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Research paper

Enhancing the prediction of the streamflow for SWAT models

Venkatesh B[1,2] and Amit B. Mahindrakar[1*]

[1]*Department of Environmental and Water Resources Engineering, School of Civil and Chemical Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India – 632014.*

[2]*Centre for Disaster Mitigation and Management, Vellore Institute of Technology, Vellore, Tamil Nadu, India – 632014.*

[*]*Corresponding author E-mail: amahindrakar@vit.ac.in*

Abstract

The prediction of streamflow helps to identify the disasters and sources of water resources. Different ways to predict the streamflow, among the conceptual models have been gained more popularity due to explanation of processes and visualization in water resources systems. Any model may not obtain the acceptable performance at initial setup and it has to go through calibration or optimization (either manual or auto-calibration). Moreover, the calibration procedure is more concern of computational time for complex conceptual models like Soil and Water Assessment Tool (SWAT). Where, meta models are the alternative approach to restrict the computationally intensive optimization problems because it is cheaper models to enhance the performance and shows the relationship between input-output response. Our results showed that 1) meta models mimics the original simulation models with effective and efficient outputs and 2) it verified and satisfied the performance of SWAT model with less computational time. This study helps to planning and designing of hydrological models with effective computational time.

Keywords: *SWAT; Metamodels; Optimization; Calibration; RBFNN.*

1. Introduction

Hydrological simulation models have been evolved and implemented in different perspectives from last few decades based on distinctions from the rational methods to the conceptual models [1]; their manifold uses on different applications like land use changes [2], climate changes [3], rainfall-runoff modeling [4] and flood prediction [5]. In hydrological modelling, the greater number of parameters present in conceptually or empirically based functions and it effects in complexity and computational burden of calibration [6], [7]. But, the advances in computer technology has been made easier to predict the accurate streamflow in hydrological modelling by using the auto-calibration techniques [8], [9]. Due to the development of technology, the model can be processes from short time intervals to forecast long-time intervals based on the observed data [10]. For accurate and reliable streamflow predictions can enhance the proper water resources allocation and management usually it accesses based on historical data for effective decision making.

For obtaining accurate and reliable forecasts, two steps of characteristic approaches are developed [11]; among the first approach is based on dynamic forecasting models (hydrological model) for developing the watershed and second approach is statistical forecasting for calibration or optimization (Meta modelling). Dynamic forecasting model constitutes the water balance components for prediction of streamflow based on combination of both watershed characteristics and weather variables like precipitation and temperature etc. While statistical forecasting model, represents the initial catchment conditions and targets the optimization to enhance the performance of a conceptual model. Conceptual hydrological models have been following the dynamic forecasting approach which derives the monthly streamflow with daily or sub-daily basis of weather variables and physically relates whole parameters in the catchment. Different hydrological models are available in rainfall-runoff modelling like MIKE-SHE, SWAT, TOP-MODEL etc., Among, SWAT has increased worldwide acknowledgment as an interdisciplinary watershed modelling tool and is as of now being utilized in near 100 nations. It has been widely used to explore water asset and non-point source contamination issues for a scope of scales and ecological conditions over the globe [12], [13] and it contains enormous number of parameters which is used to describe the water movement in the watershed system. However, the greater number of parameters, interval of parameters and their interactions can cause complication and complexity of calibration and validation [14]. These models represent the simplified physical process within the hydrological system and visualize the flow path which is based on empirical equations. Where, meta models obtain the solutions without any physical process of hydrological system and vitally focus on the model outputs and its optimization [15].

Recently, the meta models have gained lot of prominence in the field of simulation and optimization of complex systems such as hydrological modelling [16]–[18], aerodynamics [19], geology [20], metallurgy [21], electro-magnetics [22], electronics [23], and economics [24]. The general principle of the meta model is to develop a meta-simulator using a pseudo-function between original model parameters and its outputs through the design of experiments (DOE's). Different studies are focused on meta modelling optimization in the field of water resources using artificial neural networks, support vector machines and Gaussian process [11], [16], [18]. Among, the artificial intelligence is highly capable to handle the predictions that have widely adopted in the field of hydrological modelling [25].

Radial basis artificial neural networks are gaining more popularity because radial basis functions use as activation functions and learning process is much faster. These studies targeted on the computationally intensive optimization problems. In this study, we aim to show computational efficient with accurate analysis for hydrological modelling and comparisons of manual and auto-calibration tools. This study will help understand the performance of SWAT model with meta model and eventually aid the regional state water boards in planning, designing and managing the hydrologic systems.

This paper is constructed like Section 2 explains the framework and methods involved in study. Section 3 shows the study area and data sets information. Section 4 presents the procedures and results and Section 5 provides the conclusions.

