending on the modelling domain and the specific application aims. Depending on whether output variability is obtained by changing the inputs around a reference value, or across their entire feasible space, SA is either referred to as local or global.

In general, SA methods can be broadly categorized into two main classification, local SA and global SA. The difference between these two approaches laid on their characteristics, scope and applicability [5]. Partial derivatives or finite differences are used as sensitivity indices in the context of local approaches [6]. Local approach does not consider any existing interaction between inputs. Since local SA consider model parameters as varying inputs and aim at assessing how their uncertainty impacts model performance, i.e. how model performance changes when moving away from some optimal or reference parameter set. Therefore, when we estimate the model parameters, irrelevant or insensitive parameters must be locked at a fixed value to enable more effective SA. In contrast, Global SA applications may consider model parameters and other input factors of the simulation procedure, like the model's forcing data or its spatial resolution simultaneously [7]. Global SA is used for diverse purposes, like verification, supporting model calibration, diagnostic evaluation or simplification [8]; and supporting robust decision-making [9-10].Beside the local and global SA, several SA methods such as qualitative or quantitative methods, refined or screening methods have been

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 5, Issue 11, November 2018

broadly used in different fields, like economics, complex engineering systems, social sciences, and the physics [11-12]. However, there are large differences among these methods in terms of their applicability, sampling schemes, algorithm structures. Given the extensive range of available SA methods, it is very imperative that a practitioner has a clear thoughtful of the appropriate approaches for a specific application. These approaches include choosing an efficient SA method, fitting the method to existing models, and presenting and construing the results. In the context, different types of sensitivity indices can be applied, ranging from correlation trials between inputs and output to statistical properties of the output dispersal. However, analytical computation of all these indices is unbearable for the most models, sensitivity indices can usually be approximated from a sample of inputs and output evaluations [13].More importantly, the limited data available for physical parameterization of the SA approaches required a substantial dependence on model calibration with large amount of data input [14]. This dependence occasionally ended in parameterization schemes that are uneven with physical characteristic of the hydrology of region [15]. Therefore, these limitations are expected to present considerable uncertainty into model projections, particularly in situations where climatic or environmental conditions differ from those experienced in the calibration period. However, several studies relied on empirical relationships, like curve numbers and the Hargreaves equation, which developed for the moderate regions [16], there are a few studies from these regions to develop a modelling approach which does not rely on complex SA. The complex SA approaches are enabled by the constant progress in various area including: computing capabilities, a better understanding of the physical processes and their relations throughout all compartments of the Earth system and the availability and use of more and better observational data which is scarce in ungauged region. The present rapid development has commanded our systems to be ever more data hungry, thereby growths in model complexity. These computationally expensive developments are not always achievable; hence, model developers must be creative and regularly balance the costs and benefits of improving one aspect over another including: increasing the complexity, different parameter selection or fluctuating the models resolution [17]. However, the Various selection of the parameters will encourage a large variety of simulation results; while, considering that the most existing hydrological models hold complex structures with large number of parameters, the optimization choice of parameters is a difficult and time-consuming task. Therefore, sensitivity analyses must be easily reproducible to be effective in supporting each new model, and the results should easily be applied to establish a ‘‘continuous learning process’’ [7]. In other words, a sensitivity analysis should be a simple, tractable tool for addressing a complex system.

This is the motivation for the use of NESN-MP[18] (called NESN in this paper) engine in streamflow forecasting to guide future developments for accurate daily stream flow prediction and is the basis for this paper[19].The strategy of the proposed forecasting method is to move toward more accurate modelling and forecasting approaches, which dose need an accurate data entry, and beyond that, complex data pre- processing and Sensitivity Analysis. This paper addressed the robustness of model proposed by Bahrami et.al in which the daily stream flows have been predicted in whether gauged or ungauged basins in different climatic and geographic region[20]. The input data consist of various time series forcing-data including daily precipitation, precipitation duration, solar radiation, temperature and vapor pressure as well as daily streamflow. The nonlinear relations between the internal states increase the learning capability, which results in high forecasting accuracy while ensuring that the quality of forecasting does not deteriorate significantly with time. Our goal is to verify the consistency of the model behaviour and to assess the robustness of the simulation results to uncertain inputs or model assumptions.

