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Application of Non-Dominated Sorting Genetic Algorithm in Calibration of HBV Rainfall-Runoff Model: A Case Study of Tsengwen Reservoir Catchment in Southern Taiwan

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ABSTRACT

The objective of this study is to apply a multi-objective optimization algorithm for tuning parameters of the HBV rainfall-runoff model. This study selected the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) as optimization algorithm and examined various objective functions for investigating the performance of the HBV model in different flow situations (e.g., low flow and high flow). Three common performance indexes were chosen as objective functions: root mean squared error (RMSE), mean absolute percentage error (MPE) and Nash-Sutcliffe (NS). Previous studies (e.g., Getahun and Van Laned, 2015) showed that the HBV might give bias estimates for low and high flow situations. Thus, the study proposed a season-dependent calibration strategy for further improving the bias estimates in different flow situations. The strategy is composed of three parts: (1) the RMSE-based objective function is used for wet seasons only (i.e., high flow situations); (2) the MPE-based objective function is used for dry seasons only (i.e., low flow situations); (3) the NS-based objective function is used for both wet and dry seasons. The preliminary results suggest that the proposed season-dependent strategy can improve the bias problems of HBV model.

KEY WORDS: multi-objective optimization algorithm; the HBV rainfall-runoff model; calibration strategy.

INTRODUCTION

Conceptual rainfall-runoff models are widely used in hydrology for plenty of applications. However, a calibration procedure is need first and after that the models can be further applied for providing simulations or projections. The quality and accuracy of estimations largely depend on calibrating methods in conceptual rainfall-runoff models. Many methods have been used for estimating model parameters such as sensitivity and uncertainty analysis and ussing Multi-objective Shuffled Complex Evolution (MOSCEM) (Abebe, 2010); Particle Swarm Optimization (PSO) for calibration of HEC-1 lumped conceptual rainfall-runoff model (M.Zakermoshfegh, 2008) and Zhou *et al.*, 2014 proposed a self-adaptive parameter and cultural algorithm are used successfully in calibration hydrological model. Among them, one attractive kind of methods, so called optimization algorithm, which has been received lots of attentions. This study attempts to apply an optimization algorithm (i.e., Non-Dominated Sorting Genetic Algorithm II, NSGA-II) for estimating model parameters and further investigate the benefit of using various objective functions. In terms of objective function, it is difficult when we use single-objective function for calibration good in both of low flow and high flow as the same time. Therefore, using multi-objective function to find the best parameter set is very important.

This study used NSGA-II to investigate tunning parameters of a conceptual rainfall-runoff model (i.e., Modified Hydrologiska Byråns Vattenbalansavdelning Model, MHBV model) for Tsengwen reservoir catchmentin Southern Taiwan. The main objectives of this study are:

- Integration of NSGA-II and MHBV. Using MATLAB to combine NSGA-II script and MHBV model in Fortran.
- To investigate model performance by using various single and multi-objective functions.
- Season-dependent strategy.

STUDY AREA AND DATA SETS

Study Area

The Tsengwen Reservoir, with a storage capacity of about 7.8×10^8 m^3, is the largest reservoir in Taiwan. The Tsengwen Reservoir was completed in 1973, having multifunction of the demands for agriculture, domestic use, flood control and hydropower generation. The Tsengwen Reservoir basin encloses area of 481 km^2 (Figure 1), and is at an elevation of from 157 to 3,514 m above sea level. The mean annual precipitation is about 2,740 mm, of which nearly 90% occurs during the wet season (Figure 1).

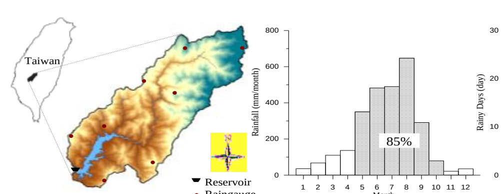

Fig. 1. Tsengwen Reservoir basin and the monthly precipitation

Data Sets

Climate and hydrological data used in this work includes precipitation, streamflow and temperature, provided by Water Resource Agency, Taiwan. Long-term daily precipitations (1975-2014) are available from eight rain gauges, from which areal precipitations on the Tsengwen

Reservoir basin were computed using the Thiessen polygon method. In this study, all the hydrological data were divided into two parts: (1) the calibration period is from 1975 to 2000 (26 years) and (2) the calibration period is from 2001 to 2014 (14 years).

