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Automatic calibration and sensitivity analysis of DISPRIN model parameters: A case study on Lesti watershed in East Java, Indonesia

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Abstract

The Dee Investigation Simulation Program for Regulating Network (DISPRIN) model consists of eight tanks that are mutually interconnected. It contains 25 parameters involved in the process of transforming rainfall into runoff data. This complexity factor is the appeal to be explored in order to more efficiently. Parameterization process in this research is done by using Differential Evolution (DE) algorithm while parameters sensitivity analysis is done by using Monte Carlo simulation method. Software application models of merging the two concepts are called DISPRIN25-DE model and compiled using code program M-FILE from MATLAB. Results of research on Lesti watershed at the control point Tawangrejeni automatic water level recorder (AWLR) station (319.14 km^2) in East Java Indonesia indicate that the model can work effectively for transforming rainfall into runoff data series. Model performance at the calibration stage provide value of *NSE* = 0.871 and *PME* = 0.343 while in the validation stage provide value of *NSE* = 0.823 and *PME* = 0.180. Good performance in the calibration process indicates that DE algorithm is able to solve problems of global optimization of the equations system with a large number of variables. The results of the sensitivity analysis of 25 parameters showed that 3 parameters have a strong sensitivity level, 7 parameters with a medium level and 15 other parameters showed weak sensitivity level to performance of DISPRIN model.

Key words: *differential evolution, Dee Investigation Simulation Program for Regulating Network (DISPRIN) model, Lesti watershed, simulation*

INTRODUCTION

Metaheuristik is a method for finding the optimal solution approach by combining search procedures between local and higher strategies to create a process that is able to get out of local optima points and do a search in the space of solutions to determine the global solution. Analytical techniques on the metaheuristic method are generally stochastic and solved through the iteration process. The optimal solution produced maybe not the best conditions, but a solution that is near optimal. The reliability and ease of its application in solving complex and high-dimensional equations systems makes it attractive to be applied to solve problems in various fields, including the field of hydrological engineering. Efforts to improve the performance of hydrological conceptual models by combining them with metaheuristic methods have been widely published by world researchers. Merging metaheuristic methods with conceptual hydrologic models can produce new models that are reliable and practically applied to transform climate into runoff data series. The new model can perform automatic calibration with only utilize climate and runoff data series with length limited.

Many new models generated from combination between metaheuristic methods and hydrological models developed by previous researchers. Hydrologiska Byråns Vattenbalansavdelning (HBV) model and Ge'nie Rural a' 4 parame'tres Journalier (GR4J) model combined with Diferential Evolution (DE) algorithm and Particle Swam Optimization (PSO) algorithm [PIOTROWSKI *et al.* 2016]. A combination between Genetic Algorithm (GA) and the North American Mesoscale (NAM) model can present the rainfall-runoff relationship with daily periods. Although its performance is not as good as the application of Tank model based GA with the same data set [NGOC *et al.* 2012]. Other models that are successfully developed are modified HBV model in combination with GA [SEIBERT 2000], HBV model and NAM model with the Continous Time Stochastic Modelling (CTSM) optimization [JONSDOTTIR *et al.* 2005], A spatially distributed grid based rainfall runoff model for continuous time simulations of river discharge (AFFDEF) model and Shuffle Complex Evolution (SCE) algorithm [DARIKANDEH *et al.* 2014], Kieistau Model Discharge Simulation (KIDS) model with Sufi-2 method from SWAT (Soil and Water Assessment Tool) Software [ZHANG*et al.* 2012]. The combination between SWAT 2000 model and Dynamically Dimensioned Search (DDS) algorithm also SWAT 2000 model and SCE algorithm show that both methods can work well on a daily or monthly data analysis [TOLSON *et al.* 2007]. Xin'anjiang model combined with SCE algorithms [BAO *et al.* 2008], GA and GA hybrid [WANG *et al.* 2012] also can show satisfactory performance on a variety of issues over the data-rain runoff.

Metaheuristic method for automatic calibration Tank model parameters has been proposed by many researchers in the world. Exploration of Tank model combined with PSO algorithm successfully applied to the Shigenobu Watershed Japan [SANTOS *et al.* 2011]. Tank model combined with Marquard algorithm [SETIAWAN *et al.* 2003], GA [NGOC *et al.* 2012] also managed to show a good performance. Combination of SCE, GA, PSO, Artificial Imune System (AIS) and DE algorithm with Tank model that are applied to the Yellow River watershed in China and Reynolds Creek Boise ID watershed, Mahantango Creek University Park watershed, Little River Tifton watershed in United States indicate that the combination in of five methods can work well [ZHANG *et al.* 2012].

Combination between Tank model and PSO algorithm for flood analysis with hourly period in urban areas in Taiwan also shows very good performance [HSU, YEH 2015]. Modification of Tank model into Multi Tank model combined with metaheuristic to monitor ground water level fluctuations have also been conducted by previous researchers. Multi Tank model with 6 tanks system arranged in parallel-series (27 parameters) combined with DDS algorithm shows better results than the output from finite element method (FEM) [KENJI *et al.* 2008]. Para Tank models with 8 tank system (32 parameters) combined with DDS Algorithm and GA shows good performance in predicting fluctuations in groundwater levels in Yamagata, Japan. In this case both the developed model show the same error rate, but the model with DDS algorithm is more effective in terms of speed in reaching convergent conditions [HUANG, XIONG 2010].

Dee Investigation Simulation Program for Regulating Network (DISPRIN) model as described by JAMIESON and WILKINSON [1972] in SHAW [1985], is a lumped model that has more complex parameters than Tank model by Sugawara. The DISPRIN model application involves 8 tanks and contains more than 20 parameters. This complexity factor makes the DISPRIN model unpopular to be applied to solve practical problems. This article aims to improve the performance of the DISPRIN model to be more practical. Technically, it is done by combining it with DE algorithm in automatic calibration process of its parameters. Calibration should include estimation of uncertainty, not only identify and set the parameter value [GHOLAMI *et al.* 2016; ZHANG *et al.* 2012]. In this connection, the author accommodate uncertainty analysis parameter value by applying the Monte Carlo simulation method [CHEN *et al.* 2006; RAMIRES *et al.* 2012; UHLENBROOK *et al.* 1999]. The new model as a results from combination between DISPRIN model simulation concept and DE algorithm called the DISPRIN25-DE model. Index "25" indicates the number of DISPRIN model parameters to be studied further. The results are expected to be an alternative solution in solving the problem of limited data stream flow that often become a classic problem in water resources development activities in developing countries.

MATERIAL AND METHOD

DISPRIN MODELS SIMULATION

Dee Investigation Simulation Program for Regulating Network (DISPRIN) model included in the lumped models category which technically can be solved by using the analogy of a Tank model simulation by Sugawara. In "The UK the Water Resources Board's DISPRIN Models", this model was developed in a research program of the Dee River [SHAW 1985]. The simulation scheme of the DISPRIN model 25 parameters in this research is shown in Figure 1.

