Computers, Materials & Continua CMC, vol.65, no.3, pp.2189-2199, 2020

Parameter Calibration of SWMM Model Based on Optimization Algorithm

Fengchang Xue[1, *], Juan Tian[1], Wei Wang[2], Yanran Zhang[1] and Gohar Ali[3]

Abstract: For the challenge of parameter calibration in the process of SWMM (storm water management model) model application, we use particle Swarm Optimization (PSO) and Sequence Quadratic Programming (SQP) in combination to calibrate the parameters and get the optimal parameter combination in this research. Then, we compare and analyze the simulation result with the other two respectively using initial parameters and parameters obtained by PSO algorithm calibration alone. The result shows that the calibration result of PSO-SQP combined algorithm has the highest accuracy and shows highly consistent with the actual situation, which provides a scientific and effective new idea for parameter calibration of SWMM model, moreover, has practical guidance for flood control and disaster mitigation.

Keywords: SWMM, parameter calibration, PSO, SQP.

1 Introduction

China is located in the southeast Asia, influenced by active summer monsoon, and complex terrain effect in addition, heavy rains and other convective weathers often occur [Shi and Tang (1979)]. If the precipitation arriving in the earth's surface cannot flow into pipe network and other drainage facilities, it will cause the overflow of rivers and pipes, and lead to the rainstorm waterlogging. Once waterlogging is too serious or drainage duration is too long, people's daily trips, safety of life and properties will be threated.

In order to simulate the surface runoff caused by rainstorm and pipe running status efficiently, developed countries in Europe and the United States began very early to do research on urban waterlogging model, and have achieved fruitful results. The typical one is the storm water management model (SWMM) developed by the United States Environmental Protection Agency during 1971-2008, which is mainly used to implement the simulation of urban rainfall runoff process and the numerical simulation of drainage system [Su, Cho, Yoon et al. (2007)]. Mouse model developed by Denmark water resource environment research institute provides a favorable calculate method for

[1] Nanjing University of Information Science & Technology, Nanjing, 210044, China.

[2] Zhejiang Meteorological Bureau, Hangzhou, 31000, China.

[3] Pakistan Meteorological Department, Islamabad, Pakistan.

[*] Corresponding Author: Fengchang Xue. Email: xfc9800@126.com.

Received: 03 March 2019; Accepted: 10 September 2019.

rainstorm loss in complex terrain situation. Correlation studies in China started relatively late, and has put forward the city rainwater runoff model (CSYJM), rainwater pipeline calculation model etc., but because of the interface，operation and accuracy of the result and other factors, the application is very limited [Wang, Chao, Zhang et al. (2011)]. In recent years, lots of scholars use the SWMM model to do research on the Chinese urban regional waterlogging and achieve favorable results. SWMM model was used to simulate the storm water drainage system in city Changsha Xia Ning port area [Ren (2004)] and the result showed that the model can reflect the actual situation of the study area. SWMM was applied to simulate and calculate the urban designed flood of study area and achieved favorable simulation effect [Huang (2010)]. Scholars research above show that SWMM has a good adaptability and high accuracy in china, however in the progress of model application, still, many problems such as difficulty in the calibration of parameter should be faced with. Whether the parameters are accurate or not has great influence on the accuracy of the urban waterlogging simulation results. The main parameter calibration methods are interactive and automatic methods. Genetic algorithm was used to calibrate the sensitive parameters and got highly accurate simulate result [Wan (2002)]. Liu took the runoff coefficient as calibration target and calibrated the parameters [Liu (2012)]. Wu used modified morris screening method to calibrate the parameters [Wu, Xiong, Ren et al. (2015)]. Zhao referred to the parameters' range, artificially adjusted the parameters, took the relative error of the flow as evaluation criterion to calibrate the model's prams [Zhao, Pang, Xu et al. (2014)]. Now the major calibration methods are human-interactive method and single optimization algorithm, which may be not efficiency and accuracy enough. In this paper, we use Particle Swarm Optimization and Sequence Quadratic Programming in combination to make full use of these two kinds of intelligent optimization algorithm for parameter calibration, realizing the automatic rate for the solution of the optimal parameters. By considering microcapsules as dissimilar inclusions in the material, Zhou and Zhuang ploy the discrete element method (DEM) to study the effects of loading rates on the fracturing behavior of cementitious specimens containing the inclusion and the crack [Zhou and Zhuang (2018)].