METHODOLOGIES

MHBV Model

The HBV hydrological model was designed at the Swedish Meteorological and Hydrological Institute and has been applied more than 40 countries (Bergström, 1976, 1992, 1995) all over the world. However, in this study the snow accumulation and melt routine of HBV was not used because snowy days are rarely occurred in Taiwan. HBV model was adjusted for the hydrological conditions of Taiwan and successfully tested in Taiwan (Yu and Yang, 2000; Yu et al., 2002; Yang et al., 2005) and so it was adopted for this study.

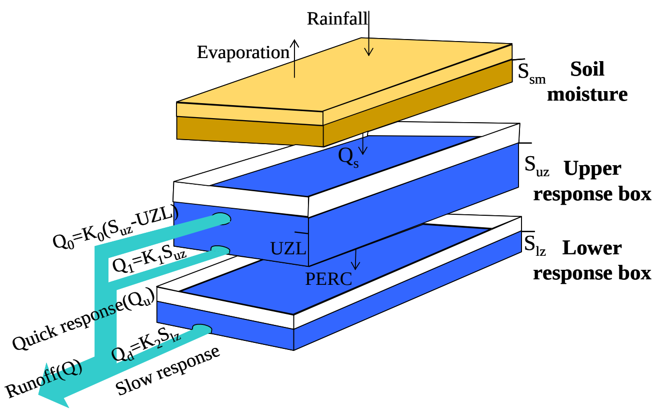

Fig. 2. Runoff responses, conceptual soil storage structure and water fluxes considered by the continuous rainfall-runoff model modified from HBV of Bergström (1976, 1992), which is referred to as MHBV

NSGA-II Algorithm and Framework for Linking with MHBV

NSGA-II algorithm is for resolving multi-objective problems. In this section, NSGA-II is introduced to solve study problems. It is very uncommon to have problems composed by only a single objective when dealing with real-world applications. Generally multiple, often conflicting, objectives arise naturally in most practical optimization problems.

Optimization a problem means finding a set of decision variables which satisfies constraints and optimizes simultaneously functions of all decision makers. This vector optimization leads to a non-unique solution of the problem.

There are a plenty of methods for solving multi-objective problem, but this study chooses NSGA-II as a tool to examine and simulate.

NGSA-II is the second version of the famous “Non-dominated Sorting Genetic Algorithm” based on the work of Prof. Kalyanmoy Deb for solving non-convex and non-smooth single and multi-objective optimization problems. Its main features are:

- A sorting non-dominated procedure where all the individual are sorting according to the level of non-domination
- It implements elitism which stores all non-dominated solutions, and hence enhancing convergence properties
- It adapts a suitable automatic mechanics based on the crowding distance in order to guarantee diversity and spread of solutions
- Constraints are implemented using a modified definition of dominance without the use of penalty functions

NSGA-II is a multi-objective genetic algorithm based on NSGA. However, Deb *et al.* (2002) called this algorithm as NSGA-II. This new algorithm from NSGA in a number of different points. In NSGA-II, non-dominated sorting mechanism has been changed, density estimation and crowded comparison operator is used instead of niche formation and finally elitist strategy is added to algorithm.

For calibration and validation by using NSGA-II, there is an important thing which must be finished, that is linking NSGA-II and MHBV model. In this study, linkage process is based on NSGA-II version open source code in MATLAB.

The basic idea for linking: All the input data for simulation MHBV model such as temperature, rainfall, streamflow,… must be added with 9 parameters in MHBV in the first step. After that, the output of MHBV would be calculated with observation data as objective function. After getting objective function for NSGA-II, all scripts of NSGA-II will be iterated for tuning the best parameter set. (Fig. 3)
Figure 3 shows the detail procedure for linking MHBV and NSGA-II.