On the application of the DISPRIN model, a watershed should be divided into three zones according position and physical characteristics, namely up-land, hill-slope and bottom-slope zone. Up-land zone is

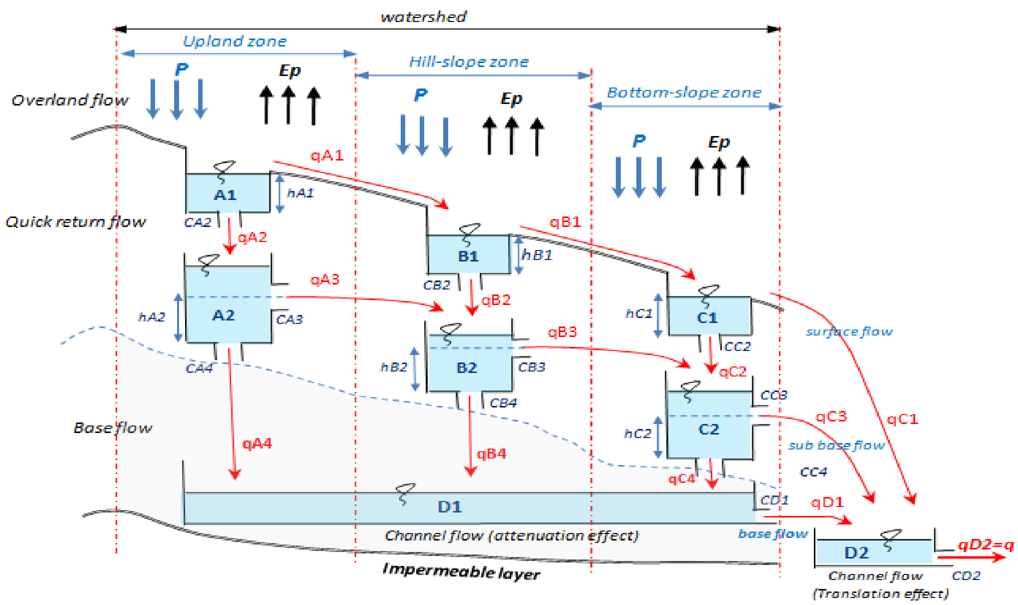


Fig. 1. Simulation schematic of Dee Investigation Simulation Program for Regulating Network (DISPRIN) model; source: own elaboration

located in the upstream of watershed that physically have sloped surface of a steep slope. Hill-slope zone lies in the middle of watershed, where the slope of the surface is relatively moderate. Bottom-slope zone is located in downstream of watershed, where the slope of the land surface is relatively flat. Each watershed zones are presented by two tanks and arranged in vertically series. The first tank or top tank presents a combined surface and intermediate reservoir that contributes to the surface flow and intermediate flow. The second tank or the bottom tank is sub base reservoir that contributes to the sub base flow. The tanks in each watershed zone are mutually interconnection with the principle of gravity flow. Horizontal outflow from the tank group of up-land zone will flow to the tank group of hill-slope zone and then the tank group of hill-slope zone will drain the water in the bottom-slope zone. In the vertical direction, top tank outflow will fill the bottom tank when the top tank underneath provided sufficient water reserves. However, when evapotranspiration is dominant, that cannot be fulfilled by a water reserve of the top tank, the water reserves in the bottom tank will be taken as the value of the deficit. This process applies to the both groups of tanks, namely on the hill-slope zone and bottom-slope zone.

As shown in Figure 1, initially the water can fill the top tank or even going out of the tank corresponding in climatic conditions occurred. If rainfall is greater than the evapotranspiration, the top tank in all three zone will experience the charging amount of the difference between the amount of rainfall and evapotranspiration values $[P(t) - Ep(t)]$. But if it turns out that evapotranspiration is more dominant than rainfall, then the water level in the tank will shrink as the difference between the value of evapotranspiration and rainfall that occurred during that period $[Ep(t) - P(t)]$.

Horizontal flow of the top tank $(qA1)$ as surface flow will occur when the water level in the tank A1 exceeds the outlet hole horizontal position. The amount stated:

$$qA1(t) = SA1_{mean}(t) - hA1 \tag{1}$$

Where: $hA1$ = height of the horizontal outlet tank A1.

Vertical flow in the top tank ($qA2$) present the process of infiltration and happened when there is sufficient height of water in tank. It will increase the flow of high water tank underneath, ie; tank A2. The flow of infiltration $qA2(t)$ can be calculated by the equation:

$$qA2(t) = CA2 \cdot SA2_{mean}(t) \tag{2}$$

$$SA2_{mean}(t) = \frac{SA2(t-1)+SA2(t)}{2} \tag{3}$$

Where: $CA2$ = bottom outlet coefficient of the tank A2, $SA2_{mean}(t)$ = the average water level in tank A2 (mm), $SA2(t)$ = height of water level in tank A2 period t (mm), $SA2(t-1)$ = height of water level in tank A2 period $t-1$ (mm).

In the same period the bottom tank of up-land zone will also change in water reserves. The addition of the flow of $qA2(t)$ will occur when the flow is positive. But if $qA2(t)$ worth negative, it mean that water reserves are not sufficient to meet the needs of the process of evapotranspiration and the amount should be taken from the reserves of water in the bottom tank. Water storage of bottom tank in the up-land zone period t can be expressed mathematically:

If $qA2 \geq 0$, then

$$SA2(t) = SA2(t-1) + qA2(t) - [qA3(t) + qA4(t)] \tag{4}$$

and if $qA2 < 0$, then

$$SA2(t) = SA2(t-1) - [Ep(t) - P(t) - SA1(t)] - + [qA3(t) + qA4(t)] \quad (5)$$

Horizontal flow ($qA3$) as a sub-base flow will occur when the water level in the tank A2 is higher than the horizontal outlet position ($SA2(t) > hA2$). The amount of flow is expressed as:

$$qA3(t) = cA3 \cdot (SA2_{mean}(t) - hA2) \quad (6)$$

$qA3(t)$ will fill the bottom tank in the hill-slope zone. Because there is a wide area difference between up-land and hill-slope zone, the height of the water that goes into the tank B2 proportionally can be calculated by the equation:

$$qA3t(t) = (Au/Ah) \cdot qA3(t) \quad (7)$$

Where: $qA3t(t)$ = inflows into the tank B2 (mm·week^{-1}), Au = area of up-land zone (km^2), Ah = area of hill-slope zone (km^2).

Vertical flow in the bottom tank illustrates the percolation process in the soil. This flow will fill water reserves in the soil. Vertical flow ($qA4$) can be calculated by the equation;

$$qA4(t) = cA4 \cdot SA4_{mean}(t) \quad (8)$$

In DISPRIN model stream flow is the result of translation effect from superposition surface flow, sub base flow and base flow. Translation effect was presented by tank D2. Height of water in the tank D2 calculated by the equation:

$$SD2(t) = SD2(t-1) + qC1t(t) + qC3t(t) + qD1(t) \quad (9)$$

$$qC1t(t) = (Ab/Aw) \cdot qC1(t) \quad (10)$$

$$qC3t(t) = (Ab/Aw) \cdot qC3(t) \quad (11)$$

Where: $SD2(t)$ = height of water level in tank D2 period t, $SD2(t-1)$ = height of water level in tank D2 period $(t-1)$, Ab = area of bottom-slope zone (km^2).