2. Methodology Framework

The following steps explain about methodology are:

1. Build the SWAT model with the help of topographical and meteorological data.
2. Select influential parameters and objective function of SWAT model to construct the meta modelling for optimization.
3. Generate the specified number of parameters sets and obtain the objective function for each set using SWAT simulator.
4. Fit the meta model based on the available samples and terminate the model by maximum number of iterations or objective function convergence.
5. Finally verify the model by using validation dataset without any training.

Methods used in this study are:

- Simulator – SWAT model
- Selection of influential parameters – filter through sensitivity analysis.
- Objective function – Nash Sutcliffe Efficiency (NSE).
- Generation of parameter sets – Latin Hypercube sampling.
- Meta model – Radial Basis Function Neural Networks (RBFNN).
- Termination Criteria – K-fold Cross-Validation.
- Verification performance metrics - Nash Sutcliffe Efficiency (NSE) and Percent Bias (PBIAS).

For in detail explanation of each method are explained below and flow chart of the methodology is shown in Fig. 1:

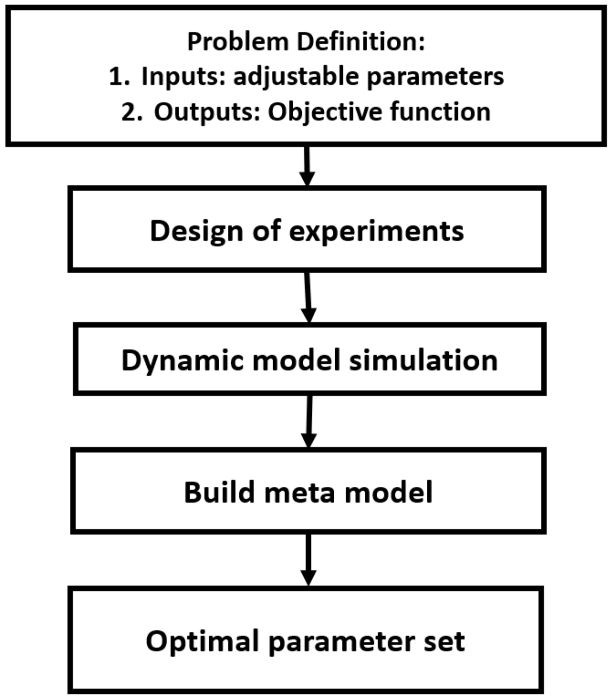

Figure 1: Flow chart of SWAT parameters optimization using meta models.

2.1. SWAT model

The SWAT model is a quasi – distributed, continuous – time, watershed scale simulation model to predict the effect of water quantity and quality on land management practices [26]. According to topographical features, SWAT delineates a watershed into sub-basins with the basis of flow accumulation and stream networks. With the influence of different land-use, soils and slopes within the sub-basins, further split into Hydrologic Response Units (HRUs), where HRU's analysis provides the various reports of water, sediment, nutrient, plant growth and agricultural management. All the hydrologic process is incentive by water balance and HRU is a topographical component to compute the processes. These processes are classified into two types: Land and in-stream phase, where land phase is totally checks and simulates the model from each HRU of streamflow, sediments, pesticides and nutrients but stream phase routes the catchment from each sub-basin throughout the flow path and network. In SWAT, weather inputs are taking consideration into daily based, where all HRU's get same weather data with respective sub-basins.

SWAT integrates a set of physical and empirical based equations to simulate and predict the hydrological as well as water quality processes [27]. Basically, SWAT performs with the help of water balance equation. Therefore, soil water content at a specific time 'm' on every sub-basin can be tracked based on the water balance equation:

$$SWC_m = SWC_o + \sum_{n=1}^{m} (PCP_n - SUR_n - EAT_n - BAF_n - DPW_n) \quad (1)$$

Where, SWC is soil water content, subscripts like O is initial values, PCP is precipitation depth, SUR is surface runoff, EAT is evapotranspiration, BAF is baseflow to the stream and DPW is exiting depth of water in root zone to vadose zone.

2.2. Orthogonal Latin Hypercube Sampling (OALH)

The parameter sets are generated using the Orthogonal Array Based Latin Hypercube (OALH) sampling. These points are used to run the hydrological simulation model and objective function to show input-output relationship. Generally, this step requires the prior knowledge of parameters and particularly in parameter space of lower and upper intervals for stratified sampling. Latin Hypercube Sampling (LHS) is a stratified sampling approach but lack of uniformity. [28] proposed the OA based LHS shows the substantial improvement over the standard LHS. This can help in identification and effective cover of sampling for model development.

