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An Integration Based Optimization Approach (ABC and PSO) for Parameter Estimation in BLRP Model for Disaggregating Daily Rainfall

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ABSTRACT

Fine resolution (hourly rainfall) of rainfall series for various hydrological systems is widely used. However, observed hourly rainfall records may lack in the quality of data and resulting difficulties to apply it. The utilization of Bartlett-Lewis rectangular pulse (BLRP) is proposed to overcome this limitation. The calibration of this model is regarded as a difficult task due to the existence of intensive estimation of parameters. Global optimization algorithms, named as artificial bee colony (ABC) and particle swarm optimization (PSO) were introduced to overcome this limitation. The issues and ability of each optimization in the calibration procedure were addressed. The results showed that the BLRP model with ABC was able to reproduce well for the rainfall characteristics at hourly and daily rainfall aggregation, similar to PSO. However, the fitted BLRP model with PSO was able to reproduce the rainfall extremes better as compared to ABC.

Keywords: Bartlett-lewis rectangular pulse, disaggregation, optimization, rainfall

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INTRODUCTION

In many regions, the rainfall data are recorded based on the daily time step. However, many hydrological studies and designs require a fine-scale data, such as hourly rainfall rather than daily rainfall (Debele et al., 2007; Vanhaute et al., 2012a). Therefore, it is necessary to obtain a fine-scale data (e.g. hourly time step) from the higher time scale (e.g. daily time step) and this transformation is named as disaggregation. Many disaggregation theories were developed for this purpose such as Poisson cluster-based models (Rodriguez-Iturbe et al., 1987), Markov chain models (Hutchinson, 1990; Sansom 1998) and semi-empirical models. The scope of this study is limited to Bartlett–Lewis Rectangular Pulses (BLRP), which utilizes the stochastic models based on the Poisson cluster.

Pui et al. (2009) stated that the BLRP model was developed for the simulation of rainfall and was modified to disaggregate rainfall. Intensive studies were conducted in many regions, which included the United States (Velghe et al., 1994; Rodriguez-Iturbe et al., 1987), United Kingdom (Abdellatif et al., 2013), Australia (Hansen 1982), New Zealand (Cowpertwait et al., 2007) and Africa (Smithers et al., 2002). Based on these studies, it was revealed that the use of the BLRP model in matching the statistical properties including the extremes of the rainfall for a wide range of temporal scales was a success. Recently, the application of the BRLP model was extensively studied in Malaysia. Hanaish et al. (2013) evaluated two types of BLRP, namely the original and modified BLRP models in Peninsular Malaysia. The findings of their study found that the modified BLRP fitted well with Malaysia's rainfall condition as compared to the original BLRP model. Yusop et al. (2014) also studied the use of the BLRP model in the centre of Peninsular Malaysia and found that the BLRP model was able to disaggregate hourly to 48 hours rainfall that closely matched the observed series. However, both studies suggest that the model is not able to disaggregate well the extreme rainfall for the Malaysia region.

Since the BLRP model is complex to calibrate due to the application of the formulation of stochastic approaches, there was no previous studies in Malaysia [including the research by Hanaish et al. (2013) and Yusop et al. (2014)] and only a few studies worldwide, which had been conducted to find and/or to optimize the calibration of the BLRP model. Therefore, an evaluation of the recent optimization algorithm towards the calibration of the BLRP model becomes the main focus to improve the fitness of this model in this study, especially to the humid tropical region like in Malaysia.

Generally, in order to obtain the fitness of the BLRP model to an observed series, the generalized method of moments is applied (Rodriguez-Iturbe et al., 1987; Cowpertwait et al., 1996; Verhoest et al., 1997). This method is implemented by fitting the BLRP model to the observed rainfall characteristics at different aggregation levels. Therefore, function of the model parameters is expressed based on the derivation of the analytical expression of an expected value (Rodriguez-Iturbe et al., 1987). Verhoest et al. (1997) reported that the calibration of BLRP was a burdensome process due to the existence of multiple local minima. The local search techniques in which sub-optimal solution was applied to the optimization problem failed to overcome these local minima. Vanhaute et al. (2012a) stated that global optimization approaches were expected to be more accurate in searching the BLRP parameters compared to the local search techniques.