So the river flow in the watershed control point can be stated:

$$q(t) = CD1 \cdot SD2_{mean}(t) \quad (12)$$

$$SA4_{mean}(t) = \frac{SA4(t-1)+SA4(t)}{2} \quad (13)$$

Percolation flow will further increase in the ground water reserves (tank D1). Since the watershed parts of the up-land zone and the total watershed have different areas, the water level in tank D2 can be proportionally calculated by the equation:

$$qA4t(t) = (Au/Aw) \cdot qA4(t) \quad (14)$$

Where: Aw = total watershed area (km^2).

The flow calculation procedure tank systems of hill-slope zone and bottom-slope zone by analogy can follow these principles by observing the flow configuration as described Figure 1.

Tank D1 to accommodate the channel flow on the attenuation effect component. Water reserves in the tank is not influenced by the process of evapotranspiration. Replenishing water in the tank D1 only influenced by the flow of the percolation of the third the watershed zone. At the beginning of the dry season base flow in river flow caused by the intermediate components and sub base flow. But at the end of the dry season when the water reserves in the intermediate zone is running out to meet the needs of evapotranspiration, then the flow of the river is only supported by tank D1. Water level in the tank D1 stated:

$$SD1(t) = SD1(t-1) + qA4(t) + qB4(t) + qC4(t) \quad (15)$$

flow towards the river channel expressed as:

$$qD1 = CD1 \cdot SD1_{mean}(t) \quad (16)$$

with

$$SD1_{mean}(t) = \frac{SD1(t-1)+SD1(t)}{2} \quad (17)$$

Stream flow is the result of translation effect of superposition surface flow, sub base flow and base flow. Translation effect factor was presented by tank D2. Height of water level in the tank D2 calculated by the equation:

$$SD2(t) = SD2(t-1) + qC1t(t) + qC3t(t) + qD1(t) \quad (18)$$

$$qC1t(t) = (Ab/Aw) \cdot qC1(t) \quad (19)$$

$$qC3t(t) = (Ab/Aw) \cdot qC3(t) \quad (20)$$

$$qC1t(t) = (Ab/Aw) \cdot qC1(t) \quad (21)$$

Where: $SD2(t)$ = height of water level in tank D2 period t, $SD2(t-1)$ = height of water level in tank D2 period $t-1$, $qC1t(t)$ = inflow from tank C1 to tank D2 period t, $qC3t(t)$ = inflow from tank C3 to tank D2 period t.

So river flow at the watershed control points can be expressed:

$$q(t) = cD1 \cdot SD2_{mean}(t) \quad (22)$$

Where:

$$SD2_{mean}(t) = \frac{SD2(t-1)+SD2(t)}{2} \quad (23)$$

$q(t)$ is the discharge period t at a control point watershed (mm·week^{-1}). The value of river runoff (m^3·s^{-1}) can be converted by the equation:

$$Q(t) = Aw \cdot q(t) : 604.80 \quad (24)$$

CALIBRATION AND VALIDATION MODEL

Calibration of model parameters are an analogy to the completion of the optimization problem to generate optimal parameters value of DISPRIN model. The objective function of the optimization process is minimization of deviation between the observation flow curve and the flow curve from model simulation. In the metaheuristic method objective function is expressed as a fitness function. In this article the fitness function is expressed as *RMSE* and calculated by the equation [HSU *et al.* 2015; SETIAWAN *et al.* 2003; ZHANG *et al.* 2012]:

$$F = RMSE = \sqrt{1/_N \sum_{i=1}^{N}[Q_{\mathrm{train},t} - Q_{\mathrm{sim},t}]^2} \quad (25)$$

Where: F = fitness, $RMSE$ = root mean square error, $Q_{\mathrm{sim},i}$ = discharge of simulated result in period t ($m^3 \cdot s^{-1}$), $Q_{\mathrm{train},i}$ = discharge training in period t ($m^3 \cdot s^{-1}$), N = number of data points.

In this article the problem solving optimization is done by using Differential Evolution (DE) algorithm. DE algorithm is combination between stochastic and population based search methods. DE has similarities with other evolutionary algorithms (EA), but differs in terms of distance and direction information from the current population used to guide the process of finding a better solution [STORN, PRICE 1997]. In the field of hydrological modelling, DE algorithm has been successfully applied to the optimization SWAT model parameters [ZHANG, LIEW 2008] and the optimization HBV and GR4J model parameters [PIOTROWSKI *et al.* 2016]. DE also successfully applied in the case of a multi objective optimization of in-situ bioremediation of groundwater [KUMAR *et al.* 2015]. DE algorithm contains 4 components, namely 1) initialization, 2) mutation, 3) recombination or crossover and 4) selection. The relationship of the four components is shown in Figure 2.

The model application of the results combines the Dee Investigation Simulation Program for Regulating Network model 25 parameters and Differential Evolution Algorithm (DISPRIN25-DE) in this research was compiled using M-FILE MATLAB. Systematically the calibration parameters process in DIPRIN25-DE models can be explained as follows.

1) Input data, including data training sets; evapotranspiration ($Ep(t)$), precipitation ($P(t)$), discharge observation ($Q_{\mathrm{train}}(t)$) and watershed section area; upland zone (Au), hill-slope zone (Ah), bottom-slope zone (Ab).

2) Setting DE parameters, dimension (D), the number of individuals on a population (N), the upper boundary (ub_j) and the lower boundary (lb_j) value of the variable, and the maximum number of generations (maximum iteration). In DISPRIN25-DE model, D = 25 according to the number of parameters in DISPRIN model.

3) Initialization: generate the initial value of variable generation-0, the j^{th} variable and i^{th} vector that can be represented by the following notation.

$$x_{j,i,0} = lb_j + \mathrm{rand}_j(0,1)(ub_j - lb_j) \quad (26)$$

Where: i = 1, 2, 3, … N and j = 1, 2, 3, …, D. Random number is generated by the rand function, where the resulting number is between (0, 1).

4) Mutations. This process will produce a population of size N vector experiment. Mutation is done by adding the difference of two vectors against a third vector by the following formula:

$$v_{i,g} = x_{r0,g} + F(x_{r1,g} - x_{r2,g}) \quad (27)$$

It appears that the difference between two randomly selected vector needs to be scaled before they are added to the third vector, $x_{r0,g}$. Scale factor $F \in (0, 1)$ bound the rate of population growth. Vector index base $r_0$is determined in a random manner that different from the index for the target vector, i. Besides different from each other and different from the base index for the vector and the target vector, vector index difference between r_1 and r_2 can be chosen once per mutant.