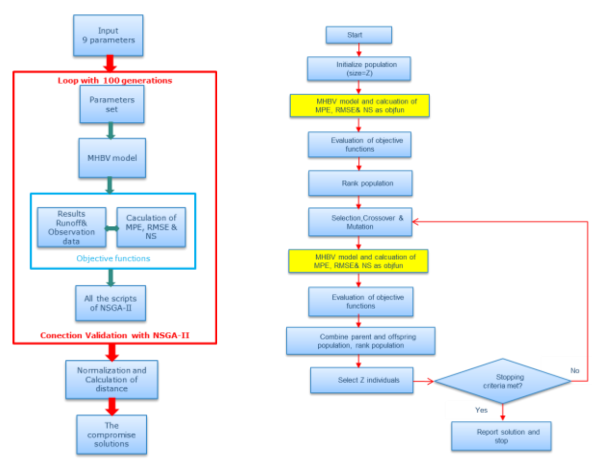

Fig. 3 Flowchart of linking MHBV model and NSGA-II algorithm

**** With the 100th generation, using 2 steps as below to get the compromise solution: Normalization and Calculation of distance***
+ Normalization

To normalize data, traditionally this means to fit the data within unity (1), so all data values will take on a value of 0 to 1. The following equation is what should be used to implement a unity-based normalization for RMSE, MPE and Nash-Sutcliffe

$$S\_RMSE(i) = \frac{RMSE(i) - RMSE_{\min}}{RMSE_{\max} - RMSE_{\min}} \tag{1}$$

$$S\_MPE(i) = \frac{MPE(i) - MPE_{\min}}{MPE_{\max} - MPE_{\min}} \tag{2}$$

$$S\_NS(i)=\frac{NS(i)-NS_{\min}}{NS_{\max}-NS_{\min}} \tag{3}$$

where:
RMSE(i), MPE(i), NS(i) = Each data point i
$RMSE_{min}$, MPE_{min}, NS_{min} = The minima among all the data points
$RMSE_{max}$, MPE_{max}, NS_{max} = The maxima among all the data points
S_RMSE(i), S_MPE(i), S_NS(i) = The data point i normalized between 0 and 1

+ Calculation of distance

3D Distance from one point to (x,y,z)=(0,0,0):

$$Dis=\sqrt{S\_RMSE^2+S\_MPE^2+S\_NS^2} \tag{4}$$

Pop_size= 250 => Having 250 distance is estimated
The shortest (smallest) distance is the compromise solution.

Calibration Strategies for MHBV Model

There are three calibration strategies to tune parameter set for MHBV model. Three strategies are given as below:
(1) Three single-objective functions
(2) Multi-objective function
(3) Multi-objective function with season-dependent data

Firstly, three single-objective functions was introduced, that was single-objective function with three objectives were chosen: root mean squared error (RMSE), mean absolute percentage error (MPE) and Nash-Sutcliffe (NS) (see equation 5, 6 and 7). With each single-objective function, the best one parameter set would be found. Secondly, applying multi-objective function to get the compromise solution and compare with Strategy 1.

RMSE, MPE and Nash-Sutcliffe formula:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Obs(i)-Sim(i))^2} \tag{5}$$

$$MPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{(Obs(i)-Sim(i))}{Obs(i)}\right|\times 100\% \tag{6}$$

$$NS=1-\frac{\sum_{i=1}^{n}(Obs(i)-Sim(i))^2}{\sum_{i=1}^{n}(Obs(i)-Obs\_mean)^2} \tag{7}$$

Lastly, the study proposed a season-dependent calibration strategy in Strategy 3 for further improving the bias estimates in different flow situations. This strategy is composed of three parts: (1) the RMSE-based objective function is used for wet seasons only (i.e.., high flow situations); (2) the MPE-based objective function is used for dry seasons only (i.e.., low flow situations); (3) the NS-based objective function is used for both wet and dry seasons. Based on this idea and real climate in Taiwan, Strategy 3 was divided into 2 cases: Case 1 with two parts of data, dry and wet season; Case 2 with typhoon season and dry season. These two cases would make three objective function changes.

