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RESEARCH ARTICLE

AUTOMATIC CALIBRATION OF DISPRIN MODEL PARAMETERS USING METAHEURISTIC METHODS TO GENERATE HISTORICAL DAILY DISCHARGE DATA SERIES

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ABSTRACT

The Dee Investigation Simulation Program for Regulating Network (DISPRIN) model is a type of lumped model. This model has 25 parameters whose values are continuous so that it is difficult to apply to solve practical problems. This study aims to improve the performance of DISPRIN so that it is effective and applicable to generate historical discharge data series in a watershed. The combination of the simulation equation system from the DISPRIN model with the parameter optimization method based on the metaheuristic method is expected to produce a new model that is able to carry out the calibration process automatically so that the model becomes easy to apply. The metaheuristic methods involved are: Differential Evolution (DE) Algorithm, Particle Swam Optimization (PSO), synthesis of chaotic search-opposition based learning-differential evolution-quantum mechanism (CODEQ) algorithm, and Shuffled Complex Evolution (SCE). The new models produced are then called the DISPRIN-de, DISPRIN-pso, DISPRIN-sce, and DISPRIN-codeq models. All models were tested in Lesti watershed (314.19 Km^2), Malang Regency, East Java Province, Indonesia. The model calibration stage using hydroclimatology data from 2006 to 2014 showed that all models had an accuracy level equivalent to NSE ranging from 0.892 to 0.931, and the model validation stage using hydroclimatology data from 2014 to 2020 produced NSE values ranging from 0.918 to 0.928. The discharge distribution curve involving all generated discharges showed that the DISPRIN-codeq model was more accurate than the other three models which tended to overestimate high flow events.

KEYWORDS

Disprin model, metaheuristic, rainfall-runoff, lesti watershed.

1. INTRODUCTION

The development of revolutionary and reliable metaheuristic methods for solving large and complex equation systems has made these approaches increasingly attractive for parameterizing hydrological conceptual models. The integration of metaheuristic techniques with hydrological models has led to the emergence of new, effective, and applicable modelling frameworks. Numerous studies worldwide have introduced models that combine metaheuristic algorithms with hydrological conceptual models, including the Shuffled Complex Evolution (SCE-UA) algorithm applied to the Topography-based Hydrological Model (TOPMODEL) (Qi et al., 2016; Bao et al., 2010). The Hydrological Simulation Program–FORTRAN (HSPF) model (Seong et al., 2015). The HYMOD model (Vrugt et al., 2003). The LAvras Simulation of Hydrology (LASH) model (Beskow et al., 2011). MOHYSE by Fortin and Turcotte (Arsenault et al., 2013). The Xin'anjiang model (Chen et al., 2015; Kana et al., 2017; Jiang et al., 2014). The Sacramento Soil Moisture Accounting (SAC-SMA) model (Ajami et al., 2004; Gupta et al., 1999). The Variable Infiltration Capacity (VIC) model (Xue et al., 2015; Nandi and Reddy, 2020). The TETIS distributed hydrological model (Frances et al., 2007). The Long-Term Hydrologic Impact Assessment (L-THIA) model (Jeon et al., 2014). The National Weather Service River Forecast System–Soil Moisture Accounting (NWSRFS-SMA) model (Duan et al., 1994). The Nedbor Afstrømnings Model (NAM) (Madsen, 2000). Lastly, the Soil and Water Assessment Tool (SWAT) model (Zhang et al., 2009).

The combination of Differential Evolution (DE) algorithm with Multivariate Adaptive Regression Spline Integrated (Al-Sudani et al., 2019). SWAT model (Wang et al., 2018 and Zhang et al., 2009). GR5J hydrological model (Adeyeria et al., 2020). HBV and GR4J models (Napiorkowski et al., 2023 and Piotrowski et al., 2016). Tank model has been successfully employed for transformation of rainfall data series into streamflow in a watershed (Sulianto, 2022). The Particle Swam Optimization algorithm combined with the Variable Infiltration Capacity (VIC) model (Nandi and Reddy, 2020). Sacramento Soil Moisture Accounting (SACSMA) model and Soil Moisture Model (SVM) (Gill et al., 2006). SWAT model (Samadi and Meadows 2014, Zhang et al., 2023 and Zhang et al., 2009). Tank model (Kuok et al., 2010). GR5J hydrological model (Adeyeri et al., 2020). HBV and GR4J models (Napiorkowski et al. 2023). Distributed Xin'anjiang hydrological model (Wang et al. 2024). HBV and GR4J model (Piotrowski et al., 2016). Tank model also show very satisfactory performance (Santos et al., 2011).

The DISPRIN model is a type of lumped model that considers the flow in a watershed system as analogous to the flow through a series of tanks that have 25 parameters and their values are continuous (Shaw and Elizabeth, 1985). The success of the DISPRIN model application is highly dependent on the accuracy in determining the optimum value of the 25 parameters. Efforts to find the optimum value of these parameters can only be done by involving a reliable optimization method. Optimization of the DISPRIN model parameters using the DE algorithm has succeeded in transforming

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climate data series into monthly river flow (Sulianto et al., 2018). This study aims to improve the performance of the DISPRIN model so that it is more effectively applied to generate daily river flow data series in a watershed. The metaheuristic methods involved are: DE, PSO, CODEQ and SCE Algorithm. The new model of combining the DISPRIN model simulation equation system with the optimization equation system based on the metaheuristic method, hereinafter referred to as: DISPRIN-de, DISPRIN-pso, DISPRIN-codeq and DISPRIN-sce models. The implementation models utilize the MFile-MATLAB program code due to its simplicity and ability in matrix operations and graphical data management. Initially, the proposed model was tested using a hypothetical data set in order to study the balance and consistency of the equation system that had been built. The subsequent phase of the study involved testing model using observational data, specifically the daily hydroclimatology data set in the Lesti watershed in Malang Regency East Java, Indonesia. In this regard, the objective of this analysis is to study the behavior and performance of the model in order to identify the limitations and advantages of each model. The results of this study are expected to be an alternative solution to the problem of limited discharge data which is often a classic problem in water resource development activities in developing countries, including Indonesia.