5) Crossover. At this stage, DE crossed each vector ($x_{i,g}$) with mutant vectors ($v_{i,g}$) to form a vector of crossbred $u_{i,g}$ with the formula:

$$\text{if rand } (0, 1) \leq Cr \text{ or } j = j_{\mathrm{rand}}, \text{ then } u_{i,g} = u_{j,i,g} = v_{j,i,g} \quad (28)$$

$$\text{if rand } (0, 1) > Cr \text{ or } j \neq j_{\mathrm{rand}}, \text{ then } u_{i,g} = u_{j,i,g} = x_{j,i,g} \quad (29)$$

Where: $Cr \in (0, 1)$ is the value used to control the fraction of a variable value copied from the mutant.

6) Selection. If the trial vector ($u_{i,g}$) has a smaller objective function value of the objective function target vector ($x_{i,g}$), then $u_{i,g}$ will replace $x_{i,g}$ in population in the next generation. If the opposite occurs, the vector targets will remain in position in the population.

7) The process of analysis item 4), 5), 6) is repeated from generation-0 to generation maximum (maximum iteration). If the generation maximum is reached, the output from the analysis can be presented.

Model validation is done by reapplying DISPRIN25 model with input data testing sets and optimal parameters value resulting from the calibration process. Discharge simulation as a model output are then compared with discharge testing, and the deviation will be tested using Nash–Sutcliffe Efficiency (NSE) and Persistence Model Efficiency (PME) which are calculated by the equation:

$$NSE = 1 - \frac{\sum_{t=1}^{N}(Q_{\mathrm{sim},t} - Q_{\mathrm{test},t})^2}{\sum_{t=1}^{N}(Q_{\mathrm{test},t} - Q_{\mathrm{mean}})^2} \quad (30)$$

$$PME = 1 - \frac{\sum_{t=1}^{N}(Q_{\mathrm{sim},t} - Q_{\mathrm{test},t})^2}{\sum_{t=1}^{N}(Q_{\mathrm{test},i} - Q_{\mathrm{obs},t-1})^2} \quad (31)$$

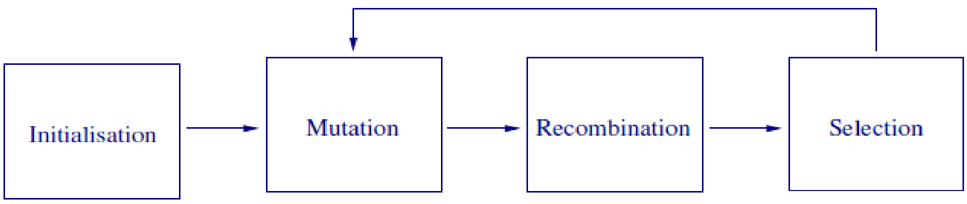


Fig. 2. Relationships of components in DE Algorithm; source: own elaboration

Both indicators provide an interesting perspective on the phenomenon of model performance. *NSE* provides a model of normal performance indicators in relation to the benchmark. *NSE* (dimensionless) measure the relative residual variance of discharge observation. The optimal value is "1" and the value must be more than "0" to indicate the minimum acceptable. *PME* measure the relative residual variance (noise) to a variant of the model errors obtained using simple persistence. Model simple persistence is minimal information on the situation where we assumed that the best estimate of river flow at the next time step is given by the flow observation at the current time [GUPTA *et al.* 1999].

SENSITIVITY ANALYSIS OF DISPRIN MODEL PARAMETERS

Monte Carlo simulation is a type of probabilistic simulation to seek resolution of the problem with random sampling. Monte Carlo method is a method for evaluating a recurring basis of a deterministic model using a set of random numbers as input data. This simulation method involves the use of random numbers to model the system, by which time has no substantive role. The series of sensitivity analysis in conceptual hydrologic model parameters can be made through the following 8 stages [RAMIRES *et al.* 2012]:

1) formulate the optimization equation system to be simulated, according to the equation (25);
2) input data training set, namely: Au, Ah, Ab, $P(t)$, $Ep(t)$ and $Q_{obs}(t)$;
3) input Monte Carlo parameters, ie: number of samples (N), and limit the sample chamber (lb_j and ub_j) of each variable analysed, ie: 25 parameters of DISPRIN model;
4) generate uniformly distributed random numbers or other probabilistic distributions worth (0, 1);
5) calculate the random variables corresponding to each of the model parameters investigated based on the number and the desired sample chamber;
6) evaluate the performance of the model using random input parameter values results from step 5) according to the equation developed in step 1);
7) step 4) and 5) is repeated a given number of samples;
8) analysis and discussion of the output of the model presented in the form of graphs and statistical parameters.

CASE STUDY

A case study in this research is Lesti watershed at the control point Tawangrejeni automatic water level recorder (AWLR) stations, as shown in Figure 3. The location of the study is administratively located in Malang District of East Java Province Indonesia, and is geographically located at 8°2'50" ~ 8°12'10" S latitude and 112°42'58" ~ 112°56'21" E longitude. Lesti watershed has an area of 319.14 km^2 which is divided into up-land, hill-slope, and bottom-slope zones row respectively of 87.02 km^2, 104.89 km^2 and 127.23 km^2. Hydroclimatology data series is the data recorded from January 1, 2007 to December 31, 2016. Evapotranspiration data obtained from analyses activity using Penmann method. The climate parameters data obtained from the recording of Karangkates station. There are four rainfall stations covered in Lesti watershed, namely; Dampit, Tirtoyudo, Wajak and Turen rainfall station. Rainfall data recorded in a daily period. Regional rainfall calculated with Thiessen polygon method. Weighting factor for all four rainfall station, respectively are 0.38, 0.09, 0.19 and 0.34. Stream flow data resulted from recording of Tawangrejeni AWLR station provided the daily average period. Furthermore, the data series is divided into two groups. The first group is used as a data training sets for the calibration of parameters process and the second group is used as a data testing sets for validation process. Data training sets is the recording data in January 1, 2007 until December 31, 2013 and data testing set is recording data in from January 1, 2014 to December 31, 2016. Hydroklimatology data in a weekly period shown in Figure 4. The result of the recording from Tawangrejeni AWLR station for ten years showed a value of minimum flow mean in the dry season is 5.22 m^3·s^{-1} and a maximum during the rainy season is 35.42 m^3·s^{-1}. Average rainfall in the Lesti watershed is 2330 mm·year^{-1}, and evapotranspiration is 1131 mm·year^{-1}.