In this study, two recent global optimization algorithms, which are artificial bee colony (ABC) and particle swarm optimization (PSO), were adopted. The PSO algorithm was developed by Kennedy and Eberhart (1995) and this algorithm is the population-based stochastic optimization techniques, in which inspired by social behavior of bird flocking. PSO is successfully applied in many applications (Eberhart & Yuhui, 2001). As the concern of the author, only a few studies on the PSO algorithm are applied with the BLRP model. Vanhaute et al. (2012a) presented and tested four global optimizations (Downhill Simplex Method, Simplex-Simulated Annealing, Particle Swarm Optimization and Shuffled Complex Evolution) for their capability to calibrate the BLRP model. Their findings suggested that the global optimizations were providing promising results in calibrating the BLRP model, in which it could disaggregate daily rainfall very well. Vanhaute et al. (2012b) extended their previous study (Vanhaute et al., 2012a) to improve the quality of disaggregation results on the extreme of rainfall using the global optimization methods. Both studies found that the performances of each global optimization were varying to each other and the PSO showed a promising tool for estimation of the BLRP parameters.

The ABC model was proposed by Karaboga (2005) and this algorithm was also the population-based stochastic optimization techniques, similar to PSO. This algorithm adopted the foraging behavior of honey bee swarm. The ABC model does not have any background application in this field (Karaboga et al., 2012), but it shows a very good performance in solving classical benchmark equations and other forms of applications. Therefore, the evaluation of the performance of ABC and PSO with the BLRP model becomes a platform of continuity in future studies.

Therefore, the objective of this study is to propose the use of the ABC algorithm in the estimation of the parameters of BLRP and to compare its performance according to the disaggregation results with the PSO model. The selected stations in Peninsular Malaysia are used to evaluate those methods. In the following sections, the materials and methods are presented and followed with the results and the discussions of this study. Next, the conclusions and recommendations are presented.

MATERIAL AND METHODS

Study Area and Data

Four rainfall stations were selected in Peninsular Malaysia to represent four regions with various climatic conditions. The locations and details of each station are shown in Figure 1 and Table 1, respectively. Generally, the rainfall occurrence of Peninsular Malaysia is influenced mostly by two monsoons, named as the south-west monsoon (from May to August) and the north-east monsoon (from November to February), with the two inter monsoons. During the south-west monsoon, Regions 1 (Alor Setar) and 3 (Melaka) receives heavy rainfall. Otherwise, those regions are the driest part of the Peninsular during the north-east monsoon period. Both regions are less influenced by the north-east monsoon because the regions are blocked by the Titiwangsa Range.

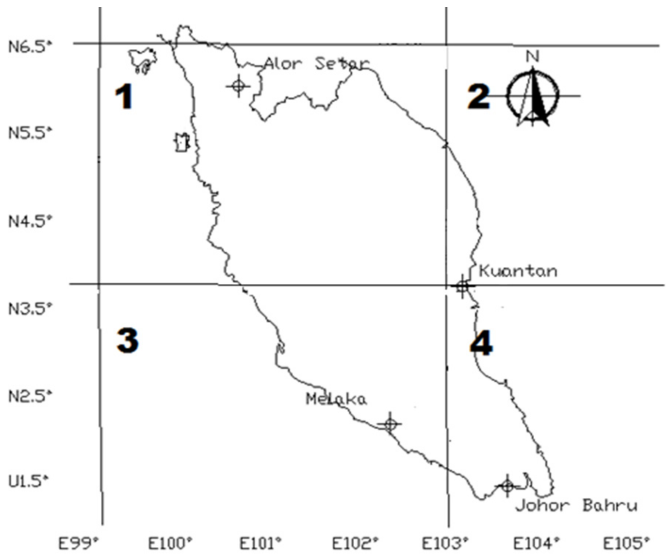

Figure 1. Location of rainfall stations

Table 1
Details and description of rainfall stations

Region	ID	Name of Station	Location		Period
			Lat (°N)	Long (°E)	
1	6108001	Alor Setar	6.11	100.85	2001-2012
2	3833002	Kuantan	3.81	103.33	2001-2012
3	2528012	Melaka	2.29	102.49	1991-2000
4	1437116	Johor Bahru	1.47	103.75	2002-2012