The proposed forecasting method appear more than ever as a computer programming tool to establish priorities in improving accurate predictions. Its application is simple, as such it does need an accurate data entry or large amount of data at the time, and beyond that, complex and computationally expensive data pre-processing along with SA.More importantly This novel is auser-friendly model such that the user can run the model without prior knowledge about input interaction. This novel model is a powerful and valuable tool to support the examination of uncertainty and predictability across spatial and temporal scales. It can be used for various applications such as accurate and timely predictions of high and low daily streamflow events at either gauged or ungauged watershed without using statically regionalization up to 4 months ahead of the lead time. It can provide truthful insights into the potential benefits of efforts to provide a forecasting system to managers with prior knowledge of their costs at various activities, including finding minimum data standards, determining model structure, creating priorities for updating forecasting systems, designing field operations. [21-22].

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 5, Issue 11, November 2018

II. NONLINEAR ECHO STATE NETWORK

NESN structure is shown in Fig. 1. In NESN, the networks consist of a reservoir including linear internal states and a readout including nonlinear functions of the internal state. The nonlinear relations between the internal states increase the learning capability, which results in high forecasting accuracy while ensuring that the quality of forecasting does not deteriorate significantly with time. Furthermore, the performance of the forecasting engine is improved by decreasing the number of the internal states, and the orders of the weight matrices which reduces the computational load considerably. Moreover, the proposed methods have simple design, far less computation, and do not require extensive training, parameter tuning, or complex optimization. The formulations are explained in detail in [18], and [23].

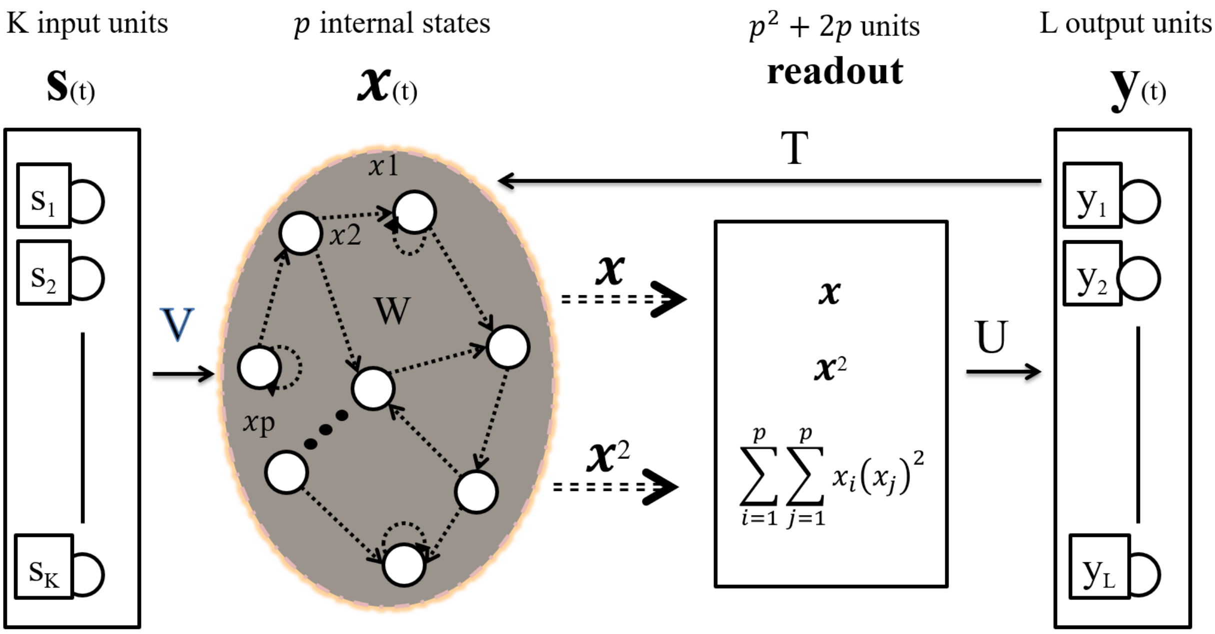

Fig. 1. Schematic of NESN-MP.