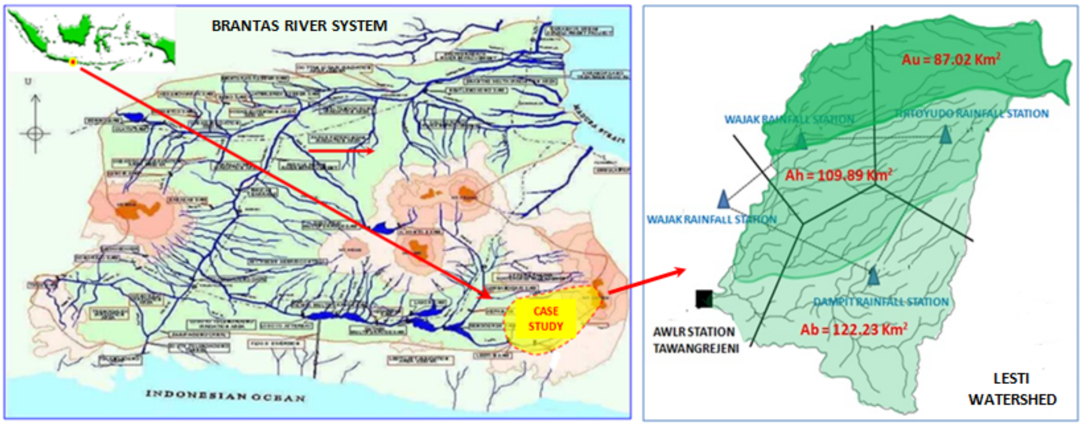


Fig. 3. Lesti watershed; source: own elaboration

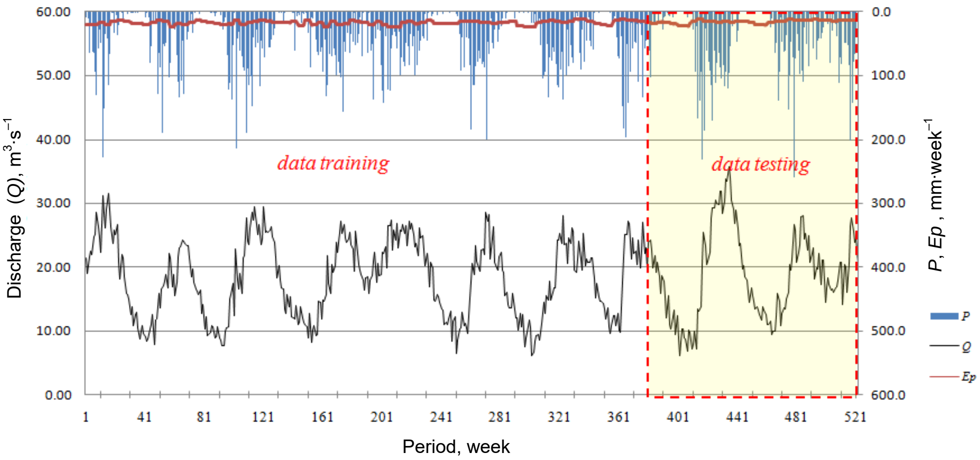


Fig. 4. Data training and data testing sets; P = precipitation, Ep = potential evapotranspiration; source: own study

RESULTS AND DISCUSSION

OPTIMUM VALUES OF DISPRIN MODEL PARAMETERS

The Dee Investigation Simulation Program for Regulating Network (DISPRIN) model application reference is limited so that the parameter value limit becomes difficult to be defined. Tank model refers to the application of various existing references which lower boundary (lb_j) and the upper boundary (ub_j) of tank outlet coefficient are respectively "0" and "1". Initial height of water level in the tank and height of outlet notch are positive numbers, whose varies depending on hydrological characteristics. In this article, the researcher tried to determine the value of lb_j and ub_j for each parameter through trial and error approach. The analysis was performed by utilizing application of DISPRIN25–DE model. The program runs for four times with input lb_j = 0 and ub_j respectively forrun-1 = 400, run-2 = 600, run-3 = 800 and run-4 = 1200 mm. By giving input the number of individuals N =800 and maximum generation N = 350, convergent condition is reached by the performance indicators shown in Table 1.

Table 1. The performance indicators of the model results combine the DISPRIN model 25 parameters and DE Algorithm (DISPRIN25-DE model)

Indicators	Run-1	Run-2	Run-3	Run-4
	ub_j			
	400 mm	600 mm	800 mm	1200 mm
1	2	3	4	5
$RMSE$, m^3·s^{-1}	0.125	0.119	0.125	0.121
NSE	0.842	0.858	0.849	0.854
PME	0.252	0.327	0.308	0.306

Explanations: $RMSE$ = root mean square error, NSE = Nash–Sutcliffe Efficiency, PME = Persistence Model Efficiency.
Source: own study.

All the results of the analysis show a good performance (Tab. 1). The results of the run-2 has the best performance compared to the results of a run-1, run-3 and run-4. If required decent value lies in the position NSE > 0.7 and PME > 0.2 then all the optimum parameters generated from the results of running program is feasible. The optimum value of the DISPRIN model parameters from run-1 to run-4 show different results as shown in Table 2 (columns 3, 4, 5 and 6. The difference is caused by two factor. First due to limiting the value of lb_j, ub_j, maximum iteration in the running process, and secondly due to the difference in the sensitivity level of each model parameter. A wide range of lb_j and ub_j values can provide opportunities for achieving global optimum conditions, but it is required large maximum iteration value and long iteration times, and vice versa. Giving the same maximum iteration input to every running program but with different lb_j and ub_j ranges will result in different minimum fitness value. Therefore, identification of the characteristic relationship between input parameter and resulting output becomes an important part in an effort to improve the effectiveness of the model. Furthermore, superposition of the optimal parameter value results from run-1 to run-4 resulting in minimum and maximum parameter values as shown in Table 2 (columns 7 and 8). The range of the minimum and maximum values of each parameter is shown graphically in Figures 5 and 6.

As an effort to find a global optimal solution then re-analyzed is done by using the minimum parameter value as the parameter lb_j and the maximum value as ub_j. The optimization process with input data training sets and DE parameters value equal to the previous analysis reach the convergent condition within 56 min. Running program is done by using CPU with Core i3 processor and 4 GB RAM specification. Optimal parameters values are shown in Table 2 (column 9).

Model performance at the calibration stage can show very satisfactory results. Analysis at this stage yields $RMSE$, NSE and PME values of 0.113 m^3·s^{-1}, 0.871 and 0.343, respectively. The model performance indicators in Table 3 (column 2) show better conditions than Table 1 (columns 2, 3, 4, 5). This indicates that the superposition way of determining lb_j and ub_j values can improve the effectiveness model. Comparison between hydrograph observation and

Table 2. Optimum value of Dee Investigation Simulation Program for Regulating Network (DISPRIN) model parameters