2.3. Radial Basis Function Neural Network (RBFNN)

RBFNN contain three layers like input, hidden and output layers which is basis on the feed-forward network. Let x be the n-dimensional input vector and the RBFNN hidden layer to be:

$$R_k = \phi(||x - C_k||) = exp(\frac{||x - C_k||}{2b^2} \quad (2)$$

where,C_k and b are the center and width, k is hidden layer neuron, k = 1,2,...,n and n is the number of hidden units. $\phi(.)$ is a radial basis function and $\| x - C_k \|$ is the normal of $x - C_k$.

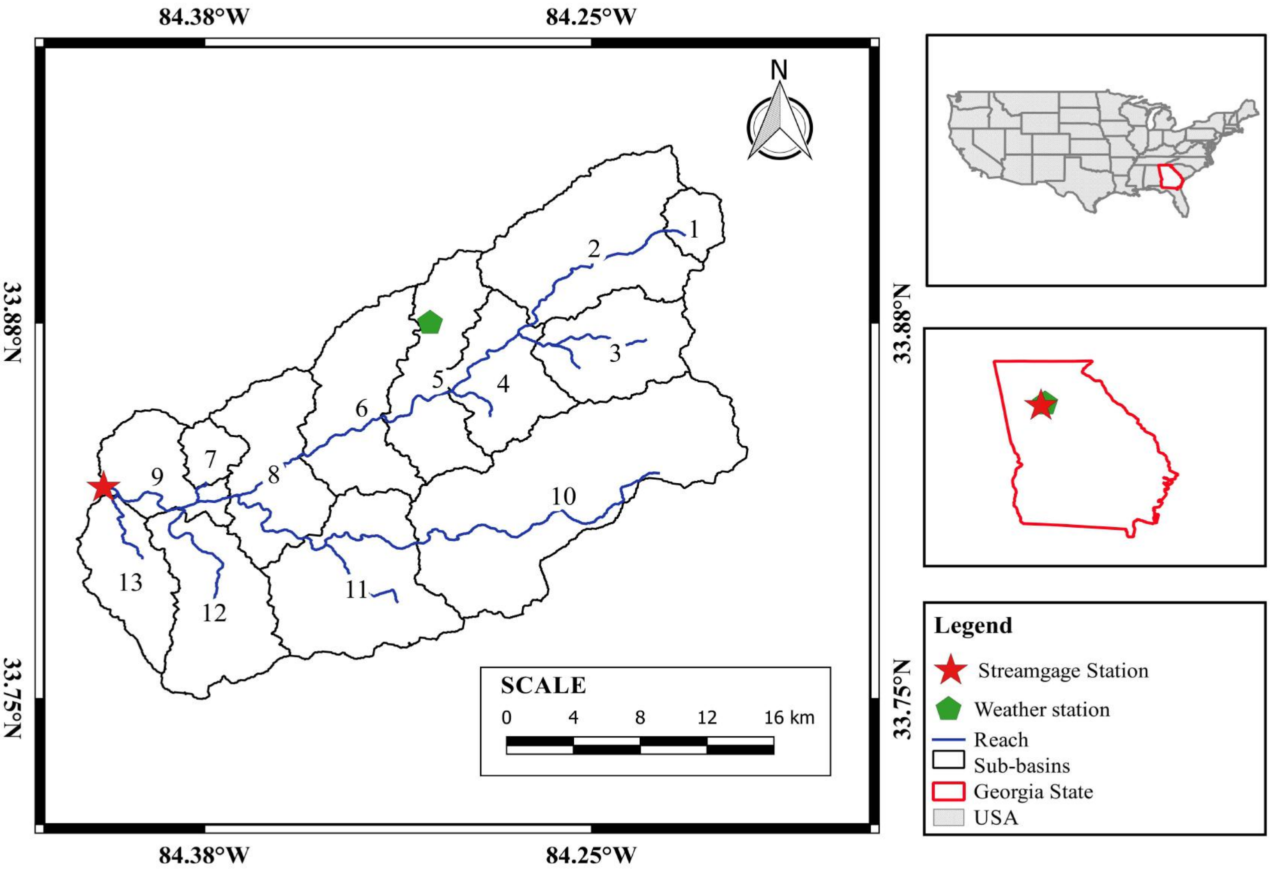

Figure 2: Map showing location of Peachtree Creek watershed, Atlanta in USA.

The outputs of the jth neuron with respective the RBFNN output layer as:

$$y_j(x) = \sum_{k=1}^{n} w_{jk} R_k(x) - \gamma_j \tag{3}$$

Here, $y_j(x)$ is the jth output variable, w_{j_k} is weights from the kth hidden layer neuron to the jth output neuron and γ_j is the threshold of the jth output neuron [29].