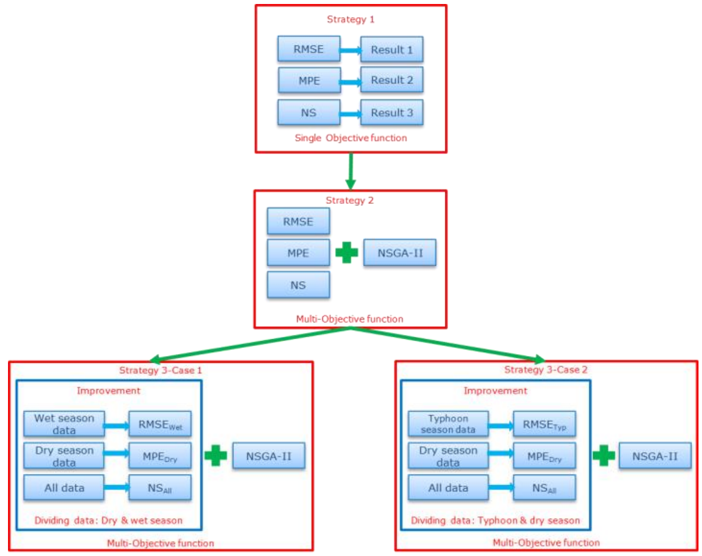

Fig. 4. Three strategies in this study

RESULTS AND DISCUSSIONS

A Comparison between the Results by Using Three Single-objective Functions and Multi-objective Function

There are three calibration strategies to tune parameter set for MHBV model. Three strategies are given as below:

Table 1 Table of comparison parameter set in single-objective function and multi-objective function

Parameters	Range of parameters	Single-objective function (Strategy 1)			Multi-objective function (Strategy 2)
		RMSE	MPE	NS	
FC	0 – 400	398.61	171.36	400.00	121.15
Beta	1 – 10	6.65	1.14	6.68	1.80
LP/FC	0 – 1	0.12	0.21	0.15	0.30
PERC	0 – 20	5.02	2.24	4.52	2.98
UZL	0 – 200	152.83	65.87	152.12	81.29
K_0	0 – 1 .0	0.41	0.36	0.40	0.54
K_1	0 – 0.5	0.43	0.14	0.44	0.19
K_2	0 – 0.5	0.09	0.03	0.09	0.03
C_e	0 – 2.0	0.98	1.47	0.99	1.21

Table 2. shows comparison three performance indexes between single-objective function and multi-objective function. RMSE-index in single-objective function RMSE is better than RMSE-index in multi-objective function (7.10 and 7.31) in both of calibration and validation, MPE-index in single-objective function MPE is also better than MPE in multi-objective function case, and the same for Nash-Sutcliffe coefficient.

However, the important thing is multi-objective function can give a good set of three performance indexes.

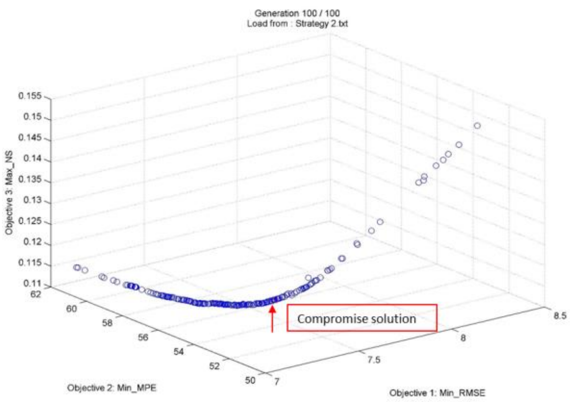

Fig. 5 Compromise solution in Pareto front of original case

The Pareto front would be shown in Figure 5 with compromise solution. The red point in Figure 5 indicates compromise solution which is found by normalization three indexes and then calculation distance between each point in Pareto front to O (0;0;0) and take the smallest value. If only focusing on one objective-function, the parameter set would not good enough for the others. Compromise solution is trade-off of three objective functions and it is contented with multi-objective function.

Table 2 Comparison three performance indexes between single-objective function and multi-objective function

Performance index	**Single-objective function (Strategy 1)**						**Multi-objective function (Strategy 2)**	
	RMSE		MPE		NS			
	C	V	C	V	C	V	C	V
RMSE (mm/day)	7.10	11.40	9.52	15.97	7.10	11.38	7.31	11.66
NS	0.88	0.88	0.79	0.77	0.88	0.88	0.88	0.88
MPE (%)	66.97	66.72	52.46	47.63	67.31	67.25	52.72	49.71

Note: C stands for calibration and V stands for validation

Improvement of Multi-objective Function

In Table 3 and Table 4 show the comparison between Strategy 2 and Strategy 3 in the calibration and validation period, respectively. For each table, [a,c] is calculated by data of wet season (in Strategy 2) and typhoon season (in Strategy 3), [b,d] is calculated by dry season in two strategies. The tables show that there is a close improvement between Strategy 3 with Strategy 2.