2 Parameters of SWMM model

There are two kinds of parameters of SWMM model [Temprano, Arango, Cagiao et al. (2006)]. One can be achieved by measured data, the other cannot be obtained directly due to difficulty of measuring and data missing, which can only be estimated according to the range of them by referring to the SWMM help document [Jin, Wu and Jiang (2011)]. In this paper, the SWMM model uses the Horton infiltration model and nonlinear reservoir model to simulate the runoff progress of catchment, hydrological parameters of runoff simulation are area of catchment (Area), average slop of surface (Slop), percentage of impervious area (%), Manning coefficient of permeable area (N-Perv), Manning coefficient of impervious area (N-Imperv), surface ponding of permeable area (S-Perv), surface ponding of impervious area (S-Imperv), characteristic width of catchment(Width), initial infiltration rate (MaxRate), stable infiltration rate (MinRate), attenuation coefficient (decay), time required from wet to dry (DryTime) etc., hydraulic parameters required are elevation of pipe (Elevate), pipe diameter (Pipe Diameter), pipe material (Material),bottom elevation (Elevate), bottom depth (Depth), conduit roughness, etc., in which Area, Slop, percentage of impervious area etc. can be obtained by means of digitalizing remote sensing image or extracting from DEM and etc., while the others cannot be obtained by measuring, the calibration is required [Mahyun, Ismail, Maznah et al. (2009)]. Parameters that require calibration and their ranges are shown in Tab. 1 below.

Table 1: Calibration parameters and their ranges

Calibration Parameters	Ranges
N-Perv	0~1
N-Imperv	0~1
S-Perv/mm	0~1
S-Imperv/mm	0~1
MaxRate/(mm*h^{-1})	0~100
MinRate/(mm* h^{-1})	0~100
Decay/h^{-1}	0~10
DryTime/d	0~10

3 Data and methods

Equations and mathematical expressions must be inserted into the main text. Two different types of styles can be used for equations and mathematical expressions. They are: in-line style, and display style.

3.1 Research data

In this paper, we use the sample data provided by the EPA SWMM (Environment Protection Agency), which contains the measured flow and water level of pipe network and nodes, sketch map of study area is shown as Fig. 1:

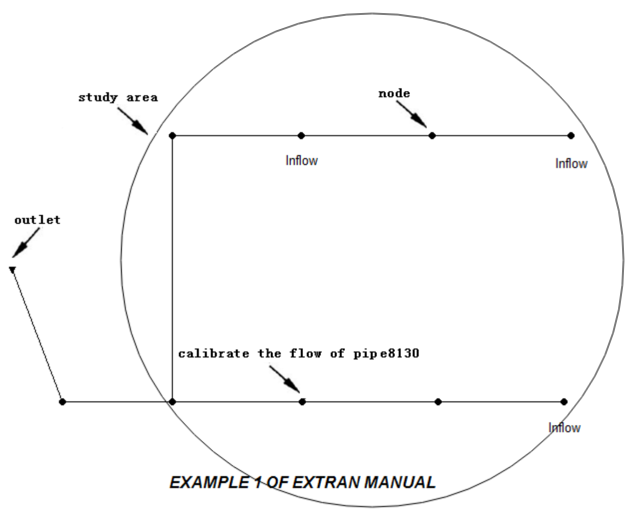

Figure 1: Study area sketch map

Sketch map of precipitation (hourly accumulated) and flow of piple8130 in sample data is shown in Fig. 2 as flows.