2.4. Performance Metrics

1. Nash-Sutcliffe efficiency (NSE): NSE is one of the best normalized static factor which determines the relative noise to the observed data variance [30]. NSE shows how well the plot is representing for observed and simulated data which optimally fits 1:1 line.

$$NSE = 1 - \frac{\sum_{t=1}^{n}(Y_i^{OBS} - Y_i^{SIM})^2}{\sum_{t=1}^{n}(Y_i^{OBS} - Y_i^{MEAN})^2} \tag{4}$$

Where, Y_i^{OBS} is observed variables of ith time, Y_i^{SIM} is predicted value of i th time, Y_i^{MEAN} is mean of observed values and n is the number of values.
It ranges between $-\infty$ and 1.0, where $NSE = 1$ is perfect model. Some acceptable performances like $0.75 \geq NSE \geq 1.0$ is very good model, $0.65 \geq NSE \geq 0.75$ is good model, $0.5 \geq NSE \geq 0.65$ is satisfactory and $-\infty \geq NSE \geq 0.5$ is unsatisfactory [31].

2. Percent bias (PBIAS): PBIAS measures the mean capability of the model data to be larger or smaller than observed values. The accurate model simulation having low-magnitude and its perfect fit is 0. Where, positive values indicate the underestimation of model error and negative values indicates the overestimation of model error.

$$PBIAS = \frac{\sum_{t=1}^{n}(Y_i^{OBS} - Y_i^{SIM}) * 100}{\sum_{t=1}^{n}(Y_i^{OBS}} \tag{5}$$

Where PBIAS expressed in percentages. Some acceptable performances like $\leq \pm 10\%$ is very good model, $\pm 10\% \leq PBIAS < \pm 15\%$ is good model, $\pm 15\% \leq PBIAS < \pm 25\%$ is satisfactory and $PBIAS \geq \pm 25$ is unsatisfactory [31].

2.5. K-fold Cross-Validation

It is a technique to evaluate the predictive models by partitioning the original sample into a training set to train the model, and a test set to evaluate it. Meta model samples formed in k times, where each time leave one-fold out applied to samples for training and remaining one would work for testing. Where, root mean square error (RMSE) represents the performance of response surface models through cross-validation. As computational is a major concern, optimum 5-fold cross-validation schemes are evaluated. The objective function used in the cross-validation (k-fold) is

$$Err = \frac{1}{k} \sum_{i}^{k} RMSE_i \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - Y_t^1)^2}{n}} \tag{7}$$

Where, $n-$number of samples, Y_t is observed value and Y_t^1 is predicted value.

Table 1: Data sources of Peachtree Creek Watershed.

Data Type	**Summary**	
Variable	Time step	Period of Study
Streamflow	Monthly	2005-2014
Rainfall	Daily	2005-2014
Temperature	Daily	2005-2014
Wind speed	Daily	2005-2014
Humidity	Daily	2005-2014
Solar radiation	Daily	2005-2014
Topographic Data	**Resolution**	**Period of acquisition**
Digital elevation model (DEM)	30 m x 30 m	2006
Land-use map	30 m x 30 m	2011
Soil map	1 km x 1 km	1995

Table 2: Selected influential parameters for optimizing the SWAT model.

Rank	**SWAT Parameters**	**Rank**	**SWAT Parameters**
1	CN2	9	ALPHA_BF
2	SOL_AWC	10	SURLAG
3	GWQMN	11	SMTMP
4	GW_REVAP	12	SFTMP
5	ESCO	13	SMFMN
6	RCHRG_DP	14	SMFMX
7	CH_K2	15	REVAPMN
8	GW_DELAY	16	TIMP

Table 3: Table 3. Statistics of cross-validation score for 200, 500, 700, and 1000 samples. Minimum and maximum error obtained from 1000 and 200 samples respectively.

Cross-Validation (RMSE)	**Max**	**Min**	**Standard Deviation**	**Mean**
5-fold	0.96 (200)	0.46 (1000)	0.03	0.52

3. Case Study

3.1. Site Description

The proposed study area is located in Peachtree Creek Watershed, Atlanta (Fig. 2). The elevation of the watershed ranges from 165 m to 513 m, with an average of 232 m; the city is located among the foot hills of the Appalachian Mountains of 320 m from mean sea level and it is one of the highest elevations in major cities in USA. The watershed is completely dominated by urban area which is covered more than 70%. The climate of Atlanta is humid subtropical with mean daily temperature of 26°C and average annual precipitation of 1,260 mm, respectively. The local geography effects from anticyclone which will blow cold air over the warmer Atlantic Ocean. This city has a type of dramatic variations in microclimate usually not near water bodies or nearby mountains.