Table 3 Comparison parameter set of Strategy 2 and Strategy 3 in calibration period time

Parameters	Multi-objective function (Strategy 2 and 3)			
	Strategy 2	Strategy 3-Case 1	Strategy 2	Strategy 3-Case 2
FC	121.15	176.74	121.15	197.28
Beta	1.80	2.65	1.80	3.32
LP/FC	0.30	0.53	0.30	0.74
PERC	2.98	2.52	2.98	3.26
UZL	81.29	109.68	81.29	90.19
K_0	0.54	0.42	0.54	0.50
K_1	0.19	0.35	0.19	0.26
K_2	0.03	0.03	0.03	0.03
C_e	1.21	1.07	1.21	1.19
RMSE (mm/day)	10.25[a]	10.03[a]	13.17[c]	13.01[c]
NS	0.88	0.88	0.88	0.88
MPE (%)	70.24[b]	72.74[b]	61.56[d]	62.96[d]

Table 4 Comparison parameter set of Strategy 2 and Strategy 3 in validation period time

Parameters	Multi-objective function (Strategy 2 and 3)			
	Strategy 2	Strategy 3-Case 1	Strategy 2	Strategy 3-Case 2
FC	121.15	176.74	121.15	197.28
Beta	1.80	2.65	1.80	3.32
LP/FC	0.30	0.53	0.30	0.74
PERC	2.98	2.52	2.98	3.26
UZL	81.29	109.68	81.29	90.19
K_0	0.54	0.42	0.54	0.50
K_1	0.19	0.35	0.19	0.26
K_2	0.03	0.03	0.03	0.03
C_e	1.21	1.07	1.21	1.19
RMSE (mm/day)	16.42[a]	15.93[a]	20.73[c]	16.14[c]
NS	0.88	0.88	0.88	0.88
MPE (%)	66.11[b]	65.77[b]	60.26[d]	65.67[d]

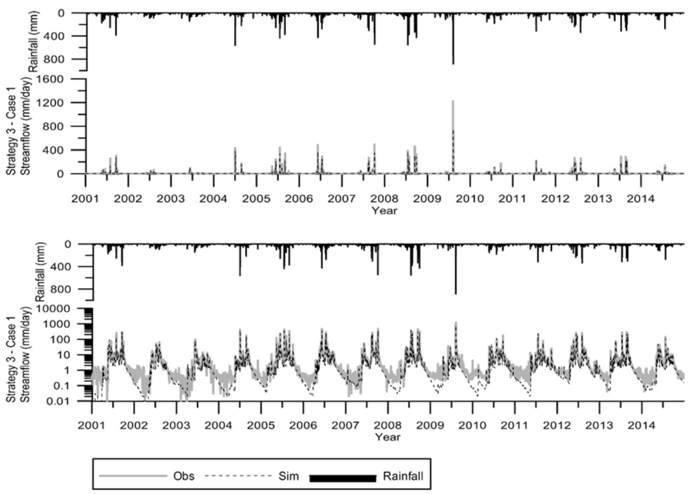

Fig. 6 Multi-objective function for simulated and observation hydrographs in validation period time (Strategy 3 – Case 1)

In this case, the bias between simulated from model and observation data are good enough. The first hydrograph is in mathematical scale shows high flow bias, and the second one shows low flow clearly (Figure 6). In validation period time from 2001 to 2014, the simulation have a good trend in both high flow and low flow.

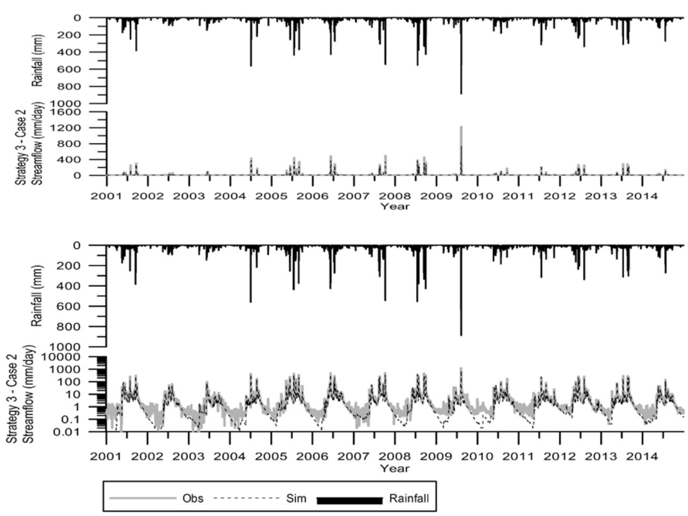

Fig. 7 Multi-objective function for simulated and observation hydrographs in validation period time (Strategy 3 – Case 2)