The hourly and daily rainfall data were obtained from the Department of Irrigation and Drainage Malaysia (DID) and their detail periods are illustrated in Table 1. All stations contained smaller missing data (<5%), and the missing data were filled with the expectation-maximization algorithm using PASW software. Before the rainfall data series were applied, the homogeneity of rainfall time series data was tested. In this study, the Pettitt, SNHT, Buishand, and von Neumann tests were applied to the annual rainfall series of each station. Results revealed that the graph produced for each test was almost a straight line and no breakpoints were detected. The p-value for each test was also computed using the Monte

Carlo simulation in order to enhance the reliability of the tests. The p-value was greater than the significance level alpha (α=0.05) were obtained. Therefore, the assumption that the rainfall data series are homogenized is accepted.

Bartlett-Lewis Rectangular Pulse

Description of the BLRP Model. The basic structure of the BLRP model assumes the storm arrivals (*T*) developed in a Poison process with λ. Every single of *T* is tailed by the cell origins (*t*) under the Poison process with rate β. The new cell origins after the duration of period (*s*) is generated by exponential distributed with rate γ. Then, the cell origins are paired with the rainfall cell. Duration (*W*) and depth (*X*) are randomly extracted from the exponential distributions with parameters η and $1/\mu_x$, respectively. These continuous processes will develop a rainfall series.

In this study, the modified BLRP model was used. This model allows the average cell duration to vary between storm by letting the parameter η following a Gamma distribution of shape and parameters of α and v. This situation leads by the generation of $E[\eta]=\alpha/v$ and $Var[\eta]=\alpha/v^2$, with α>1 to show the expected duration to be finite. The model also applied $\kappa=\beta/\eta$ and $\varphi=\gamma/\eta$, which were introduced by Rodriguez-Iturbe et al. (1987).

Two parameters gamma with mean (μ_x) and standard deviation (σ_x) can be distributed with the value of *X*. Therefore, the number of cells per storm can be expressed as $\mu_c=1+k/\varphi$. In total, the BLRP model contains 7 parameters (λ, K, φ, α, v, μ_x and σ_x) that need to be estimated. The details of estimation process are discussed in the following section.

Estimation of BLRP Parameters. The estimation of BLRP parameters in this study is based on generalized method of moments, in which the minimum value between the observed and simulated rainfall properties was identified. The estimation was based on the monthly basis and the objective function *f(x)* can be expressed as:

$$minimum\ of\ f(x) = \sum_{i=1}^{k} w_i[M_i' - M_i(x)]^2 \quad (1)$$

where, *x* is the parameter vector, w_i is the positive weight, M_i' is the vector of observed values, $M_i(x)$ is the vector of expected values, and *k* is the defined statistical properties of rainfall to the BLRP parameters. w_i is set as 1, following the rules set by Velghe et al. (1994). This study used an alternative *f(x)* that was introduced by Cowpertwait et al. (2007) and Eq (1) is revised as follows:

$$minimum\ of\ f(x) = \sum_{i=1}^{k}\left[\left(\frac{M_i(x)}{M_i'} - 1\right)^2 + \left(\frac{M_i'}{M_i(x)} - 1\right)^2\right] \quad (2)$$

The list of *k* applied in this study includes the mean ($E\left[Y_i^{(h)}\right]$), variance ($var\left[y_i^{(h)}\right]$), , autocorrelation for lag-1hour ($cov\left[Y_i^{(h)}, Y_{i+j}^{(h)}\right]$) and the probability of rainfall days ($p(h')$).