3.2. Datasets Required

Typically, SWAT model essentially requires the datasets like digital elevation model (DEM) for watershed delineation, landuse and landcover (LULC), soil map and slopes for HRU's distribution. SWAT needs following variables like precipitation, relative humidity, solar radiation, wind speed, maximum and minimum temperature can help to predict the streamflow. Moreover, if any datasets are missing, SWAT in-cooperates with the default weather generator to fill the missing values for USA basins. For distinct data sources of study area provided in Table 1. Where, daily streamflow data obtained from model outlet (Table 1). For independent evaluation of model, 2005-2014 time-period of streamflow forecast (Table 1).

4. Results and Discussions

First step is identification of sensitive parameters of SWAT model for optimization and next step is to calibrate the parameters through meta models. In this research, we used RBFNN to optimize the SWAT model parameters. For evaluating the meta model's performance, we applied model accuracy analysis like k-folds cross-validation. Where, the model builds with 5-folds, where one-fold would go for testing the samples and remaining folds would go for training the samples iteratively. The maximum number of samples taken to train the SWAT model is 1000. Finally, we optimized or calibrated the SWAT model parameters with the following results like sensitivity, model accuracy, and verification analysis.

4.1. Sensitivity Analysis

Before optimization of a model, identified the most influencing parameters in model output and it consider as adjustable parameters for optimization (Table 2). In this study, we used Sobol's Sensitivity Analysis and selected 16 parameters which influencing the model output. In Table 2 represents, CN2 is considered the most effective sensitive parameter and snow melt parameters have least influence in the Peachtree Creek watershed. As watershed comprises of major amount of urban area, hence the management and the ground water parameters are acting sensitively, while other related parameters shown insensitive.

4.2. Model Accuracy Analysis

This section explains about the performance of meta model, we used RBFNN model to optimize SWAT parameters for prediction of the streamflow. Initial, the SWAT model has setup based on the available dataset and checked the performance. If the performance failed to meet the acceptable limits and it must go to calibration. For calibration of SWAT model, we used RBFNN meta model. The meta model is designed within 1000 samples to enhance the performance. For controlling the samples, we checked with 200, 500, 700 and 1000 sets respectively. In this study, the model focused on the global minima of the entire space. SWAT has greater number of parameters, for manual calibration of each simulation it can take several minutes. While, meta models are cheaper models which approximate the original simulation model with input-output response. In Table 3 shows the overall meta model score of 200, 500, 700 and 1000 samples, we focused global minima of the entire space. The default model performance of SWAT without any optimization or calibration was around 2.2 RMSE. Once optimized the model, the error drastically reduced to 0.46 RMSE. It nearly 80% of error minimized from default SWAT model performance. It clearly showed meta model provided accurate results comparing with default performance.

4.3. Verification Analysis

In previous section explained about the meta model accuracy and this section explains about the validation results. The validation or verification results shows the accuracy of prediction. In Fig. 3, two performance metrics are taken under consideration for analyze

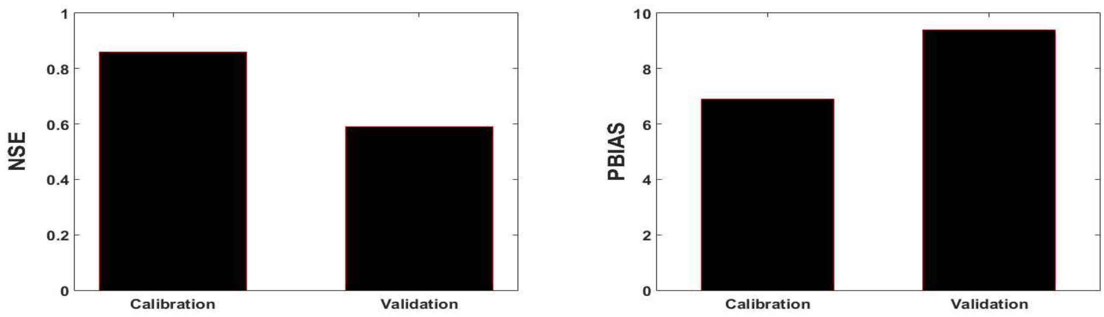

Figure 3: Performance metrics for both calibration and validation of optimized SWAT model.