Parameter	Description	Run-1	Run-2	Run-3	Run-4	Min	Max	Optimum
1	2	3	4	5	6	7	8	9
*h*A1	height of surface outlet up-land zone	0.00	406.79	64.46	0.00	0.00	406.79	25.92
*h*A2	height of sub-surface outlet up-land zone	366.61	27.28	134.10	786.61	27.28	786.61	38.26
*C*A2	infiltration coefficient up-land zone	0.000	0.703	0.975	1.000	0.00	1.00	1.000
*C*A3	sub-surface coefficient up-land zone	1.000	0.598	0.000	0.593	0.00	1.00	0.825
*C*A4	percolation coefficient up-land zone	0.285	0.973	1.000	0.449	0.28	1.00	0.526
*S*A1_0	initial storage of tank A1 up-land zone	347.39	0.00	362.43	265.17	0.00	362.43	319.14
*S*A2_0	initial storage of tank A2 up-land zone	276.50	130.20	224.80	651.95	130.20	651.95	553.59
*h*B1	height of surface outlet hill-slope zone	0.59	538.82	699.29	1200.00	0.59	1200.00	1200.00
*h*B2	height of sub-surface outlet hill-slope zone	382.35	457.27	800.00	1073.19	382.35	1073.19	927.56
*C*B2	infiltration coefficient hill-slope zone	0.660	0.465	0.424	0.575	0.42	0.66	0.660
*C*B3	sub-surface coefficient hill-slope zone	0.037	0.000	0.000	0.000	0.00	0.04	0.005
*C*B4	percolation coefficient hill-slope zone	0.008	0.000	0.000	0.000	0.00	0.01	0.010
*S*B1_0	initial storage of tank B1 hill-slope zone	0.00	600.00	696.48	606.25	0.00	696.48	631.37
*S*B2_0	initial storage of tank B2 hill-slope zone	160.10	29.75	268.12	495.68	29.75	495.68	467.65
*h*C1	height of surface outlet bottom-slope zone	0.00	0.23	0.00	0.00	0.00	0.23	0.00
*h*C2	height of sub-surface outlet bottom-slope zone	400.00	74.18	0.00	0.54	0.00	400.00	322.27
*C*C2	infiltration coefficient bottom-slope zone	1.000	0.331	0.594	0.905	0.33	1.00	0.605
*C*C3	sub-surface coefficient bottom-slope zone	0.000	0.474	0.000	0.744	0.00	0.74	0.000
*C*C4	percolation coefficient bottom-slope zone	0.000	0.877	0.650	0.264	0.00	0.88	0.001
*S*C1_0	initial storage of tank C1 bottom-slope zone	51.38	0.00	0.00	69.30	0.00	69.30	11.99
*S*C2_0	initial storage of tank C2 bottom-slope zone	300.24	531.02	706.16	888.60	300.24	888.60	302.98
*C*D1	runoff coefficient	0.894	0.011	0.808	0.004	0.00	0.89	0.785
*C*D2	runoff coefficient	0.050	0.069	0.045	0.059	0.04	0.07	0.070
*S*D1_0	initial storage of tank D1 (attenuation effect)	386.36	500.91	542.45	960.93	386.36	960.93	411.11
*S*D2_0	initial storage of tank D2 (translation effect)	395.30	499.61	55.65	63.00	55.65	499.61	228.43

Explanations: "0" in *S*A1, *S*A2, *S*B1, *S*B2, *S*C1, *S*C2, *S*D1, *S*D2 parameters show the condition of the initial water level in each tank (water level at $t = 0$ in the simulation process).
Source: own study.

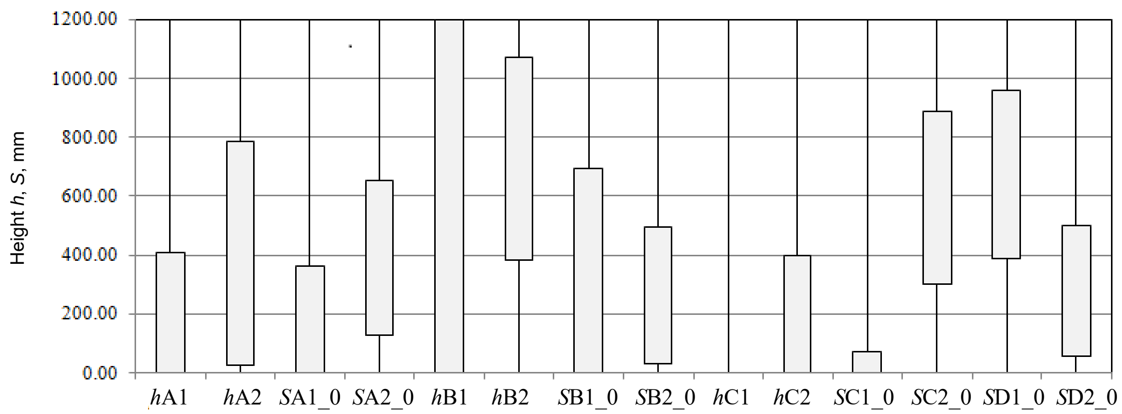


Fig. 5. Space eligibility initial value of water level
and outlet of tank position parameters; parameters notations as in Tab. 2; source: own study

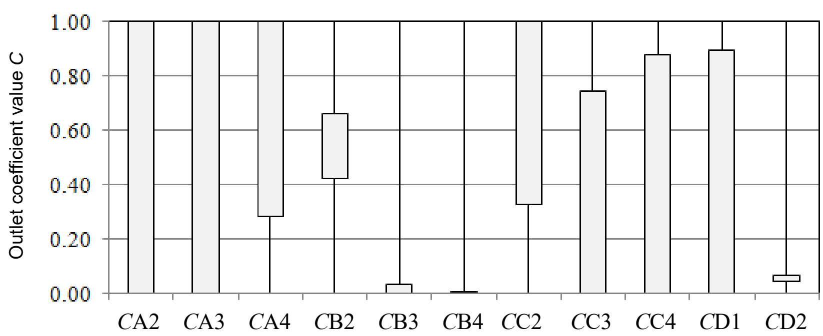


Fig. 6. Space eligibility outlet of tank coefficient parameters; parameters notations as in Tab. 2; source: own study

Table 3. Model performance

Indicator	Calibration stage	Validation stage
1	2	3
RMSE, $m^3 \cdot s^{-1}$	0.113	0.224
NSE	0.871	0.823
PME	0.343	0.180

Explanations as in Tab. 1.
Source: own study.

model simulation are presented in Figure 7. Distribution of data training and output model indicate the coefficient of determination (r^2) of 0.863. The flow curve from the model outline can generally follow the fluctuation pattern of the seasonal flow data training. Low flow, medium flow and high flow conditions can be responded well except in the period of 170 to period 230. In that period the discharge model tend to be under estimated.