The list of k can be defined as (Rodriguez-Iturbe et al., 1988):

$$E\left[Y_i^{(h)}\right] = \lambda h \mu_x \left(\frac{1+\kappa/\phi}{\alpha-1}\right) \tag{3}$$

$$var\left[y_i^{(h)}\right] = 2A_1[(\alpha-3)h\nu^{2-\alpha} - \nu^{3-\alpha} + (\nu+h)^{3-\alpha}] - \\ 2A_2[\phi(\alpha-3)h\nu^{2-\alpha} - \nu^{3-\alpha} + (\nu+\phi h)^{3-\alpha}] \tag{4}$$

$$cov\left[Y_i^{(h)}, Y_{i+j}^{(h)}\right] = A_1\{[\nu+(j+1)h]^{3-\alpha} - 2(\nu+jh)^{3-\alpha} + [\nu+(j-1)h]^{3-\alpha}\} - A_2\{[\nu + \\ (j+1)\phi h]^{3-\alpha} - 2(\nu+j\phi h)^{3-\alpha} + [\nu+(j-1)\phi h]^{3-\alpha}\} \tag{5}$$

$$p(h)' = exp\left\{-\lambda h - \lambda\mu_T + \lambda G_p^*(0,0)\frac{\phi+\kappa\left[\frac{\nu}{\nu+(\kappa+\phi)h}\right]^{\alpha-1}}{\phi+\kappa}\right\} \tag{6}$$

where;

$$A_1 = \frac{\lambda\mu_c\nu^\alpha}{(\alpha-1)(\alpha-2)(\alpha-3)}\left[E(X^2) + \frac{\kappa\phi\mu_x^2}{\phi^2-1}\right] \tag{7}$$

$$A_2 = \frac{\lambda\mu_c\kappa\mu_x^2\nu^\alpha}{\phi^2(\phi^2-1)(\alpha-1)(\alpha-2)(\alpha-3)} \tag{8}$$

In these equations, X is the cell depth, i is the current time, j is the lag-1 time, and T is the data set of selected k of various time scale.

The study performs at aggregation levels of 1 hour and 1 day. As discussed previously, the BLRP parameters were distributed in the different probabilities. The range of values for those parameters are shown in Table 2.

Table 2

Boundary constraints of parameters used at the four sites

Parameter	Lower Limit	Upper Limit
λ (mm/day)	0	0.1
κ = β/η	0	20
φ = γ/η	0	1
α	1	20
ν (day)	0	20
μx (mm/day)	0	99
σx (mm/day)	0	99

Hyetos. The current BLRP model is not able to derive a synthetic disaggregation of hourly rainfall series independently. Therefore, Hyetos developed by Koutsoyiannis and Onof (2001), which utilized the BLRP model for rainfall disaggregation was applied in this study. This model itself was not able to estimate the BLRP parameters. Therefore, global optimization approaches were used to fit the model and it will be discussed in the following section.

Based on the Hyetos model, the first step is to distribute the total daily observed rainfall to hourly rainfall based on the wet days using the BLRP parameters. Each distribution or group of wet days are finalised until its arrangement matches the arrangement of observed daily rainfall with a tolerance distance (d_t) and d_t is defined as;

$$d_t = \left[\sum_{i=1}^{L} ln\left(\frac{Z_i+0.1}{\bar{Z}_i+0.1}\right)^2\right]^{0.5} \quad (9)$$

where, Z_i and $\bar{Z}_i$ are the observed and simulated total daily rainfall and L is the length of arrangement wet days.

The next step is to adjust the disaggregated hourly rainfall (X_s) produced from the first step. This adjustment is to ensure that the new disaggregated rainfall ($\check{X}_s$) is consistent with the given total daily rainfall (N). The adjustment is written as:

$$X_s = \hat{X}_s\left(\frac{N}{\sum_1^{24}\check{X}_s}\right), \qquad s=1,2, \ldots,24. \quad (10)$$

Optimization of BLRP using ABC and PSO

Estimation of the BLRP parameters (Equations 3-6) is a cumbersome task. Artificial bee colony (ABC) and particle swarm optimization (PSO) are introduced to tackle this task. The description and details of each optimization will be discussed in detail in the following section. To utilize both optimization methods, the possible solution of BLRP parameters are needed to organize for both, ABC and PSO. Size of possible solution need to be similar for both optimizations and this expression can be written as:

$$Solution = \begin{bmatrix} Particle_1 \\ Particles_2 \\ Particles_3 \\ \vdots \\ Particles_{NS\ or\ N} \end{bmatrix} \quad (11)$$

where, *Particle* = [$\lambda, \kappa, \varphi, \alpha, \nu, \mu_x$] is the set of BLRP parameters, *Solution* is the possible solution and *NS* or *N* is the size of *Solution.* For these optimizations, $\mu_x = \sigma_x$