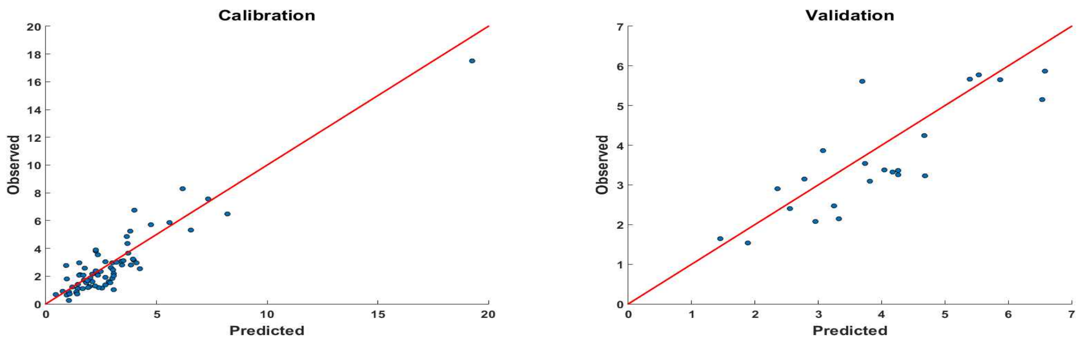

Figure 4: Comparison of calibration and validation performance via scatter plots.

the model. As mentioned above performance ratings in section 2.3, NSE and PBIAS for both calibration and validation achieved satisfactory limits (Fig. 3). While, PBIAS obtained best results in calibration and validation. Moreover, the validated model contained less error and it follows similar trend of observed data. The scatter plot shows the correlation between observed and predicted values; it shows how much of predicted data can able to achieve near to observed data. In Fig. 4, the points of both calibration and validation spotted near to exact fitted line. Compared to calibration, validation points little diversified but it provided the acceptable performance. For analyzing detail flow-wise prediction; Flow duration curves (FDC) are appropriate choice to check in various sections of flow concepts, it derives into different levels of flow like high, medium, and low flows. In Fig. 5, x-axis split into certain classification like 0 to 20 (high flows), 20 to 75 (medium flows) and 75 to 100 considered as (low flows). The calibration followed similar way of trend in all sorts of flows, but validation achieved good performance with over-prediction. Finally, the time series plot illustrates the hydrograph of whole period of calibration and validation as well as it captured effectively in the peaks which helps in flood prediction (Fig. 6). Hence, the model verified with accurate results for streamflow prediction.

4.4. Computational Burden

The entire work done in QSWAT 2012 for developing SWAT models and Matlab 2015a environment for optimization of parameters with the system configuration of Core i5 3.2 GHz processor and 8 GB RAM. In this study, it is observed that the RBFNN model took an average of 20 seconds to train the respective models. The total simulation time to get the optimal SWAT model including with parameter sets generation for RBFNN (1000 samples) was 1.5 hours respectively. Similarly, for manual calibration of SWAT can take 10 minutes to run for one simulation. With the help of meta model, the optimized model can get accurate results with effective computational time.

5. Conclusions

In this study, we proposed meta modelling framework for optimization of SWAT model parameters and enhanced the streamflow . RBFNN has taken as a meta model for finding optimal parameter set with OA-LHD sampling. For selecting adjustable parameters to optimize the model, we used sensitivity analysis to screen out most influential parameters. The developed framework was evaluated by 5-fold CV. The CV score obtained for the sets of 200, 500, 700 and 1000 are range between 0.96 to 0.46 nearly. After training, the model verified through validation results. The performance wise, the model satisfied all the criterion and reduced nearly 50% of error from the default values. While computational wise, it showed better performance over the manual calibration. At an average, the meta model took 20 sec to optimize the parameters and manual calibration can take more than 5 minutes for single simulation. It clearly showed large varaition in computational time between meta model to conceptual model. Here, meta model mimics the original simulation model and explains the input-output relationship. Hence, the prediction of streamflow captured peaks of hydrogrpah with less bias. This study helps to understand the auto-calibration of SWAT model using meta modelling and it provides effective and efficient way to analyze the streamflow for planning and decision making of watershed.

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References

[1] I. Pechlivanidis, B.Jackson, and N. Mcintyre, "Catchment Scale Hydrological Modelling: A Review of Model Types, Calibration approahces and Uncertianty Analyis", Glob. NEST J., vol. 13, pp. 193-214, 2011.

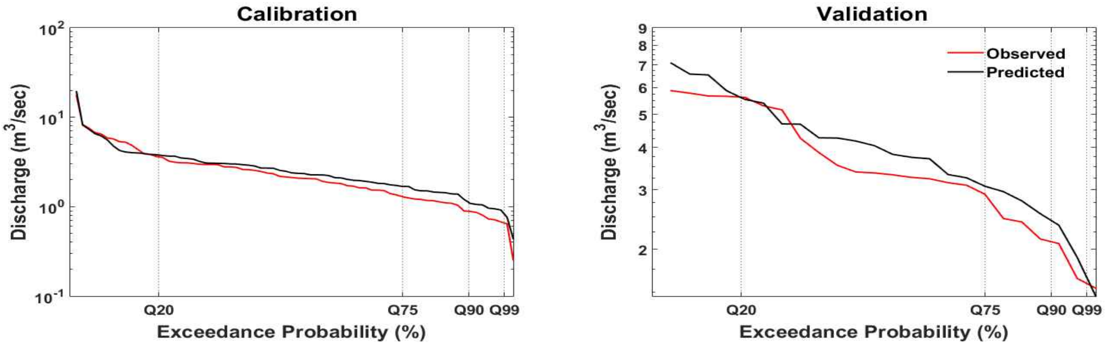

Figure 5: Flow duration curves of calibration and validation with signatures of high flows (Q0 to Q20), medium flows (Q20 to Q75), low flows (Q75 to Q90), and very low flows (Q90 to Q100).