2. Materials And Methods

2.1 Research Stage

The research procedure is schematically shown in Figure 1, and is carried out through the following 7 stages : 1) literature study, 2) designing algorithms and compiling program codes for the application of the DISPRIN-de model, DISPRIN-pso model, DISPRIN-codeq model and DISPRIN-sce using MFILE MATLAB, 3) running the model to test the balance and consistency of the model that has been built using a controlled hypothetical data set to ensure the model logic is in accordance with the scenario, 4) collecting and processing field data, and determining the training data set and testing data set to test the model, 5) running the model; the calibration process and model validation test using the field observation data set, and 6) reviewing the model behavior based on the analysis results obtained from the previous stage, and 7) concluding the research results.

2.2 Case Study

The research study is the Lesti watershed at the control point of the Tawangrejeni AWLR station as shown in Figure 2. The watershed is geographically located at 8°2'50" - 8°12'10" S latitude and 112°42'58" - 112°56'21" E longitude, and administratively located in Malang Regency, East Java Province, Indonesia. Lesti is included in the Upper Brantas watershed, with an area of 314.19 km².

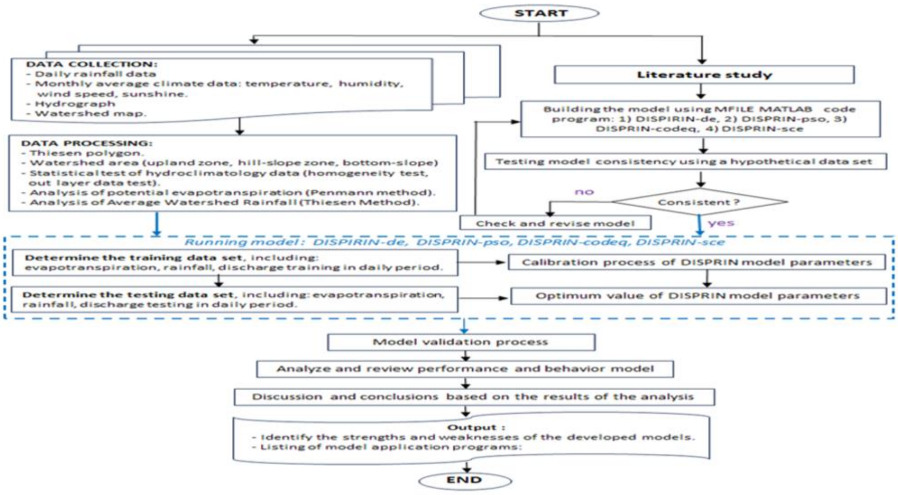


Figure 1: Research procedure

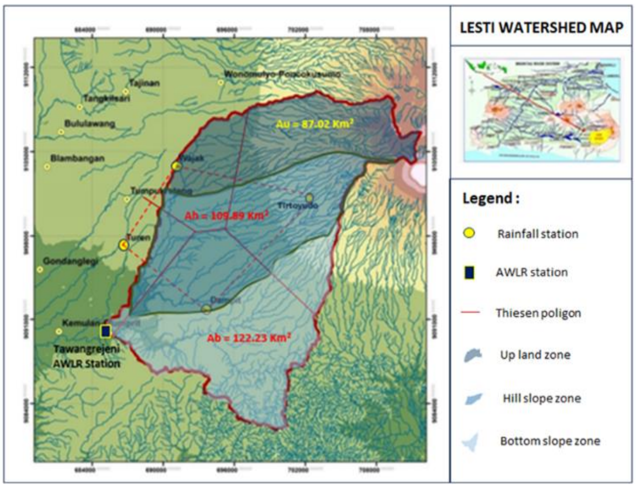


Figure 2: Location of study area

In order to evaluate the model, the hydroclimatological data from 14 years of recording (from January 1, 2007 to December 31, 2020) will be analysed. The rainfall data is recorded on a daily basis at four locations: Dampit, Turen, Wajak and Tirtoyudo station. The regional rainfall of the Lesti watershed was analysed using the Thiesen method, with each station assigned a weighting factor of 0.38, 0.09, 0.19 and 0.34, respectively. The climate data utilises the monthly average data from the Karangkates Climatology Station, comprising the following variables: air temperature, air humidity, sunshine duration and wind speed. The climate data are processed to produce potential evapotranspiration utilising the Penman method (Baskoro et al., 2024). The data pertaining to discharge was obtained from the Tawangrejeni automatic water level record (AWLR) station. The data set comprises daily average discharge values. The data series are divided into two groups. The series from January 1, 2007 to 31 December 2014 are employed as the training data set for the model calibration process, while the series from 1 January 2015 to 31 December 2020 are used as the testing data set for model validation. A statistical comparison of the training and testing hydroclimatology data sets is presented in Table 1. The results of the two-way statistical test of the two data groups using the mean test (t-test) and variance test (F-test) demonstrated that the training and testing data sets were homogeneous. The interrelationship between the rainfall, evapotranspiration and discharge data series is illustrated in Figure 3.