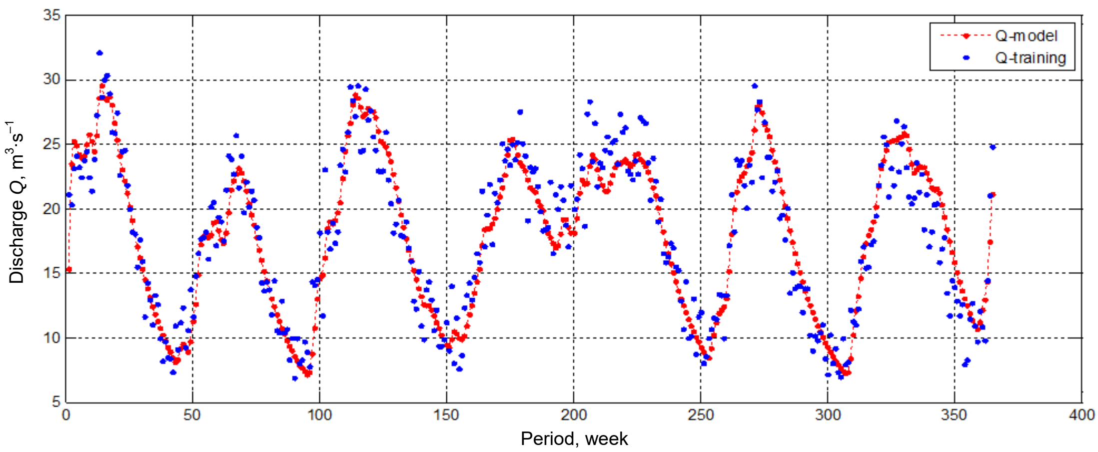
VALIDATION OF DISPRIN25-DE MODEL

The model validation process uses the optimum parameter input resulting from the calibration process and the data testing sets. Comparison of model performance indicators at the calibration and validation stage is shown Table 3. Model performance in the validation stage worse than the result from the calibration stage. The *NSE* indicator does not differ much, but the *RMSE* and *PME* indicators show a significant difference. Figure 8 presents a comparison between the flow curve of the model output and the data testing. The flow curve of the model output is generally less able to approach fluctuations of data testing. Plotting the distribution of discharge testing and discharge models tends to be above the equation line, meaning the discharge model tends to overestimate. This is the cause of the small value of the coefficient of determination (r^2) produced. Poor model performance in the validation stage is caused by differences in statistical characteristics of data training and data testing sets. Comparison of statistical parameters of both groups of data are presented in Table 4. The average, minimum, maximum and standard deviation values of discharge training and discharge testing data differs significantly. The maximum, mean

Table 4. Characteristic of statistics set data

Statistical parameters	Data training		Data testing	
	precipitation mm·week^{-1}	discharge $m^3 \cdot s^{-1}$	precipitation mm·week^{-1}	discharge $m^3 \cdot s^{-1}$
Min	0.00	5.22	0.00	5.81
Max	228.10	32.24	258.90	35.42
Average	43.26	17.84	47.21	19.02
Standard deviation	46.00	6.03	51.44	6.98
Coefficient of determination	0.244		0.271	

Source: own study.