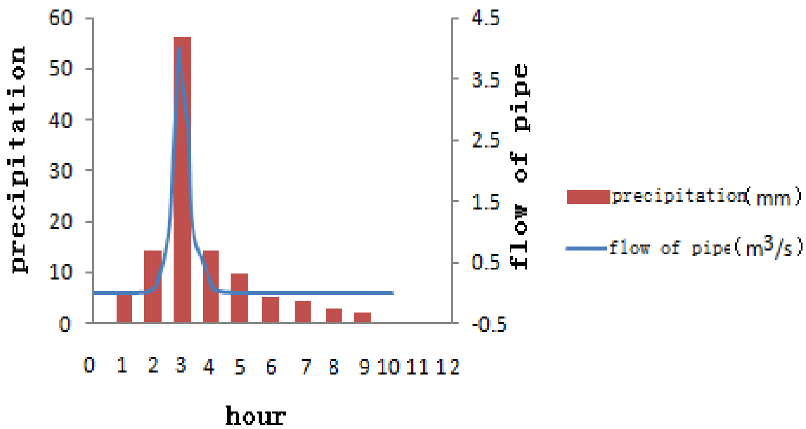

Figure 2: Time series of precipitation and flow of pipe

In this study, we calibrate the flow of the pipe 8130 in a rainfall progress, attempting to verify the feasibility of the scheme, which will provide a new way of thinking for the parameters calibration of the model.

3.2 Research methods

Artificial and machine are two major parameters calibration methods. Compared with artificial calibration which is only suit for few prams and needs to calibrate for several times, machine calibration gets more attention and much more widely application thanks to its fast speed high accuracy and other advantages. The SWMM model is a highly non-linear and complex model, which has various affecting factors and combination number between each other is huge. Calibrating by intelligent optimization algorithm is efficient and the results have higher fitting degree with the measured value.

However, due to the limitation of the algorithm itself, using a single optimization algorithm for parameter rate timing, is easy to fall into local optimal solution, appearing weak local search ability. Combining stochastic (PSO) and deterministic (SQP) algorithms to calibrate provides a scientific-new idea for parameters calibration, which promises the ability of local research and at the same time, won't fall into local optimal solution. Particle Swarm Optimization (PSO) algorithm and Sequence Quadratic Programming (SQP) Algorithm are widely studied and applied in china and foreign countries owing to their unique advantages. We combine PSO and SQP to calibrate in this paper. First, we use PSO by invoking SWMM model through C# code, taking the measured pipe values as optimization value, then in order to acquire the best combination of parameters, we use the SQP algorithm to strengthen the local search ability. Repeating the progress until up to the number of iterations, the final optimal combination is the global optimal solution of the parameters.

3.2.1 PSO algorithm

PSO is a random, group based evolutionary algorithm， putting forward by imitating the behavior of birds group [Eberhart and Kennedy (1995)], which initializes a group of particles, each of them represents a candidate solution. PSO complies a simple rule: imitating the adjacent excellent particle and global best particle. Therefore, the location of particles influenced by neighboring best particle Pbest and the global best particle Gbest. The location of particle Xi updating formula is as follows:

$$x_i^{k+1} = x_i^k + \Phi_i^{k+1} \tag{1}$$

In which Φ_i represents speed, updating formula is as follows:

$$\Phi_i^{k+1} = \omega\Phi_i^k + c_1 r_1 \left\{P_{best} - x_i^k\right\} + c_2 r_2 \left\{G_{best} - x_i^k\right\} \tag{2}$$

In which ω is inertia weight, c_1、c_2 is acceleration coefficient, r_1, $r_2 \in U(0,1)$, P_{best} is the best position of particle i, G_{best} is the best position of global particle. Particle update their location and speed according to formula (1), (2) until finding the best solution.

3.2.2 SQP algorithm

SQP acquires the best solution by transforming the original problem into a series of quadratic programming sub problems and solving them [Fletcher (1987)]. It was put forward to solve nonlinear programming problems by Dr. Wilson in 1963 [Wilson (1963)]. The formula of QP sub problem is as follows:

$$\min_{d \in R^n} \frac{1}{2} d^T H_k d + \nabla f(x_k)^T d, \tag{3}$$

$$s.t. \nabla g(x_k)^T d + g(x_k) \ \leq 0 \tag{4}$$

In which k is current iteration number; H is the Hessian matrix, which can be approximated by the quasi Newton method, f,g are continuously differentiable functions, N dimension vector , named as ∇f (xk) is the gradient of target function f (xk) in xk, N dimension vector , named as ∇g (xk) is the gradient of constraint function g (xk) in xk, s is the feasible region of the problem, and the solution of the QP sub problem is the linear search direction of the next iteration.