III. SENSITIVITY ANALYSIS FOR NESN AND ANFIS

The sensitivity analysis for two different areas with NESN and ANFIS is explained in this section. Two error indices including the MAE, and RMSE are used to show the sensitivity of the forecasting results for the forecasting engines for specific changes in the input data. The error indices are shown as following:

$$\mathrm{RMSE} = \frac{1}{n_{max}}\sqrt{\sum_{i=1}^{n_{max}} [y(i) - \hat{y}(i)]^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n_{max}}\sum_{i=1}^{n_{max}} |y(i) - \hat{y}(i)| \tag{2}$$

where $\boldsymbol{y}$ are the actual output values,$\hat{\boldsymbol{y}}$ is the predicted output, and$n_{\max}$ is the number of sample points.The input data is set for three changes including the real data, 10 % and 30% of the real data. Table 1 and 2 show the simulations results

ISSN: 2350-0328
International Journal of AdvancedResearch in Science, Engineering and Technology
Vol. 5, Issue 11, November 2018

of sensitivity analysis using ANFIS and NESN for three case studies. As shown in Table 1, the RMSE for case study I is calculated as 115 and 21 for ANFIS and NESN respectively. The RMSE for case study II and III are also calculated as 98 and 127 for ANFIS and 16 and 11 for NESN respectively. The changes in difference parameters including the precipitation, temperature and vapor pressure are applied for sensitivity analysis.

It is shown that the NESN outperform ANFIS considerably. In case study I, the RMSE changes just by 4 in NESN compared to 51 in ANFIS when there is a 30% change in precipitation. The RMSE in second case study, changes just 1 in NESN while it increases by 13 in ANFIS when the temperature is increased by 10%. In case study III, as expected, NESN shows its robustness during changes while ANFIS could not track the real output in significant changes in the input data. The MAE for both forecasting engines are calculated based on the different changes in the input data. It is shown that NESN is a powerful tool in streamflow forecasting which helps as a robust engine and does not need complex SA and accurate observational data input.

Table 1: RMSE for sensitivity analysis

		ANFIS			NESN		
		Precipitation	**Temperature**	**Vapor pressure**	**Precipitation**	**Temperature**	**Vapor pressure**
Case Study I	**real**	**115**	**115**	**115**	**21**	**21**	**21**
	10%	**124**	**122**	**117**	**23**	**22**	**22**
	30%	**166**	**136**	**122**	**25**	**22**	**23**
Case Study II	**real**	**98**	**98**	**98**	**16**	**16**	**16**
	10%	**111**	**126**	**105**	**17**	**15**	**18**
	30%	**135**	**174**	**117**	**21**	**18**	**19**
Case Study III	**real**	**127**	**127**	**127**	**11**	**11**	**11**
	10%	**145**	**122**	**136**	**12**	**11**	**13**
	30%	**198**	**101**	**156**	**14**	**12**	**12**

Table 2: MAE for sensitivity analysis

		ANFIS			NESN		
		Precipitation	**Temperature**	**Vapor pressure**	**Precipitation**	**Temperature**	**Vapor pressure**
Case Study I	**real**	**76**	**76**	**76**	**15**	**15**	**15**
	10%	**81**	**80**	**79**	**17**	**16**	**16**
	30%	**88**	**82**	**82**	**21**	**17**	**14**
Case Study II	**real**	**54**	**54**	**54**	**11**	**11**	**11**
	10%	**59**	**62**	**59**	**12**	**12**	**11**
	30%	**72**	**68**	**63**	**14**	**13**	**13**