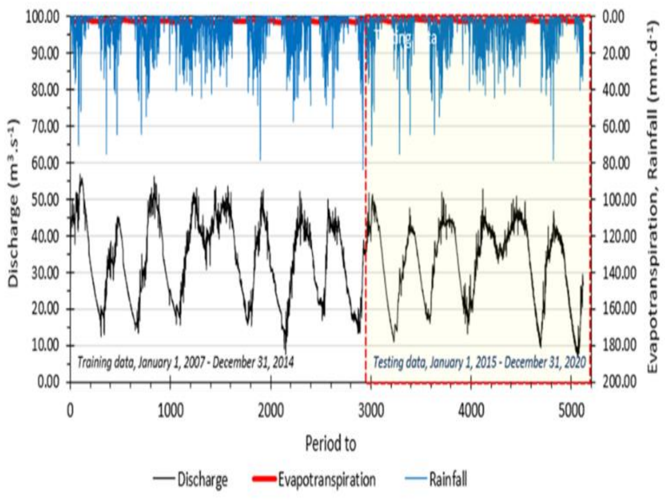


Figure 3: Hydroklimatology data set in Lesti watershed

Table 1. Statistical of training and testing data sets				
Data	Statistic of parameters	Unit	Data Training	Data Testing
Period		day	Jan,1 2007- Dec, 31 2014	Jan,1 2015–Dec,31 2020
Point data			2925	2194
Evapotranspiration	Mean	mm/year	897.78	856.78
Procipitation	Mean	mm/year	2235.73	2659.41
Discharge	Mean	m^3/s	33.61	32.59
	Minimum	m^3/s	7.55	7.06
	Maximum	m^3/s	56.81	52.83
	Deviation standard	m^3/s	10.99	10.61

2.3 DISPRIN model simulation

The DISPRIN model is similar to the Tank model by Sugawara. Both assume that the flow of water in a watershed is analogous to the flow through a series of tanks. The 17 model consists of 4 tanks arranged in series and has 17 Tank model parameters (Sulianto et al., 2022). The DISPRIN model consists of 8 tanks and has 25 parameters as shown in Figure 4 (Shaw 1985; Sulianto et al., 2018).

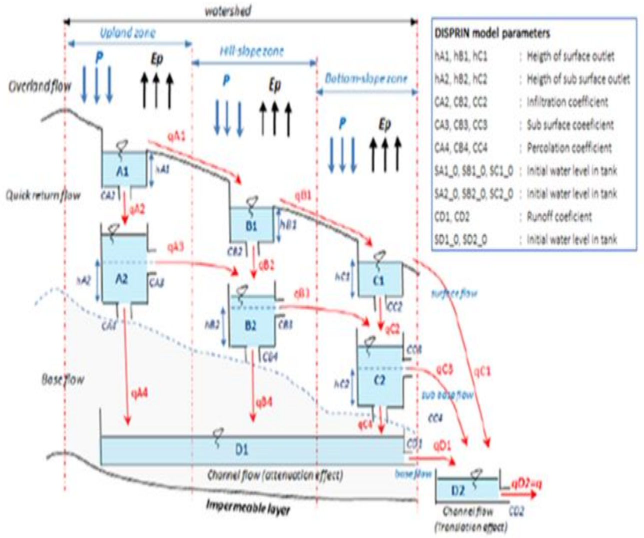


Figure 4: DISPRIN model simulation scheme (Sulianto et al., 2018)

In order to apply the DISPRIN model, it is necessary to divide the watershed into three distinct zones, according to its position and physical characteristics. These zones are up land zone, hill slope zone, and bottom slope zone. Each zone of the watershed is represented by two vertically arranged tanks. The upper tank serves as a surface reservoir, contributing to overland flow, and an intermediate reservoir, contributing to quick return flow. The base tank represents channel flow, which contributes to base flow. The tanks within each watershed zone are interconnected via a gravity-fed system. The horizontal flow from the tank group situated in the upland zone will proceed to the hill slope zone tank group, which will then convey the flow to the bottom slope zone tank group. In the vertical direction, the upper tank flow will fill the lower tank when the water reserves in the upper tank are sufficient. However, when evapotranspiration is dominant and cannot be met by the upper tank water reserves, the water reserves in the lower tank will be taken as a deficit value. This process applies to the three groups of tanks in the upland zone, hill slope zone and bottom slope zone. Figure 4 illustrates the potential for water to initially fill the upper tank or even flow out of the tank according to the climate conditions that occur. If rainfall is greater than evapotranspiration, the upper tank in the three zones will experience a filling amount from the difference between the amount of rainfall and the evapotranspiration value [P(t)–Ep(t)]. However, if evapotranspiration is greater than rainfall, the water level in the tank will shrink by the difference between the evapotranspiration value and the rainfall that occurred in that period [Ep(t) – P(t)].

The magnitude of overflow, infiltration and percolation through the tank outlet is directly proportional to the height of the water against the position of the tank outlet, expressed as:

Tank A:

$$qA1 = (SA1 - hA1);\ \ qA2 = CA2 \,.\, SA1 \tag{1}$$

$$qA3 = CA3 \,.\, (SA2 - hA2);\ \ qA4 = CA4 \,.\, SA2 \tag{2}$$

Tank B:

$$qB1 = (SB1 - hB1);\ qB2 = CB2.(SB1) \tag{3}$$

$$qB3 = CB3 \,.\, (SB2 - hB2);\ qB4 = CB4.SB2 \tag{4}$$

Tank C:

$$qC1 = (SC1 - hC1);\ qC2 = CC2.SC1 \tag{5}$$

$$qC3 = CC3 \,.\, (SC2 - hC2);\ qC4 = CC4.SC2 \tag{6}$$

Tank D:

$$qD1 = CD1 \,.\, SD1 \tag{7}$$

$$qD2 = CD2 \,.\, SD2 \tag{8}$$

CA2, CA4, CB2, CB4, CC2, CC4 are the vertical outlet tank coefficients, *CA1, CA3, CB1, CB3, CC1, CC3, CD1, CD2* are the horizontal outlet tank coefficients, and *SA1, SA2, SB1, SB2, SC1, SC2, SD1, SD2* are the average values of water table height in each tank at the t and *t-1* period. The equilibrium volume of water at each tank is expressed by the following equation.