3.2.3 Algorithm implementation process

In this paper, we establish a combined algorithm based on stochastic (PSO) and deterministic (SQP) algorithms. The PSO is regarded as global convergence of global search while the SQP is regarded as the local research to strengthen the local research. The implementation flow chart of algorithm is shown in Fig. 3 as follows:

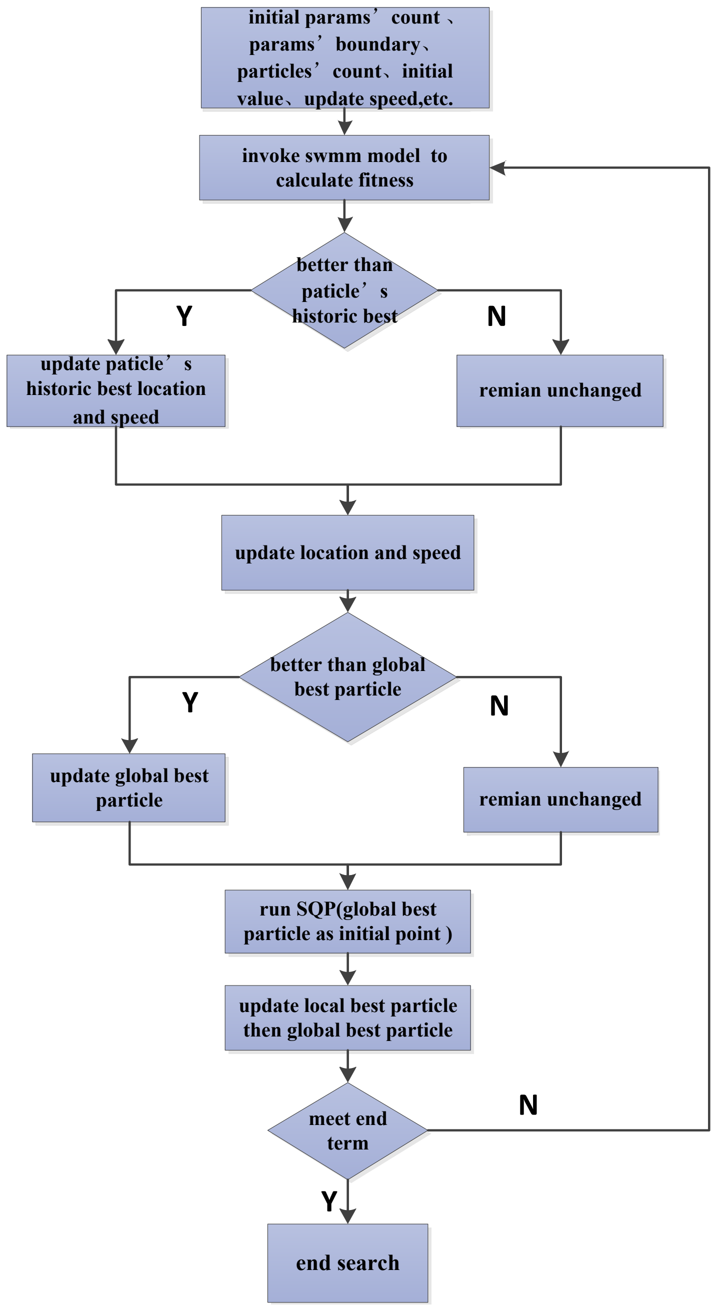

Figure 3: Implementation flow chart of algorithm

Implementation steps of algorithm:

(1) Initialize parameters: the number of parameters、the boundary constraints of parameters, number of particles, initial value of parameters, update speed of parameters' value;

(2) Call the SWMM model to calculate the difference between measured flow and simulated flow, which is so-called value of particle's fitness, if the current particle's fitness is better than the history's, update the combination of parameters, otherwise, remain unchanged;

(3) Update particles' location and speed according to formula (1), (2). If the global best fitness is better than the historical global best fitness, update the particle's global best fitness and the combination of parameters, otherwise, remain unchanged;

(4) Take the combination of parameters of global best particle as the initial point to run the SQP algorithm and update the local best fitness;

(5) If the end condition (two common kinds: number of iterations and accuracy of result) is satisfied, save the optimization result, otherwise turn Step (2).