ISSN: 2350-0328

International Journal of AdvancedResearch in Science, Engineering and Technology

Vol. 5, Issue 11, November 2018

Case Study III	real	83	83	83	18	18	18
	10%	88	87	79	19	16	19
	30%	94	90	78	22	19	21

IV. CONCLUSION AND FUTURE WORK

Hydrological models regularly comprise uncertainties which have negative effects on the estimated results, thereby the model accuracy. Therefore, to acquire more accurate model estimates, we better to assess and improve models using different approaches like sensitivity analysis (SA), parameter optimization, operative management, design space exploration, and uncertainty analysis. In the context, this paper aims to address an introduction on sensitivity analysis for streamflow forecasting. The strength of the NESN forecasting engine is also evaluated. The robustness andease of operationin NESN method is high and appear even more than ever as a computer programming tool to establish priorities in improving Accurate predictions. This user-friendly modelling approach does need an accurate data entry or large data entry at the time, or even computationally and complex expensive Sensitivity Analysis along with data pre-processing. the user can apply the model with no need of existing input interaction. This model is a valuable and powerful tool to support the uncertainty and predictability in various spatial and temporal scales.

Moreover, this model robustness can contribute to biased estimates of water availability and uncertainty in forecasting sensitivity to potential future climate changes. Thorough consideration of this accuracy and robustness is important any time that models are used for water planning and management, but especially crucial when using this model to generate insights about future streamflow levels. By considering its predictive accuracy, error structure, and uncertainties, this method can provide an empirical assessment of watershed behaviour and generate useful insights for water management and planning. This makes them a valuable complement to physical models, particularly in data-scarce regions with little data available for model parameterization and warrants additional research into their development and application. Accuracy performance indicated that, for this case study, the use of more information and data did not improve the prediction performance. Our goal is to verify the consistency of the model behaviour and to assess the robustness of the simulation results to uncertain inputs or model assumptions.

The approach utilized through this study is extendable to similar water projects, which enable reservoir operators to save water as the major contributor for environmental demands, agricultural demands, and hydropower energy production. The developed modelling approach, along with accurate daily predicted values with no need for complex, expensive and time-consuming SA provided a sound basis for the optimal integrated operation of water shed in CONUS and led to minimum evaporation loss by choosing appropriate storage volumes in any related reservoirs resulting in minimum total surface area, and therefore minimum amount of evaporation. As such, the results would provideaccurate prediction to model developers; especially those interested in using time series and artificial intelligence-based prediction models; those interested in applying intelligent models in real environments, particularly policy-makers on water and energy resources.

REFERENCES

[1] M. B. Beck, “Water quality modelling: a review of the analysis of uncertainty”, Water Resources Research, 1987, pg no:1393-1442.

[2] M. A. Chitsazan, M. S. Fadali, A. M Trzynadlowski, “State estimation of IEEE 14 bus with unified interphase power controller (UIPC) using WLS method”, Energy Conversion Congress and Exposition (ECCE), 2017 IEEE, pp. 2903-2908, Oct. 2017.

[3] V. Sarfi, H. Livani, “An Economic-Reliability Security-Constrained Optimal Dispatch for Microgrids”, IEEE Transactions on Power Systems, 2018, pg no: 6777-6786.

[4] M. A. Chitsazan, A. M Trzynadlowski, “State estimation of IEEE 14 bus with interphase power controller using WLS method”, Energy Conversion Congress and Exposition (ECCE), 2016 IEEE, pp. 1-5, Sep. 2016.

[5] V. Griensven, T. Meixner, S. Grunwald b, T. Bishop, M. Diluzio, R. Srinivasan, “A global sensitivity analysis tool for the parameters of multi-variable catchment models”, Journal of Hydrology, 2006, pg no: 10–23

[6] M. C. Hill, C. R. Tiedeman, “Effective groundwater model calibration. John Wiley & Sons, Hoboken”, 2007.

[7] G. Baroni, , S. Tarantola, , 2014. “A general probabilistic framework for uncertainty and global sensitivity analysis of deterministic models: a hydrological case study”, Journal of Environ. Modell. Softw,2017, pg no: 26–34.