Upland zone:

$$\text{Tank A1:}\ \ dSA1/dt = P(t) - Ep(t) - qA1(t) - qA2(t) \tag{9}$$

$$\text{Tank A2:}\ \ dSA2/dt = qA2(t) - qA3(t) - qA4(t) \tag{10}$$

Hill slope zone:

$$\text{Tank B1:}\ \ dSB1/dt = P(t) - Ep(t) + qA1(t) - qB1(t) - qB2(t) \tag{11}$$

$$\text{Tank B2:}\ \ dSB2/dt = qA3(t) + qB2(t) - qB3(t) - qB4(t) \tag{12}$$

Bottom slope zone:

$$\text{Tank C1:}\ \ dSC1/dt = P(t) - Ep(t) + qB1(t) - qC1(t) - qC2(t) \tag{13}$$

$$\text{Tank C2:}\ \ dSC2/dt = qC2(t) + qB1(t) - qC3(t) - (t)qC4 \tag{14}$$

Attenuation effect:

$$\text{Tank D1:}\ \ dSD1/dt = qA4(t) + qB4(t) + qC4(t) - qD1(t) \tag{15}$$

Translation effect:

$$\text{Tank D2:}\ \ dSD2/dt = qC1(t) + qC3(t) + qD1(t) - qD2(t) \tag{16}$$

The total runoff of period t in units of mm/day is identical to equation (8), in units of m^3/s, expressed as:

$$Q(t) = qD2(t) * At/86.4 \tag{17}$$

with,

$$At = Au + Ah + Ab \tag{18}$$

where, t = period (daily), At = watershed area (km^2), Au = upland zone area (km^2), Ah = hill slope zone area (km^2), Ab = bottom slope zone area (km^2).

2.4 Model calibration and validation

The parameters calibration of the DISPRIN model is analogized as an optimization process aimed at finding the optimum value of the parameters of the DISPRIN model, which is determined by the minimum value of the intersection of the observation discharge curves (Q_t^{obs}) and the simulated discharge of the model (Q_t^{sim}). In metaheuristics method the objective function can be expressed as a fitness function. The definition of the fitness function in the case of hydrological model parameter optimization has been extensively put forward by previous researchers, including ; minimizing the root mean square error (RMSE) minimizing the sum squared error (SSE) maximization of Nash-Sutcliffe Efficiency (NSE) minimization of mean square error (MSE), and minimization of relative error (RE) (Kuok et al., 2011; Santos et al., 2011; Hsu and Yeh, 2015; Setiawan et al., 2003; Wang et al., 2012; Sulianto et al., 2018; Darikandeh et al., 2014; Paik et al., 2005; Bao et al., 2010; Tolson and Shoemaker, 2007; Zhang et al., 2009; Ngoc et al., 2013).

The optimization objective function in this article is the maximization of the NSE value, and when expressed as a minimization function then the fitness function can be expressed as:

$$F = min[1 - NSE] \tag{19}$$

$$NSE = 1 - \frac{\sum_{t=1}^{n}\left(Q_t^{sim} - Q_t^{obs}\right)^2}{\sum_{t=1}^{n}\left(Q_t^{obs} - Q^{mean}\right)^2} \tag{20}$$

where, F = fitness value, Q_t^{sim} = discharge of model simulation period t (m^3/s), Q_t^{obs} = observation discharge period t (m^3/s), Q^{mean} = the mean observation discharge (m^3/s), t = period (daily), n = number of data points.

As the constraint function in the optimization process is:

- The system of simulated equations of the DISPRIN model, expressed as;
  $$Q(t) = F[P(t), Ep(t), Au, Ah, Ab, 25\ DISPRIN\ model\ parameters]$$
- Boundary of the minimum and maximum values of the height of the initial water table in the tank *[SA1_0, SA2_0, SB1_0, SB2_0, SC1_0, SC2_0, SD1_0, SD2_0]*.
- Boundary of minimum and maximum values of horizontal outlet height in the tank *[hA1, hA2, hB1, hB2, hC1, hC2]*.
- Boundary of the minimum and maximum values of the outlet coefficient in the tank *[CA2, CA3, CA4, CB2, CB3, CB4, CC2, CC3, CC4, CD1, CD2]*.

Model validation using a testing data set using other period data inputs not involved in the calibration process. Measurement of model accuracy using NSE, mean absolute error (MSE) and PBIAS indicators. MSE and PBIAS present the error rate of the prediction result, the smaller the value (= 0) then the more accurate the prediction result. The NSE has different perspectives, the larger the value (= 1) means the more accurate the prediction results (Duan et al., 1994).

$$MAE = \frac{1}{n}\sum_t^n\left|Q_t^{obs} - Q_t^{sim}\right| \tag{21}$$

$$PBIAS = \frac{\sum_{t=1}^{n}(Q_t^{obs} - Q_t^{sim})}{\sum_{t=1}^{n} Q_t^{obs}} . 100\% \tag{22}$$

2.5 Metaheuristic method

2.5.1 DE Algorithm

The DE algorithm was developed by Reiner Storn and Kenneth Price in 1996 (Storn and Price, 1997). In the field of hydrological modeling, the DE algorithm was successfully applied to the parameter optimization of HBV model and GR4J model (Piotrowski et al., 2017). DE has also been successfully applied in the case of multi-objective optimization of in-situ groundwater bioremediation, optimization of the DISPRIN model parameters), optimization of Tank model parameters, improved the performance of the integrated multivariate adaptive spline regression method, optimization of SWAT model parameters (Wang et al., 2019 and Zhang et al., 2009). GR5J hydrological model (Adeyeria et al., 2020; Napiorkowski et al., 2023; Kumar et al., 2015; Sulianto et al., 2022; Al-Sudani et. al., 2019; Sulianto et al., 2018). Analysis in DE Algorithm contains 4 (four) components, namely; 1) initialization, 2) mutation, 3) cross-move (crossover), and 4) selection. The application step of the DE algorithm for the minimization objective function is described in (Sulianto et al., 2018; 2022). In the case of parameter optimization of the DISPRIN model, then the vector of optimized variables (xi) is 25 parameters of the DISPRIN model as Figure 4. The optimization process will result in the progress of achieving the best fitness value and the optimum value DISPRIN model parameters which is the optimization objective function.