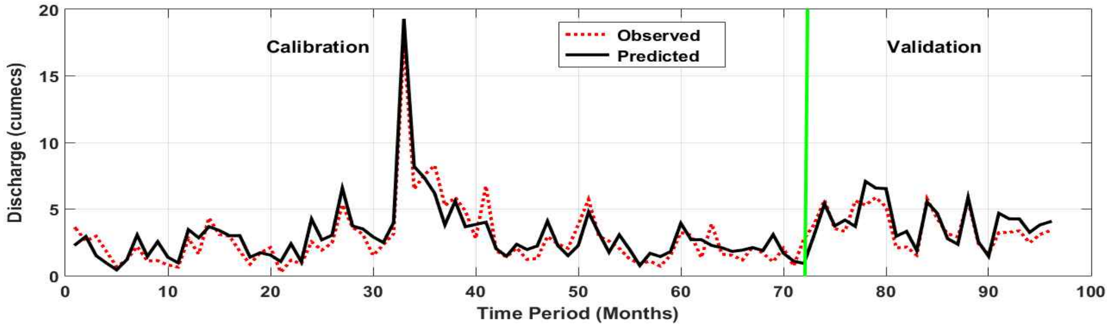

Figure 6: Time series plot of optimized SWAT model with areas of calibration and validation.

[2] M. Wegehenkel, “Estimating of the impact of land use changes using the conceptual hydrological model THESEUS — a case study,” Phys. Chem. Earth, vol. 27, pp. 631–640, 2002.

[3] H. Sellami, S. Benabdallah, I. La Jeunesse, and M. Vanclooster, “Climate models and hydrological parameter uncertainties in climate change impacts on monthly runoff and daily flow duration curve of a Mediterranean catchment,” Hydrol. Sci. J., no. July, pp. 1415–1429, 2016.

[4] A. W. Alansi, M. S. M. Amin, A. . Halim, H. Z. . Shafri, and W. Aimrun, “Validation of SWAT model for stream flow simulation and forecasting in Upper Bernam humid tropical river basin , Malaysia,” Hydrol. Earth Syst. Sci., vol. 6, pp. 7581–7609, 2009.

[5] W. Al Sabhan, M. Mulligan, and G. A. Blackburn, “A real-time hydrological model for flood prediction using GIS and the WWW,” Comput. Environ. Urban Syst., vol. 27, pp. 9–32, 2003.

[6] J. Yang, P. Reichert, K. C. Abbaspour, J. Xia, and H. Yang, “Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China,” pp. 1–23, 2008.

[7] H. Yen, A. Sharifi, L. Kalin, G. Mirhosseini, and J. G. Arnold, “Assessment of model predictions and parameter transferability by alternative land use data on watershed modeling,” J. Hydrol., vol. 527, pp. 458–470, 2015.

[8] Q. Wu, S. Liu, Y. Cai, X. Li, and Y. Jiang, “Improvement of hydrological model calibration by selecting multiple parameter ranges,” Hydrol. Earth Syst. Sci., vol. 21, pp. 393–407, 2017.

[9] Y. Wu and S. Liu, “Automating calibration , sensitivity and uncertainty analysis of complex models using the R package Flexible Modeling Environment (FME): SWAT as an example,” Environ. Model. Softw., vol. 31, pp. 99–109, 2012.

[10] H. Yen, Y. Su, J. E. Wolfe, S. Chen, Y. Hsu, W. Tseng, D. M. Brady, J. Jeong, and J. G. Arnold, “Assessment of input uncertainty by seasonally categorized latent variables using SWAT,” J. Hydrol., vol. 531, pp. 685–695, 2015.

[11] K. P. Sudheer, G. Lakshmi, and I. Chaubey, “Application of a pseudo simulator to evaluate the sensitivity of parameters in complex watershed models,” Environ. Earth Sci., vol. 26, pp. 135–143, 2011.

[12] Y. T. Dile, P. Daggupati, C. George, R. Srinivasan, and J. Arnold, “Introducing a new open source GIS user interface for the SWAT model,” Environ. Model. Softw., vol. 85, pp. 129–138, 2016.