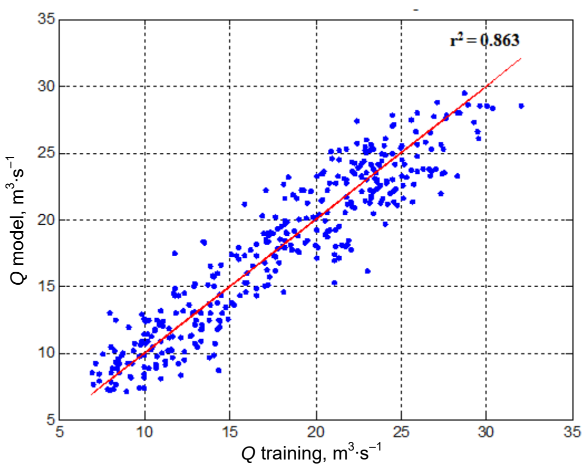


Fig. 7. Comparison of the data training and output model; source: own study

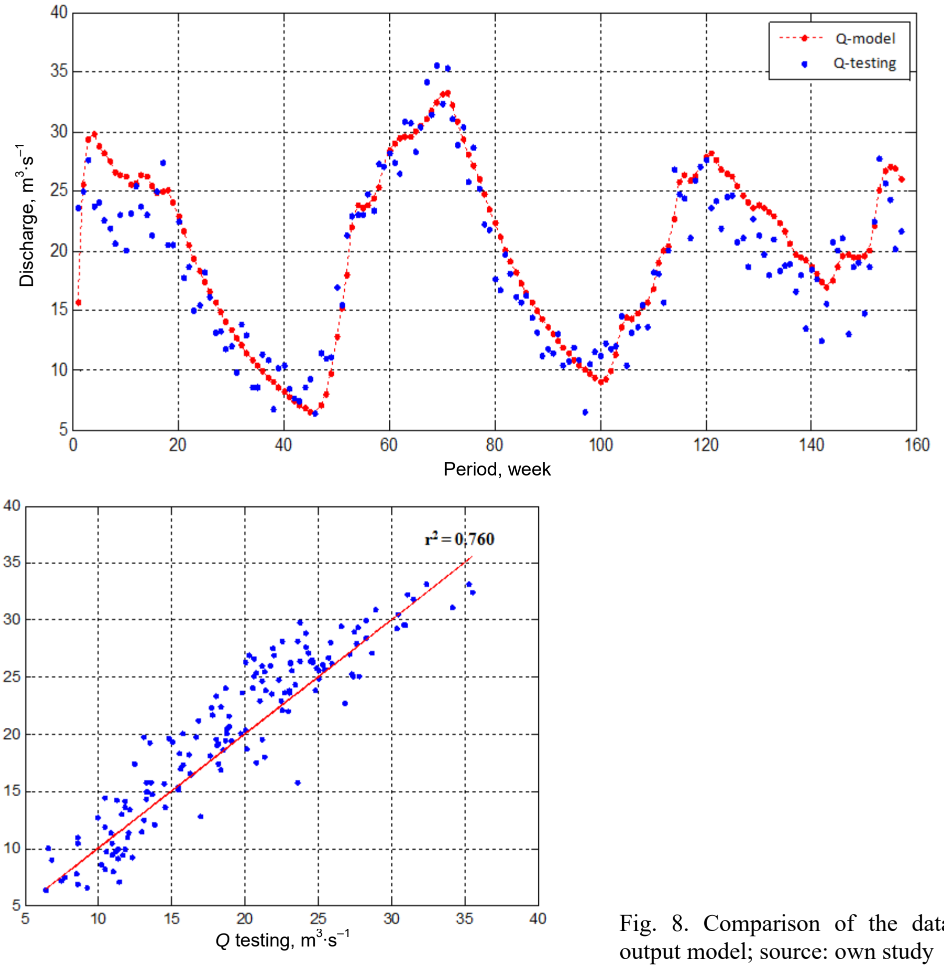


Fig. 8. Comparison of the data testing and output model; source: own study

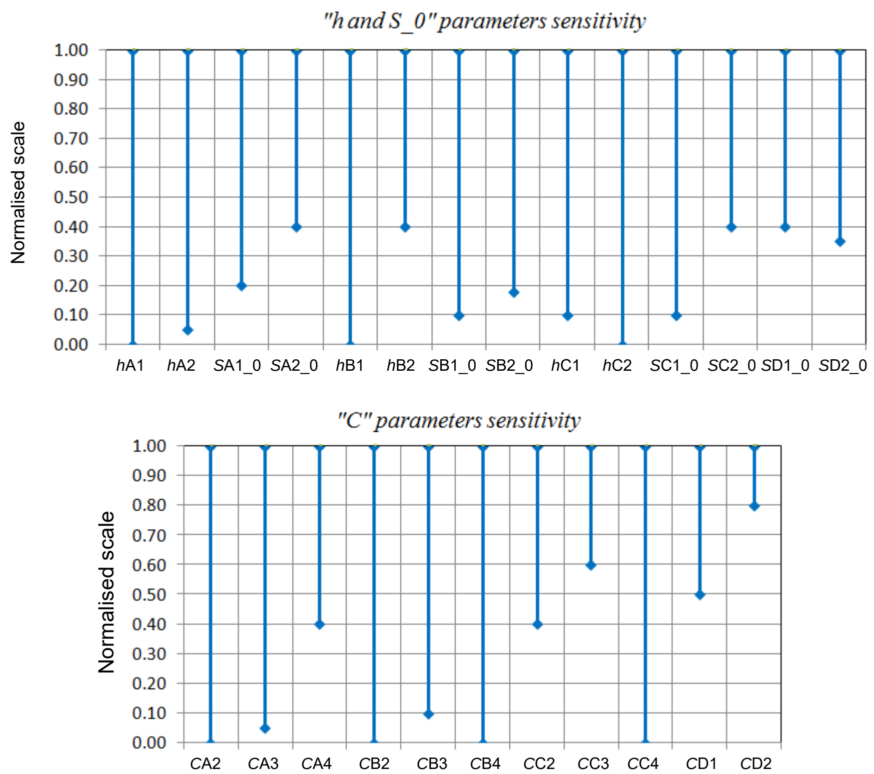


Fig. 9. Sensitivity of the Dee Investigation Simulation Program for Regulating Network model 25 parameters (DISPRIN25); parameters notations as in Tab. 2; source: own elaboration

and standard deviation values of weekly rainfall data also differ considerably. The coefficient of determination (r^2) from the relationship of precipitation and discharge data is also different although not significant. This indicates that the DISPRIN25-DE model can only predict well if the data training and data testing sets have uniform characteristic of statistic.

DISPRIN25 MODEL PARAMETERS SENSITIVITY

A sensitivity analysis of model parameters is done by using Monte Carlo simulation method with input sample size of 300,000. The limit of the sample chamber according to the value of lb_j and ub_j in as shown in Table 2 (column 8 and column 9), and the hydroclimatology data using data training set. Running program for 266 minute generates graphs of relationship between normalize scale of model parameters and type parameter based on the best *RMSE* values as shown in Figure 9. Each parameter has a different sensitivity level. If the level of sensitivity are grouped in three clusters corresponding normal scale, the level of sensitivity of each parameters can be classified as shown in Table 5. *C*C3*,* *C*D2*,* and *S*D2_0 have a very strong influence on the performance of the resulting DISPRIN25 model. *C*C4*,* *C*C2,*C*D1, *S*A2_0, *h*B2, *S*C2_0 and *S*D1_0 have medium influence, while *C*A2, *C*A3, *C*B2, *C*B3, *C*B4, *C*C4, *h*A1, *h*A2, *S*A1_0, *S*A1_0, *h*B, *S*B1_0, *S*B2_0, *h*C1, *h*C2 and *S*C1_0 have not a significant influence on performance DISPRIN25 model for its value lies between the *lbj* and ub_j as shown in Table 2.

Table 5. Sensitivity level of Dee Investigation Simulation Program for Regulating Network model parameters

Parameter *C*	low sensitivity	*C*A2, *C*A3, *C*B2, *C*B3, *C*B4, *C*C4
	moderate sensitivity	*C*A4, *C*C2, *C*D1
	high sensitivity	*C*C3, *C*D2
Parameter *h*	low sensitivity	*h*A1, *h*A2, *S*A1_0, *h*B1, *S*B1_0, *S*B2_0, *h*C1, *h*C2, *S*C1_0
	moderate sensitivity	*S*A2_0, *h*B2, *S*C2_0, *S*D1_0
	high sensitivity	*S*D2_0

Criteria:
– the range of normal scale (> 0.7) → low sensitivity
– the range of normal scale (0.4 ~ 0.7) → moderate sensitivity
– the range of normal scale (<0.4) → high sensitivity
Explanations: parameters notations as in Tab. 2.
Source: own study.

CONSCLUSIONS

Application of DISPRIN25-DE model in Lesti watershed (319.14 km^2) with weekly data period shows very good performance. The calibration process with the data training set throughout the 7 years shows the value indicator *NSE* = 0.865 and *PME* = 0.343, the validation process with input data testing set provide value *NSE* = 0.823 and *PME* = 0.180.

Good performance in the calibration process showed that DE algorithm is able to solve problems of global optimization with a large number of variables. The results are less satisfactory in the validation stage due to differences in statistical characteristics of the data training and data testing sets used in this case study. This indicates that the DISPRIN25-DE model can work only when the data set used has almost uniform statistical characteristics. The results of the sensitivity analysis with Monte Carlo simulation method shows that parameter *C*C3, *C*D2, and *S*D2_0 have a very strong influence on the performance of the resulting DISPRIN-25 model, while parameter *C*C4, *C*C2, *C*D1, *S*A2_0, *h*B2, *S*C2_0 and *S*D1_0 have a strong enough influence, and 15 other parameters did not have significant influence. This condition applies only to this case study. The application in other watersheds that have different physical and climatic characteristics will certainly give different result. Hence, the application of the model to another watershed becomes an important step to test the efficiency of the model.

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Kalibracja automatyczna i analiza czułości parametrów modelu DISPRIN: Przypadek zlewni Lesti w prowincji Jawa Wschodnia, Indonezja

STRESZCZENIE

Model DISPRIN składa się z ośmiu zbiorników wzajemnie ze sobą połączonych. Zawiera 25 parametrów zaangażowanych w proces transformacji danych opadowych w dane odpływu. Ten czynnik złożoności skłania do podjęcia badań celem zwiększenia wydajności. W badaniach prezentowanych w niniejszej pracy proces parametryzacji zrealizowano, stosując algorytm zróżnicowanej ewolucji (DE), podczas gdy analizę czułości przeprowadzono z użyciem metody symulacji Monte Carlo. Modele aplikacji polegające na łączeniu dwóch koncepcji nazywane są DISPRIN25-DE i są kompilowane za pomocą programu M-FILE z MATLAB. Wyniki badań zlewni Lesti (319,14 km^2) w punkcie kontrolnym stacji Tawangrejeni z automatycznym pomiarem poziomu wody w prowincji Jawa Wschodnia w Indonezji wskazują, że model może efektywnie działać w celu przekształcenia opadów w serie danych o odpływie. Na etapie kalibracji model dostarczył wartości NSE = 0,871 i PME = 0,343, a na etapie walidacji wartości NSE = 0.823 i PME = 0,180. Dobre rezultaty w procesie kalibracji wskazują, że algorytm DE jest zdolny rozwiązywać problemy globalnej optymalizacji systemu równań z dużą liczbą zmiennych. Wyniki analizy czułości 25 parametrów wykazały, że 3 parametry mają wysoką czułość, 7 – pośrednią, a 15 innych parametrów cechuje niski poziom czułości na zachowanie modelu DISPRIN.

Słowa kluczowe: *ewolucja różnicowa, model DISPRIN, symulacja, zlewnia Lesti*