2.5.2 PSO algorithm

PSO algorithm is a population-based stochastic optimization technique proposed by (Eberhart and Kennedy 1995). The PSO algorithm for optimization provides a population-based search procedure in which each individual called particle changes their position against time. On the PSO system, each flying particle explores the multi-dimensional search space and adjusts its position based on its personal experience and the experience of the particle next to it. The algorithm is initialized by a set of randomly evoked particles such that the generated solution is also random, and then the optimal solution is iteratively obtained. At each iteration step, the velocity of each particle is updated based on the current individual best position found by itself and the current global best position possessed by the entire group of particles. The PSO algorithm has been successfully applied for the calibration of the lumped model parameters, including; Para-Tank model (Hsu and Yeh, 2015). Tank model arrangement of 3 tanks series (Santos et al., 2011). SWAT model (Zhang et al., 2009; Samadi and Meadows, 2014; Zhang et al., 2023). Tank model (Kuok et al., 2011). SAC-SMA and SVM models (Gill et al., 2006). GR5J hydrological model (Adeyeri et al., 2020). HBV and GR4J model (Napiorkowski et al., 2023). Also, distributed Xin'anjiang hydrological model (Wang et al., 2024). The PSO-based parameter optimization step of the algorithm with minimization objective function as described in (Zhang et al., 2023; Sulianto, 2020). In the case of parameterization of the DISPRIN model then as the optimized variables are expressed as xi, are the 25 parameters of the DISPRIN model according to Figure 4.

2.5.3 CODEQ Algorithm

The CODEQ algorithm was proposed by (Omran and Salman 2009). This algorithm is a synthesis of chaotic search, opposition-based learning, differential evolution, and quantum mechanism. The CODEQ algorithm was successfully applied to solve 19 benchmark functions with performance levels as good as other well-known population-based optimizations. The advantage of this method is that it does not require performing parameter tuning. Additionally the CODEQ algorithm was successfully applied to solve high-dimensional problems with excellent results (Omran 2010). The CODEQ algorithm also successfully solved the constrained optimization problem (Omran and Salman, 2009). The CODEQ algorithm was successfully applied to solve a system of complex pipeline network hydraulic equations (Sulianto, 2020). A 17-parameters Tank model parameterization problem (Sulianto 2024). On those cases the CODEQ algorithm has similar performance to the DE, PSO, and SCE algorithms. The solution step of the CODEQ algorithm for solving the optimization problem with minimization objective function as described in (Omran and Salman 2009), (Sulianto 2020; 2024). In the case of parameterization of the DISPRIN model, then as the optimized variables are expressed as xi, i.e. 25 parameters of the DISPRIN model according to Figure 4.

2.5.4 SCE algorithm

The SCE algorithm or commonly referred to as the SCE-UA algorithm is classified as a global and probabilistic optimization algorithm. This algorithm is composed considering four basic ideas, namely: the combination of random and deterministic approaches, the concept of clustering, the concept of systematic evolution towards global improvement, and the concept of competitive evolution. Briefly, the SCE-UA method is divided into several steps (Duan et al., 1993; 1994). The initial samples are created randomly in the feasible space of each parameter to be optimized by considering the upper bound and the lower bound. All points are sorted by the objective function used. Subsequently the dots were clustered into different complexes, which were developed separately according to the Competitive Complex Evolution (CCE) algorithm. These complexes are then shuffled and other complexes are created based on the information provided by the previous complexes. The last step is to check the convergence criterion such that the evolution and randomization procedures have to be repeated until the required convergence criterion is reached.

The SCE-UA algorithm has been successfully applied to solve the parameter calibration problem of several lumped models, including : Tank model (Kuok et al., 2011). AFFDEF model (Darikandeh et al., 2014).

BTOPMC model and Xin'anjiang model (Bao et al., 2010). Soil and Water Assessment Tool (SWAT) model (Tolson and Shoemaker, 2007; Zhang et al., 2009). NAM model (Madsen, 2000). Also SAC-SMA model (Gupta et al., 1999). The SCE strategy combines the strengths of the controlled random search (CRS) algorithm with the concept of competitive evolution and the concept of complex randomization. The strategy of SCE in locating convergent conditions on the minimization case is described in (Duan et al., 1993). The solution step of the SCE algorithm for solving the optimization problem with the minimization objective function as described in (Sulianto, 2020; 2024). In the case of parameterization of the DISPRIN model then as the optimized variables are expressed as xi, i.e. 25 parameters of the DISPRIN model according to Figure 4.