Description of ABC. Artificial bee colony (ABC) algorithm was introduced by Karaboga (2005) and it is applied in many optimization applications (Karaboga et al., 2012). This algorithm was inspired by the honeybee foraging behavior and three types of honeybee are introduced: employed, onlookers and scouts. Inside the ABC algorithm, the food source collected by honeybee is an analogy to the possible solution to the optimization problem. The fitness of the objective solution is represented by the position of the food source. The number of the employed and onlooker bees is set as equal to the number of solutions in the population.

For the beginning of ABC, population of *NP* solutions is random initial, where *NP* is the size of population. The number of food source (*NS*) is introduced, where *NS* = *NP*/2. Each solution, x_i (i=1,2,3, …, *NS*) is a n-dimensional vector. Then, all honeybees are performing a cyclic search, based on the given rules.

The update solution (v_i^j) is modified by an employed bee that produces a modification on the position of solution based on the local information and tests the fitness value of the new solution. The v_i^j generated from the old solution (x_i^j) can be expressed as:

$$v_i^j = x_i^j + \emptyset_{ij}\left(x_i^j - x_k^j\right) \tag{12}$$

where $k \in \{1, 2,\ldots,NS\}$ and $j \in \{1, 2,\ldots, n\}$ are random indexes, k is different from i, $\emptyset_{ij}$ is a uniformly distributed random number in the range of -1 to 1.

Provided that the update solution of the new solution is better than the previous solution, the old solution is replaced with the new solution. Otherwise, the old solution is applied. The employed bees return to their centre (hive) and share this information with the onlooker bees. In the next step, the onlooker bee selects one of the new solution sources based on the fitness value. The probability of a solution source (p_i) that will be selected by the onlooker bees can be expressed as:

$$p_i = \frac{fit_i}{\sum_{j=1}^{NS} fit_i} \tag{13}$$

where, fit_i is the fitness value of solution source i, which is proportional to the objective function value of the solution (in the BLRP model, please refer to Eq. 2).

After the solution source is selected, each onlooker bee searches a new solution source in the neighborhood of that source by using Eq. 11. The new solution source is identified by the greedy selection to evaluate its fitness. If a position cannot be improved due to limit cycles, that solution source is abandoned. The employed bee becomes a scout bee and the solution sources are replaced with an updated solution found by the scout bee. If the scout bees discover the abandoned solution (x_i^j) and replace it with x_i, it can be expressed as:

$$x_i^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j) \tag{14}$$

where, x_{max}^j and x_{min}^j are upper and lower bonds (Table 2) of x_i^j, and rand (0,1) is a uniform distribution number in between 0 to 1.

The whole process will be repeated until the maximum iterations or it achieves the objective function.

Description of PSO. Particle swarm optimization (PSO) consists of a variable set named as swarm of the random variables and named as particles. Each particle represents the possible solution to the optimization problem. This algorithm uses the movement and velocity of particles for the search space of global optimum state. In each iteration, PSO collects the local optimum and evaluate it with the global optimum value. Generally, the PSO algorithm can be described into three main stages, which are; 1) position and velocity of swarms are initiated; 2) position of swarms is evaluated; and 3) position and velocity of swarms are updated (Shamsudin et al., 2013; Salami et al., 2018).

In the initial stage, the swarm initial of position (x_o^i) and velocity (v_o^i) stages are created randomly within the search space in a certain particle *i*, with *i* =1, 2, ..., *N*. This stage is written as:

$$x_0^i = x_{min} + rand(x_{max} - x_{min}) \quad (15)$$

$$v_0^i = \frac{x_{min}+rand(x_{max}-x_{min})}{\Delta t} \quad (16)$$

where, x_{min} and x_{max} are the lowest and highest values of x respectively (Table 2) and Δt is the time duration of swarm position.