4 Experiment of parameters calibration

In the experiment, first, we use the SWMM model's initial value of parameters to simulate then use the calibration result of PSO to simulate. Last but not the least, we combine the deterministic algorithm (SQP) and the stochastic algorithm (PSO) to calibrate the parameters and carry out the simulation experiment with the result above. Experiment above all regard the minimum sum of the square of the difference between the simulated value and the measured value as the optimized goal.

4.1 Initial parameter simulation

In the sample data the value of each parameters have been initialized, Values of the eight parameters in this study are shown as follows: 0.01 (N-Imperv), 0.01 (N-Perv), 0.05 mm (S-Imperv), 0.05 mm (S-Perv), 2.8 mm/h (MaxRate), 0.3 mm/h (MinRate), 3.8 h-1 (Decay) and 6 d (DryTime). We use the values above to simulate the flow of piple8130, the result shows that the deviation between the simulated values and the measured values is large, and the agreement is low. The comparison between the simulated result and the measured values is shown in Fig. 4:

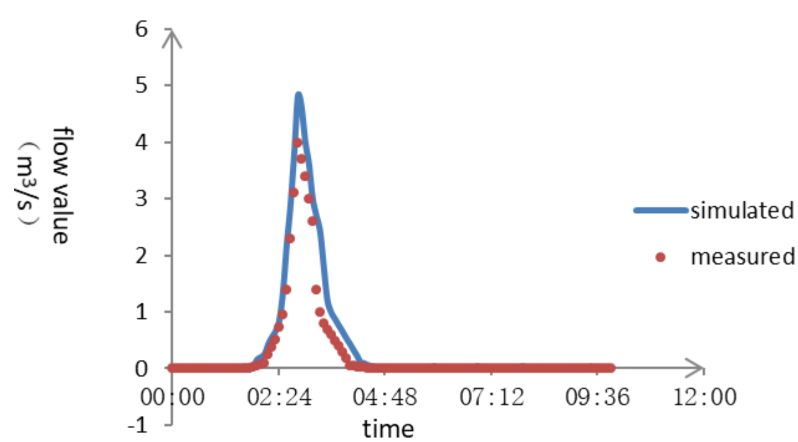

Figure 4: The comparison between the simulated values and the measured values

4.2 Simulation with the parameters calibrated by PSO

We use the single PSO algorithm to calibrate the eight parameters of the model, formula of the optimized goal is as follows:

$$\sum_{i=1}^{n}(P_i - Q_i)^2 \tag{5}$$

In which p is the simulated value, Q is the measured value, i is the time series.

By calibrating through PSO calibration, we acquire the best combination of parameters: 0.065 (N-Imperv), 0.032 (N-Perv), 0.501 mm (S-Imperv), 0.214 mm (S-Perv), 51.193 mm/h (MaxRate), 17.801 (MinRate), 2.351 h-1 (Decay) and 1.417 d (DryTime). Putting the above parameters into the model to simulate, we can get the simulated flow value of piple8130. Compared with the initial parameters experiment, the deviation between simulated and measured ones is much better, and fitting degree is much higher, but flow deviation of section moment is still great. The comparison chart of simulated values and measured values of times is shown in Fig. 5:

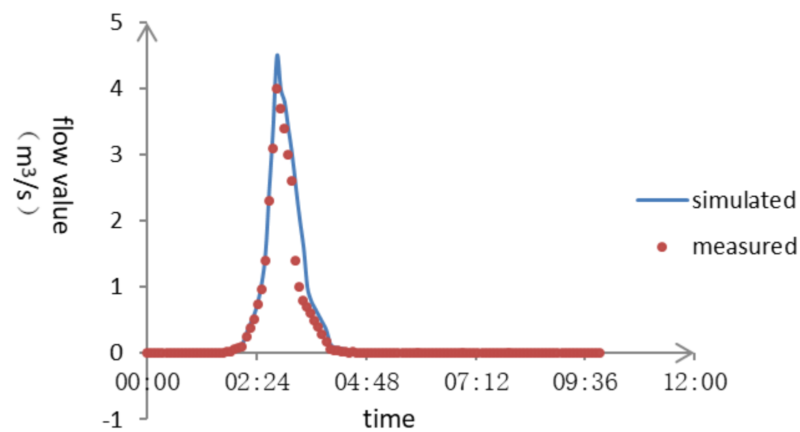

Figure 5: The comparison between the simulated values by PSO calibrated prams and the measured values

4.3 Simulation with the parameters calibrated by PSO-SQP

In order to enhance the local search capability of the algorithm, we add the SQP algorithm on the basis of the PSO algorithm to calibrate the model's parameters. The formula of the optimized goal is consistent with the formula (5).