In this case, the bias between simulated from model and observation data are good enough. The first hydrograph is in mathematical scale shows high flow bias, and the second one shows low flow clearly. However, the bias in these hydrographs are worse than Strategy 3 – Case 1 (Fig. 7).

In Strategy 3 – Case 2, the streamflow simulation are also better than simulation in Strategy 2. However, comparison with Case 1, Strategy 3 – Case 1 indicates better results in simulation than Case 2 when using two seasons in dividing data: dry and wet season.

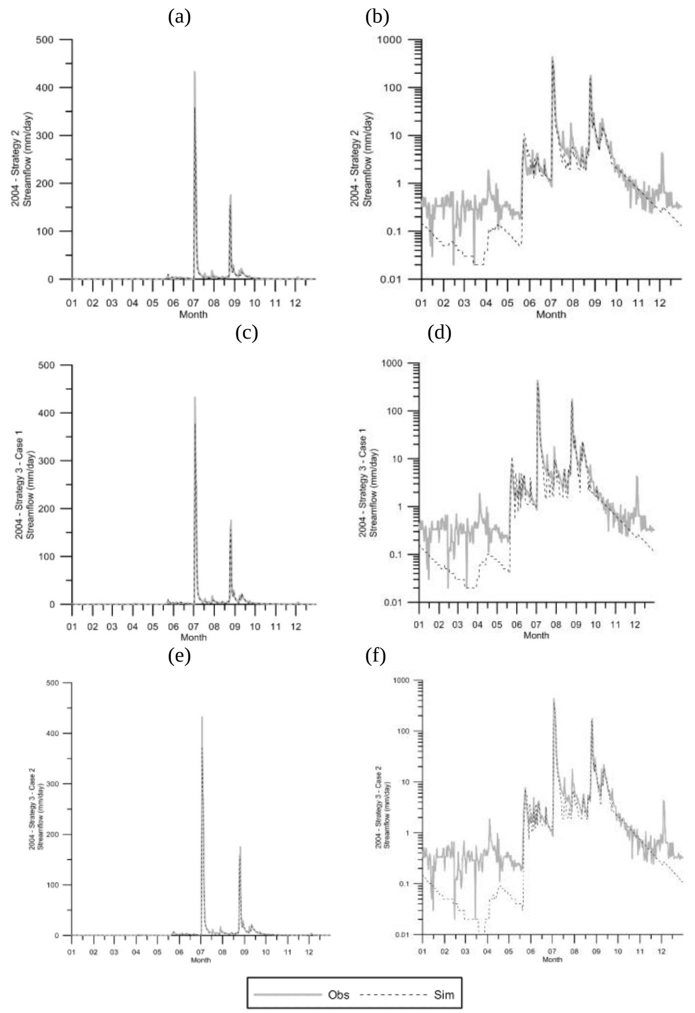

Fig. 8 The best case of simulation in validation period (2004). (a) and (b) are monthly streamflow simulation in Strategy 2, (c) and (d) are monthly streamflow simulation in Strategy 3 – Case 1, (e) and (f) are monthly streamflow simulation in Strategy – Case 2.

CONCLUSIONS

This study used multi-objective function (NSGA-II) to tune parameters set of MHBV for Tsengwen reservoir catchment and investigated the model performance by using different calibration strategies.

Firstly, the NSGA-II was applied successfully in calibration MHBV model with high performance in RMSE, MPE and Nash-Sutcliffe. Besides, the hydrographs in calibration and validation periods also show satisfactory results in both high flow and low flow situations.

Secondly, calibration strategies are also effective. They can improve the MHBV simulation. Better than original application when data were divided and lead to change meaning of objective function based on season-dependent strategy. It improved simulation in low flow and high flow not so much, but with the simulation it has meaningful.

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