For the second stage, the position x_i of a particle is improved (x_{k+1}^i) by increasing its speed vector (v_i) to the previous position. It can be defined as:

$$x_{k+1}^i = x_k^i + v_{k+1}^i \Delta t \quad (17)$$

where, $v_{k+1}^i \Delta t$ is the added velocity vector, and *k* and *k +1* represents the previous and subsequent iteration step respectively.

For the final stage (velocity update), the updated swarm velocity (v_{k+1}^i) is revised with the best position (p_i) and the global best (p_g) becomes a reference. This revision can be expressed as:

$$v_{k+1}^i = wv_k^i + c_1 rand\left(\frac{p_i - x_k^i}{\Delta t}\right) + c_2 rand\left(\frac{p_g - x_k^i}{\Delta t}\right) \quad (18)$$

$$w = (w_1 - w_2)\frac{iter_{max} - iter}{iter_{max}} + w_2 \quad (19)$$

where, c_1 and c_2 are the positive acceleration constants, *w* is the inertia weight and *rand* is the random component. In this study, the maximum number of iterations ($iter_{max}$) was 1000 and the initial (w_1) and final (w_2) weights were 0.9 and 0.4, respectively.

RESULTS AND DISCUSSION

Parameter Estimation of BLRP using ABC and PSO

Figure 2 shows the list of optimum estimation of BLRP parameters using the ABC and PSO algorithms for the selected rainfall stations in Peninsular Malaysia. The mean, variance, autocorrelation for lag-1hour (*AC Lag-1h*) and the probability of rainfall days (proportion dry) of the observed hourly and daily rainfalls were calculated as an input parameter for BLRP and optimized using ABC and PSO. The values were derived on a monthly basis. The studied rainfall properties are similar to the properties of rainfall studied by Cowpertwait et al. (2007) and Yusop et al. (2014), but the difference is in the aspect of aggregation levels (in this study the limit is between 1 and 24 hours). This limit is chosen as a way to reduce the extensive calculation. From the figure, all parameters do not show an identical value of estimated parameters between each station and the type of optimization method. The estimated parameters were randomly estimated within the range of the studied boundary constraints (Table 2). For ABC optimization, the study found that the estimated parameters were near to the value of the studied boundary constraints. It is also obviously seen that λ estimate by ABC is 0.1mm/day for almost all of the months for each station. In terms of PSO's estimation, the figure shows that the estimated parameters are well randomly estimated within the range of studied boundary constraints.