2.6 Model algorithm

The model algorithm derived from the combination of the DISPRIN model equation system and the metaheuristic method developed in this study is schematically shown Figure 5. As the input data of the model are upland zone area (Au), hill slope zone area (Ah), bottom slope zone area (Ab), the training and testing hydroclimatology data sets, as well as the metaheuristic parameters that relevant. The analysis to achieve the best fitness is performed iteratively from generation to generation using the metaheuristic method, and the iteration process will stop at the set maximum number of iterations (iter_max). At the best fitness condition will be obtained the optimum value of the DISPRIN model parameters. Further the simulation of the DISPRIN model using the optimum values of the parameters that have been found as well as with the input of the training data set will generate the model output and the model performance indicators of the calibration stage, the simulation with the input of the testing data set will generate the model output and the model performance indicator of the validation stage.

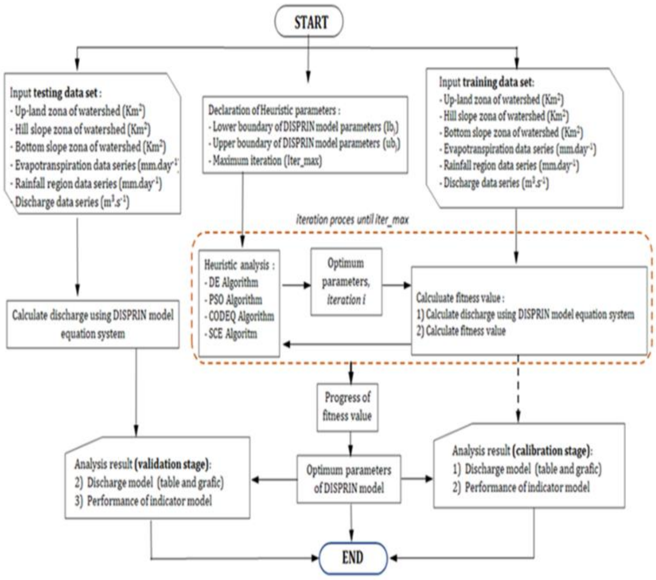


Figure 5: Model algorithm

3. Result And Discussion

Solution of the developed models using MFILE MATLAB programming code. The program code of each model consists of a main program containing the statements of solving DE, PSO, CODEQ and SCE algorithms, and 9 sub programs containing; 1) fitness function, 2) model simulation at calibration stage, 3) model simulation at validation stage, 4) evapotranspiration training data, 5) precipitation data training, 6) discharge data training, 7) evapotranspiration data testing, 8) precipitation data testing, 9) discharge data testing. The application of the DE algorithm uses the following parameter inputs: Population Size *(nPop)* = 50, Lower Boundary of Scaling Factor *(beta_min)* = 0.2, Upper Boundary of Scaling Factor *(beta_max)* = 0.8 dan Crossover Probability *(pCR)* = 0.2. The PSO algorithm uses the input parameters: Population Size *(nPop)* = 100, Inertia Weight *(w)* = 1, Inertia Weight Damping Rasio *(wdamp)* = 0.99, Personal Learning Coefficient *(c1)* = 1.5, Global Learning Coefficient *(c2)* = 2.0. The implementation of the SCE algorithm uses the parameters: Complex Size *(nPopComplex)* = 10, Number of Complexes *(nComplex)* = 5, Number of Offsprings *(cce_params.alpha)* = 3 dan Maximum Number of Iterations *(cce_params.beta)* = 5. Implementation of only CODE algorithm requires a parameter, namely the number of individuals in the population *(N)* = 30. The application of all models uses additional inputs, namely; The maximum number of iterations is 500, the lower bound *(lb)* and upper bound *(ub)* of the optimized variables. The DISPRIN model parameters include; *h* and *S* consecutively were set to 50 mm and 250 mm, the lower boundary *(lb)* and upper boundary *(ub)* of the *C* parameter were consecutively 0.0001 and 0.90, respectively. Running the fourth program of the model using the input of the number of iterations 500. The progress of achieving the best fitness is presented in Figure 6. The figure shows the best fitness having equivalent values ranging from 0.069 – 0.072. All four models show a trend of reaching almost the same convergent condition. Fitness values towards convergence can be achieved at less than 200 iterations for all scenarios.

The optimum values of the DISPRIN model parameters from the analysis results of all models are presented in Figure 7. The optimum values of the DISPRIN model parameters generally have quite significant differences, although they all produce equivalent best fitness values. This could be due to the parameter complexity factor and the non-linearity property of the DISPRIN model equations system, as well as the random nature of the metaheuristic method. The feasibility region of the value of each the DISPRIN model parameters is a superposition of the generated values. Of courses this value only applies to this case study. The range of model parameter values indicates the degree of sensitivity of those parameters to the performance indicators of the model. The smaller the range of parameter values obtained then the more sensitive the parameter is, thus vice versa (Chen *et al.,* 2014). Figure 7 shows parameters *SB1, SB2_0, hC2, SC1_0, SC2_0, SD2_0* and *CC3, CD2* are the most sensitive parameters of the DISPRIN model compared to other parameters, for this case study.