[13] P. W. Gassman, M. R. Reyes, C. H. Green, and J. G. Arnold, “The soil and water assessment tool: historical development, applications, and future research directions,” Am. Soc. Agric. Biol. Eng., vol. 50, no. 4, pp. 1211–1250, 2007.

[14] M. Rezaeianzadeh, A. Stein, H. Tabari, H. Abghari, N. Jalalkamali, E. Z. Hosseinipour, and V. P. Singh, “Assessment of a conceptual hydrological model and artificial neural networks for daily outflows forecasting,” Int. J. Environ. Sci. Technol., vol. 10, pp. 1181–1192, 2013.

[15] A. I. J. Forrester and A. J. Keane, “Recent advances in surrogate-based optimization,” Prog. Aerosp. Sci., vol. 45, pp. 50–79, 2009.

[16] X. Zhang, R. Srinivasan, and M. Van Liew, “APPROXIMATING SWAT MODEL USING ARTIFICIAL NEURAL NETWORK AND SUPPORT VECTOR MACHINE,” J. Am. Water Resour. Assoc., vol. 45, no. 2, pp. 460–474, 2009.

[17] C. Wang, Q. Duan, W. Gong, A. Ye, Z. Di, and C. Miao, “An

evaluation of adaptive surrogate modeling based optimization with two benchmark problems," Environ. Model. Softw., vol. 60, pp. 167–179, 2014.

[18] S. Razavi, B. A. Tolson, and D. H. Burn, "Review of surrogate modeling in water resources," Water Resour. Res., vol. 48, pp. 1–32, 2012.

[19] K. Lindhorst, M. C. Haupt, P. Horst, T. U. Braunschweig, and D.- Braunschweig, "Efficient Surrogate Modelling of Nonlinear Aerodynamics in Aerostructural Coupling Schemes," AIAA J., vol. 52, no. 9, 2014.

[20] I. Pan, M. Babaei, A. Korre, and S. Durucan, "Artificial Neural Network based surrogate modelling for multi- objective optimisation of geological CO 2 storage operations," Energy Procedia, vol. 63, pp. 3483–3491, 2014.

[21] J. Kusiak, Ł. Sztangret, and M. Pietrzyk, "Advances in Engineering Software Effective strategies of metamodelling of industrial metallurgical processes," Adv. Eng. Softw., vol. 89, pp. 90–97, 2015.

[22] M. Alla, M. Hinze, O. Hinze, and O. Lass, "Model order reduction approaches for the optimal design of permanent magnets in optimal desig," IFAC-PapersOnLine, vol. 48, no. 1, pp. 242–247, 2015.

[23] F. Passos, E. Roca, and F. V Fernández, "Radio-frequency inductor synthesis using evolutionary computation and Gaussian-process surrogate modeling," Appl. Soft Comput. J., vol. 60, pp. 495–507, 2017.

[24] F. Lamperti, A. Roventini, and A. Sani, "lamperti2018.pdf," Agent based Model calibration using Mach. Learn. Surrog., vol. 90, pp. 366–389, 2018.

[25] H. R. Maier, A. Jain, G. C. Dandy, and K. P. Sudheer, "Methods used for the development of neural networks for the prediction of water resource variables in river systems: Current status and future directions," Environ. Model. Softw., vol. 25, no. 8, pp. 891–909, 2010.

[26] J. G. Arnold, J. R. Kiniry, R. Srinivasan, J. R. Williams, E. B. Haney, and S. L. Neitsch, Soil & Water Assessment Tool Input-Output Documentation Version 2012. 2012.

[27] S. L. Neitsch, J. G. Arnold, J. R. Kiniry, and J. R. Williams, Soil & Water Assessment Tool Theoretical Documentation Version 2009. 2009.

[28] B. Tang, "Orthogonal Array-Based Latin Hypercubes Orthogonal Array-Based Latin Hypercubes," J. Am. Stat. Assoc., pp. 1392–1397, 1993.

[29] G. H. Roshani, E. Nazemi, and M. M. Roshani, "Intelligent recognition of gas-oil-water three-phase flow regime and determination of volume fraction using radial basis function," Flow Meas. Instrum., vol. 54, no. June 2016, pp. 39–45, 2017.

[30] J. E. Nash and J. V Sutcliffe, "River flow forecasting through conceptual models part-1 - a discussion of principles," J. Hydrol., vol. 10, pp. 282–290, 1970.

[31] D. N. Moriasi, J. G. Arnold, M. W. Van Liew, R. L. Bingner, R. D. Harmel, and T. L. Veith, "Model Evaluation Guidelines For Sytematic Quantification Of Accuracy In Watershed Simulations," Am. Soc. Agric. Biol. Eng., vol. 50, no. 3, pp. 885–900, 2007.