The optimal combination values of parameters obtained are as follows: 0.036 (N-Imperv), 0.057 (N-Perv), 0.556 mm (S-Imperv), 0.494 mm (S-Perv), 40.193 mm/h (MaxRate), 22.801 (MinRate), 5.351h-1 (Decay) and 0.827d (DryTime).

Using the combination above to simulate, the comparison between the simulated values and measured values of piple8130 is shown in Fig. 6:

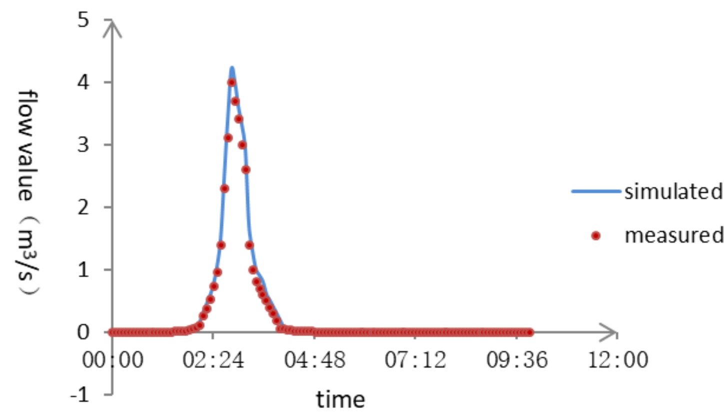

Figure 6: The comparison between the simulated values by PSO-SQP calibrated params and the measured values

It can be obviously seen that although a little deviation still exists between the simulated and measured ones, the overall fitting degree is very high, which shows an excellent parameters calibrating effect.

4.4 Result and analysis

We can see the simulated effects of the three experiments above directly through Figs. 3.1 to 3.3, the value of discrete points and peak is matching the trend gradually. In order to increase the credibility of the experimental result, we carry on experimental contrast regarding iterations valuing 100, 150 and 200 respectively as the terminal condition. the comparison of the simulation result is shown in Tab. 2:

Table 2: the comparison of simulated effects

Iterations	Simulated parameters	$\sum_{i=1}^{n}(P_i - Q_i)^2$	time (s)
100	PSO	4.156	15
100	PSO-SQP	0.883	22
150	PSO	3.908	21
150	PSO-SQP	0.796	28
200	PSO	3.892	26
200	PSO-SQP	0.788	31

Formula (5) calculates the sum of the difference between simulated values and measured ones in a time sequence, which describes the deviation degree between simulated values and measured ones. The value is higher, the deviation degree is larger, and vice versa. From the three groups experimental, we can find that using the initial parameters, the value is highest, the deviation degree is largest, using the parameters calibrated by PSO, the value is lower, the fitting degree improves a little and when using the parameters calibrated by PSO-SQP algorithm, the value is the lowest and the fitting degree is the highest, however, time required is more, which shows the excellent effects of the calibration by the method of combining deterministic algorithm (SQP) and stochastic algorithm (PSO), but the efficiency is getting lower.

5 Summary and discussion

The calibration of parameters is an important progress of model application, whether the parameters are suitable or not is a significant role for the simulation result of model. In this paper, we carried out three experiments with default parameters, parameters calibrated by PSO and parameters calibrated by PSO-SQP, and compared the results with the actual values. Through analyzing, the conclusions are as follows: (1) parameter calibration is necessary, using parameters without calibration to simulate will get large deviation, there will not be any realistic meaning. (2) using single stochastic algorithm (SQP) for parameter calibration can achieve good results, but local search capability of the algorithm is weak, and hard to achieve high accuracy. (3) using a combination of the stochastic algorithm (PSO) and the deterministic algorithm (SQP) can finish parameter calibration very well, which has strong local searching ability and won't fall into local optimal solution. This method is very suitable for SWMM model which has numerous parameter combinations, and is highly nonlinear as well. parameters combination acquired from calibration applying to storm runoff simulation will be highly accurate. Which has a certain realistic meaning for the flood control and disaster reduction.