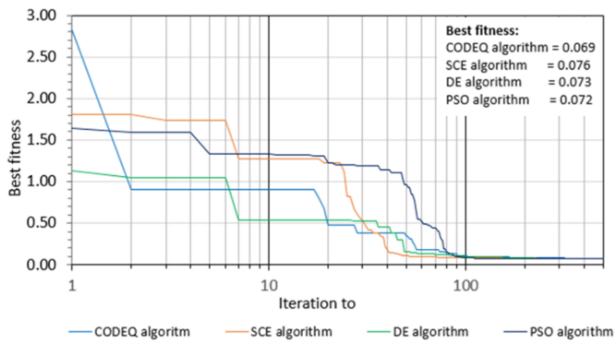
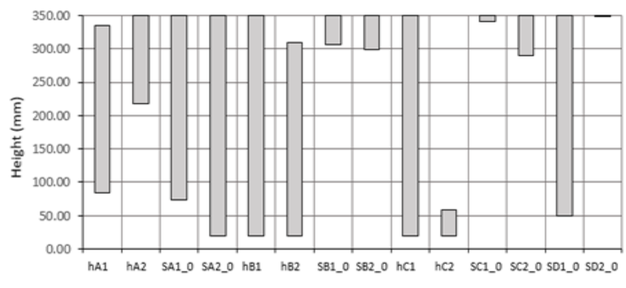
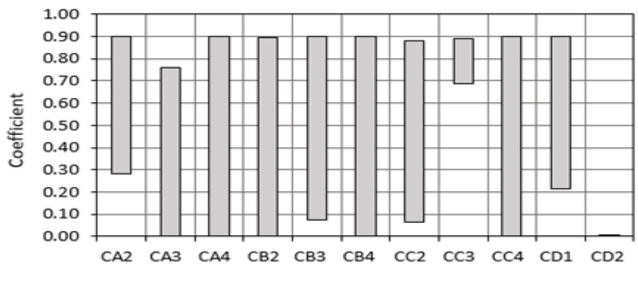


Figure 6: Progress of achieving the best fitness



h and S Parameters



C Parameter

Figure 7: Feasibility of DISPRIN model parameters value

Model performance indicators at calibration stage and validation stage are shown Table 2. Model performance indicators at calibration stage produced NSE values ranged from 0.918 – 0.928, MAE 2.256 – 2.407 m^3/s, PBIAS 6.71% - 7.16%. Quantitatively it appears that the DISPRIN-codeq and DISPRIN-pso models show better performance than the other two models. This of course cannot be a justification for legitimizing the CODEQ algorithm as more effective than the other three algorithms. The difference is only on the initialization factor only, given that all methods use random variables. At the fourth validation stage the model also showed equivalent performance indicators. Model performance indicators at the validation stage resulted in NSE ranging from 0.892 – 0.931, MAE 2.256 - 3.146 m³/s, PBIAS 6.88% - 9.55%. At the stage of model validation the DISPRIN-codeq and DISPRIN-pso models showed their consistency because the obtained analysis results were more accurate when compared to the other two models.

Table 2: Performance Indicator Of Model Calibration, In Brackets Is Model Validation

Performance indicator	DISPRIN-codeq	DISPRIN-sce	DISPRIN-de	DISPRIN-pso
Nash-Sutcliffe Coeficient (NSE)	0.928 (0.931)	0.918 (0.920)	0.924 (0.892)	0.926 (0.903)
Mean Absolute Error (MAE)	2.256 (2.376)	2.376 (2.550)	2.407 (3.146)	2.312 (2.927)
PBIAS	6.71% (7.21%)	7.07% (7.74%)	7.16% (9.55%)	6.88% (8.88%)

Comparison of model discharge fluctuations at the calibration and validation stages is shown in Figure 8, and its statistical parameters are shown in Table 3. The output discharge fluctuations of all models show almost the same trend, both at the calibration and validation stages. At the calibration stage, the training data flow fluctuation trend can be approached with a reasonable degree of accuracy, as illustrated in Figure 8. However, at the validation stage, notable discrepancies emerge, particularly in the minimum discharge. According to Table 3, the average discharge and maximum discharge of the model output do not have significant differences when compared to the testing data. The minimum discharge of the model tends to overestimate when compared to the minimum testing discharge. The minimum model discharge ranges from 11.66 - 13.42 m³/s and the minimum testing discharge is 9.23 m³/s, resulting in a deviation of around 26.33% - 45.44%. The failure of the model to respond to low flow at the validation stage is due to the training data discharge fluctuation trend which is different from the testing data, although statistically both data groups are homogeneous. Table 1 shows that the minimum training discharge data is slightly larger than the testing data. The model parameter values resulting from the calibration process are static and only suitable for the training data set. However, when applied to simulations with input data sets that have different rainfall-discharge relationship trends, the parameter values will be less relevant. This is a weakness of the developed model. Further research considering the dynamic nature of the DISPRIN model parameters may be accommodated as an alternative solution to this problem

Table 3: Statistics Of Observation Discharge Data And Model Output, In Brackets Are The Validation Results

Statistic	Unit	DISPRIN-codeq	DISPRIN-sce	DISPRIN-de	DISPRIN-pso	Observation data
Minimum	m³/s	12.43 (12.44)	13.42 (12.99)	14.00 (11.66)	13.83 (13.07)	7.55 (9.23)
Maximum		54.19 (55.98)	56.32 (58.01)	57.15 (58.95)	57.00 (58.50)	56.81 (52.79)
Mean		33.53 (33.80)	33.71 (34.01)	34.00 (34.47)	33.63 (34.12)	33.61 (32.95)
Deviation standard		10.75 (11.08)	10.56 (10.97)	10.99 (11.51)	10.90 (11.41)	10.99 (10.61)