[8] C. Mather, F. Sheila Rivera, M. Susan Butler-Wu “Comparison of the Bruker Biotyper and Vitek MS Matrix-Assisted Laser Desorption Ionization–Time of Flight Mass Spectrometry Systems for Identification of Mycobacteria Using Simplified Protein Extraction Protocols”, Journal of Clinical Microbiology,2014, pg no: 130 –138.

[9] S. Varela, P. Robert Anderson, R. García-Valdés , F. Fernández-González "Environmental filters reduce the effects of sampling bias and improve predictions of ecological niche models", Journal of Ecography, 2014, pg no: 1084–1091.

[10] X. Song, J. Zhang, C. Zhan, Y. Xuan,M. Ye e, C. Xu ," Global sensitivity analysis in hydrological modeling: Review of concepts, methods, theoretical framework, and applications", Journal of Hydrology ,2015,pg no: 739–757.

[11] F. Pianosi, K. Beven, J. Freer, J. W. Hall, J. Rougier, "Sensitivity analysis of environmental models: A systematic review with practical workflow", journal of Environmental Modelling & Software ,2016, pg no: 214-232.

[12] L. Ronald, J. C. Helton, "An Investigation of Uncertainty and Sensitivity Analysis Techniques for Computer Models" journal of Risk Analysis, 1988, pg no: 71-90

[13] H. Wan, J. Xia, L. Zhang, D. She, Y. Xiao, L. Zou, "Sensitivity and Interaction Analysis Based on Sobol' Method and Its Application in a Distributed Flood Forecasting Model", journal of Water ,2015, pg no:2924-2951

[14] V. Singh, M. Kumar Goyal, "Curve number modifications and parameterization sensitivity analysis for reducing model uncertainty in simulated and projected streamflows in a Himalayan catchment", journal of Ecological Engineering, 2017, pg no: 17–29

[15] S. A. Shoaib, L. Marshall, A. Sharma, "Attributing uncertainty in streamflow simulations due to variable inputs via the Quantile Flow Deviation metric", journal of Advances in Water Resources , 2018, pg no: 40–55.

[16] J. E. Shortridge, S. D. Guikema, B. F. Zaitchik, "Machine learning methods for empirical streamflow simulation: a comparison of model accuracy, interpretability, and uncertainty in seasonal watersheds",journal of Hydrol. Earth Syst, 2016, pg no: 2611–2628.

[17] G. M. Flato, "Earth system models: An overview", journal of WIREs Climate Change , 2011, pg no:783–800.

[18] M. A. Chitsazan, M. Sami Fadali, A. M Trzynadlowski, "Wind speed and wind direction forecasting using echo state network with nonlinear functions", Renewable Energy, 2019, pg no:879-889.

[19] S. Bahrami, P. E. Wigand, "Daily Streamflow Forecasting Using Nonlinear Echo State Network", International Journal of Advanced Research in Sience, Engineerng and T echnology, 2018, pg no:6720-6727.

[20] P. E. Wigand,S. Bahrami, "Bad Data Analysis on Streamflow Forecasting Using Nonlinear Echo State Network ", International Journal of Advanced Research in Sience, Engineerng and T echnology, 2018,pg no:7054-7060.

[21] L. Arnal, A. W. Wood, E. Stephens, "an Efficient Approach for Estimating Streamflow Forecast Skill Elasticity", Journal of Hydrometeorology, 2017, pp.1715- 1729.

[22] C. Huang, A. J. Newman, M. P. Clark, A. W. Wood, X. Zheng1, "Evaluation of snow data assimilation using the ensemble Kalman filter for seasonal streamflow prediction in the western United States",journal of Hydrol. Earth Syst, 2017, pg no: 635-650.

[23] M. A. Chitsazan, M. Sami Fadali, Amanda K. Nelson, A. M Trzynadlowski, "Wind speed forecasting using an echo state network with nonlinear output functions", American Control Conference (ACC), 2017 IEEE, pp. 5306-5311, May. 2017.