The combined PSO-SQP algorithm we used to calibrate the parameters of SWMM model in this paper achieved good performance, still there are shortcomings: combined algorithm will lead to low efficiency. Aiming at these problems, it is necessary to make further research. In the future there will be more and more scholars working on relevant aspects of the research, making efforts for the SWMM model parameters optimization, the rainstorm waterlogging accuracy of simulation, and providing more effective guidance for heavy rainfall and flood disaster prevention and mitigation.

Funding Statement: We would like to express our acknowledgements to the Fund of postgraduate training and innovation project of Jiangsu Province (NO. SJKY19_0969).

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

AlRashidi，M. R.; El-Hawary, M. E. (2009): A survey of particle swarm optimization applications in electric power systems. *IEEE Transactions on Evolutionary Computation*, vol. 13, no. 4, pp. 913-918.

Dong, X.; Du, P. F.; Li, Z. Y. (2008): Parameter identification and validation of SWMM model in the simulation of surface runoff in urban impervious area. *Environmental Science*, vol. 29, no. 6, pp. 495-1501.

Eberhart, R. C.; Kennedy, J. (1995): A new optimizer using particle swarm theory. *Proceedings of the Sixth International Symposium on Micro Machine and Human Science. MHS'95.*

Fletcher, R. (1987): Practical methods of optimization. *New York: Wiley*, pp. 304-316.

He, M.; Wang, H. B.; Zhou, L. K.; Wang, P. M.; Ju, A. (2018): Symmetric learning data augmentation model for underwater target noise data expansion. *Computers, Materials & Continua*, vol. 57, no. 3, pp. 521-532

Huang, K. (2010): Application of SWMM model in the design of flood Xin Xu jiang river in Nanning. *Red River*, vol. 2009, no. 5, pp. 36-38.

Jiang, S.; Cho, M.; Yoon, J. (2007): Using SWMM as a tool for hydrologic impact assessment. *Desalination*, vol. 212, no. 1, pp. 344-356.

Jin, X.; Wu, W.; Jiang, Y. H. (2011): Automatic calibration of SWMM model with adaptive genetic algorithm. *International Symposium on Water Resource and Environmental Protection*, pp. 891-895.

Li, X. B. (2012): Calculation method of flood control capacity of coastal city river based on SWMM. *China Water & Wastewater*, vol. 28, no. 3, pp. 57-59.

Mahyun, A. W.; Ismail, A.; Maznah, K.; Salwa, M. Z. M.; Wazira, A. et al. (2009): *Calibration of SWMM5 for local parameters at Sungai Kayu Ara, Damansara Selangor.*

Muris, J. F.; Meijer, C. J.; Vos, W.; van Krieken, J. H.; Jiwa, N. M. et al. (2006): Immunohistochemically profiling based on Bcl-2, CD10 and MUM1 expression improves risk stratification in patients with primary nodal diffuse large B cell lymphoma. *The Journal of Pathology*, vol. 208, no. 5, pp. 714-723.

Pazhi, R. (2004): *Study on the Calculation Model of Urban Design Storm and Storm Water Runoff (Ph.D. Thesis)*. Chongqing University, China.

Sadik, U. (2008): Particle swarm optimization application to microwave circuits. *Microwave & Optical Technology Letters*, vol. 50, no. 5, pp. 1333-1336.

Temprano, J.; Arango, Ó; Cagiao. J. (2006): Storm water quality calibration by SWMM: A case study in Northern Spain. *Water SA*, vol. 32, no. 1, pp. 55-63.

Tenny, M. J.; Wright, S. J.; Rawlings, J. B. (2004): Nonlinear model predictive control via feasibility-perturbed sequential quadratic programming. *Computational Optimization & Applications*, vol. 28, no. 1, pp. 87-121.

Wilson, R. B. (1963): *A Simplicial Algorithm for Cancave Programming (Ph.D. Thesis)*. Boston: Graduate School of Business Administration, Harvard University.

Wu, Y. A.; Xiao, J. Q.; Ren, X. X. (2015): The research and analysis of Shenzhen SWMM goosenecks water basin model parameter sensitivity and calibration. *Water Supply and Drainage*, vol. 30, no. 11, pp. 126-131.