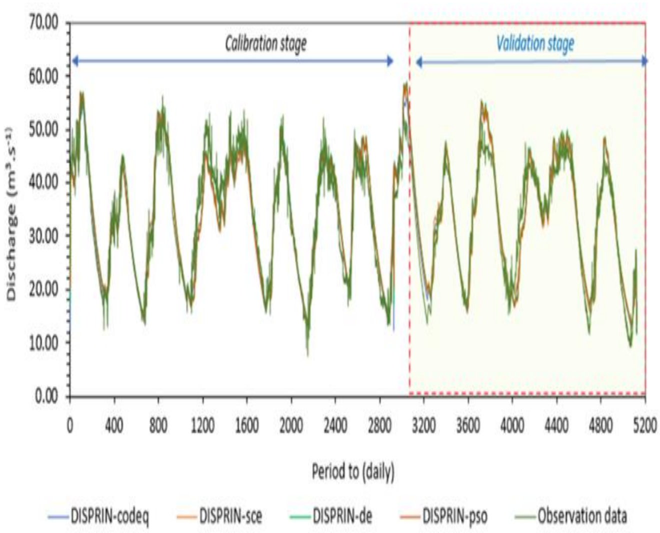


Figure 8: Comparison of model discharge and observation data fluctuations

The discharge distribution curve, which combines training and testing data, can be seen in Figure 9. Table 4 shows the statistical comparison of this curve. The discharge curves of the DISPRIN-de, DISPRIN-sce and DISPRIN-pso models coincide but tend to overestimate when compared to the observed discharge, especially at high flows ($Q > 45$ m³/s). The maximum deviation is 4.17 m³/s or 8.02% and the average deviation is 1.97 m³/s or 3.97%. The flow distribution curve of the DISPRIN-codeq model has a different perspective, the resulting curve is relatively overlapping with the observed discharge curve, both at low and high flows. The curve from the DISPRIN-codeq model slightly overestimates the discharge range of 48 - 54 m³/s with a maximum deviation of 3.76% and an average of 2.57%. Table 4 illustrates the average discharge, maximum discharge and standard deviation of the DISPRIN-codeq model which produces values that are close to the observed discharge. However, at the minimum discharge, the results of the DISPRIN-de model are closest to the observed discharge. These results indicate that qualitatively the developed models can work quite well, and quantitatively the DISPRIN-codeq model is more accurate because it is able to show better performance indicators. It should be noted that the DISPRIN model is a conceptual model developed from the simplification of the watershed system, so that the optimum values of the parameters obtained are only the results of adjustments from the training rainfall-discharge data pairs and the watershed area. As is known, the process of flow in a watershed is a very complex phenomenon, and is often considered a "black-box" system. Therefore, it is difficult to conclude that the optimum values of the parameters from the model output are a representation of the actual physical characteristics of the Lesti watershed.

Table 4: Statistical comparison of observed discharge data and model output

Statistic	Unit	DISPRIN-codeq	DISPRIN-sce	DISPRIN-de	DISPRIN -pso	Observation data
Mean	m³ /s	33.64	33.84	34.20	33.84	33.33
Maximum		55.98	58.01	58.95	58.50	56.81
Minimum		12.43	12.99	11.66	13.07	7.55
Deviation standard		10.89	10.74	11.22	11.13	10.84

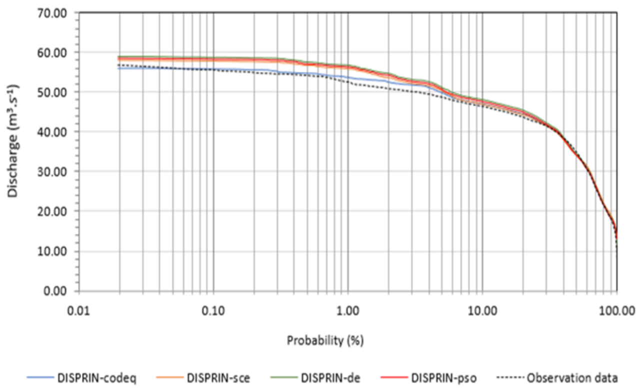


Figure 9: Comparison of distribution discharge curve of observed data and model output

4. Conclusion

The DE, PSO, SCE and CODEQ algorithms have been proven to be able to improve the performance of the DISPRIN model to generate historical daily discharge data series at Lesti watershed. The DISPRIN-de, DISPRIN-pso, DSPRIN-sce and DISPRIN-codeq models developed from the combination of the DISPRIN model simulation equation system with the four metaheuristic methods can work effectively and show accurate results. At the calibration and validation stages, all models show equivalent deviation indicators. The calibration stage produces NSE values ranging from 0.918 - 0.928, MAE ranging from 2.256 - 2.407 m^3/s, PBIAS ranging from 6.71% - 7.16%, at the validation stage produces NSE values ranging from 0.892 - 0.931, MAE ranging from 2.256 - 3.146 m^3/s, PBIAS ranging from 6.88% - 9.55%. At the validation stage, the model's output discharge tends to overestimate when compared to testing data, especially in low flow conditions, this is caused by the different trends in the relationship between rainfall and discharge in training data and testing data. This is a weakness of the developed models. Further research by considering the dynamic nature of the DISPRIN model parameters may be considered as an alternative solution to solve this problem.

The global optimum value of the DISPRIN model parameters is difficult to find, due to the large number of parameters and their continuous parameter values, as well as the non-linear nature of the DISPRIN model simulation equation system. This is indicated by the different optimum values of the DISPRIN model parameters for each model, although all of them produce the same level of deviation. Efforts to find the global optimum condition by applying discrete analysis with narrow parameter value limits can be considered, but are technically inefficient. Further research related to the relationship between watershed parameters, characteristics of the relationship between climate data and discharge to the feasibility limits of the DISPRIN model parameter values is needed, so that the application of the DISPRIN model can be applied more practically.

The success of the DISPRIN model application with metaheuristic-based automatic calibration is determined by the quality of the data involved in the calibration process, therefore the involvement of statistical tests of hydroclimatology data is essential. Homogeneity tests and outlier tests of hydroclimatology data are important parts to ensure the level of accuracy of the analysis results obtained. The DISPRIN model is a high-dimensional and non-linear equation system. Each parameter has a different level of sensitivity. As an effort to find the global optimum solution, a sensitivity analysis of the DISPRIN model parameters is needed. A simple way can be done by conducting experiments several times running the program with varying input of variable boundary values. In the Lesti watershed case study, the parameters SB1, SB2_0, hC2, SC1_0, SC2_0, SD2_0 and CC3, CD2 are the most sensitive DISPRIN model parameters when compared to other parameters.

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