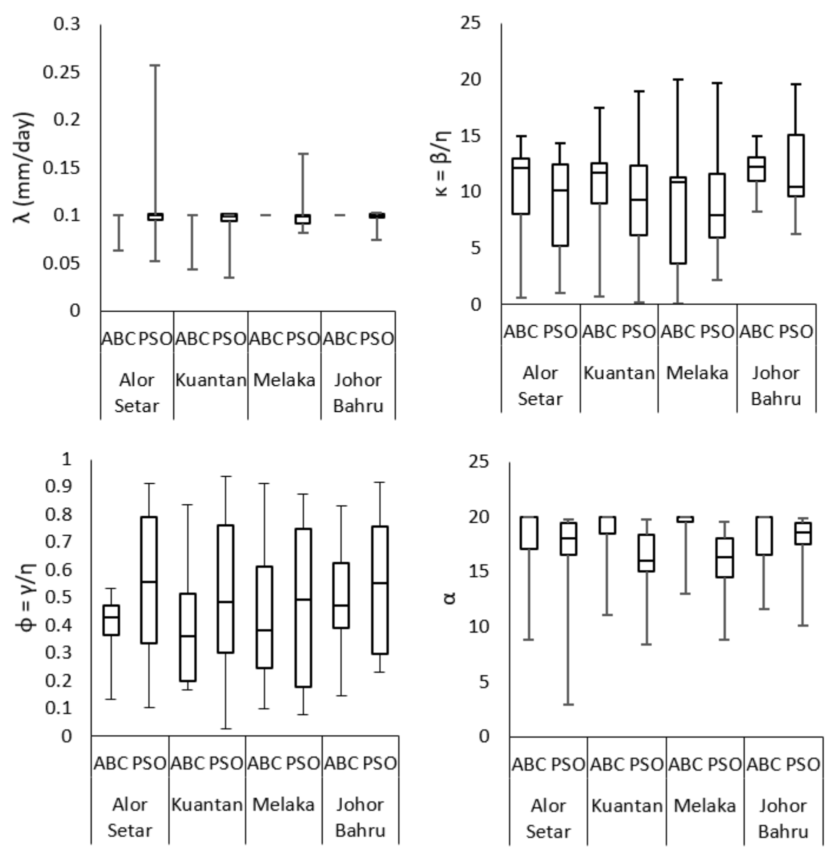

Figure 2. Global estimated BLRP parameters using ABC and PSO for each parameter

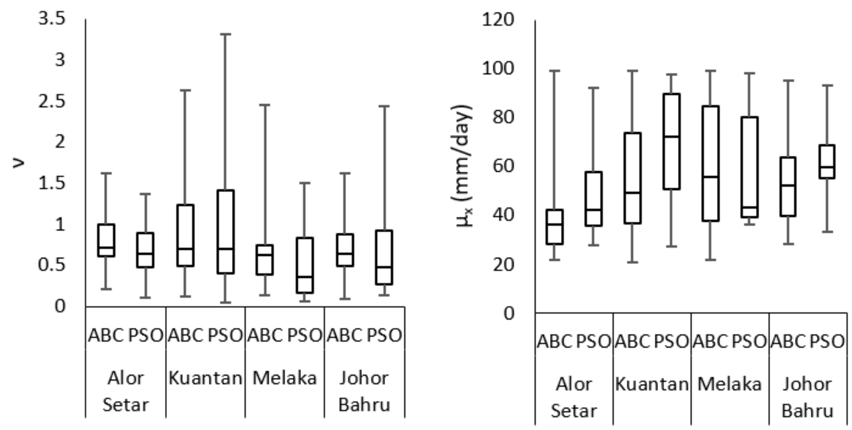

Figure 2. (Continued)

The minimum of the objective function (*f(x)*) for each month can also be referred to as detailed in Figure 3. The closer *f(x)* value to 0, the fitter the BLRP model. Based on Figure 3, it is clearly seen that the ABC and PSO algorithms give almost similar values. The range of *f(x)* is between 0.4260 and 13.8882, with the highest recorded *f(x)* can be obtained from Melaka, with the values of 13.8882 and 13.5263 for ABC and PSO, respectively.

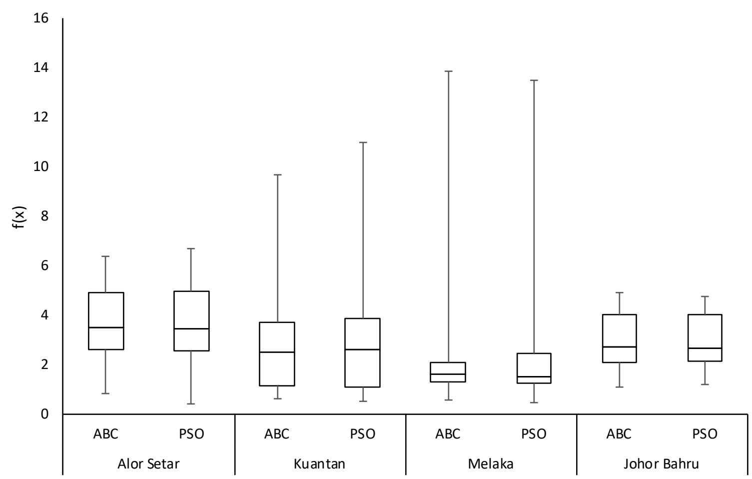

Figure 3. Comparison between the optimum of minimum objective function (*f(x)*) of the ABC and PSO

Generation of Disaggregated Hourly Rainfall Series using Hyetos

Performance of ABC and PSO to Disaggregate Temporal Rainfall Distribution. Figures 4-7 illustrate the comparison of the performance of Hyetos to simulate hourly rainfall using the optimum parameters generated by the ABC and PSO approaches for the studied stations. Four statistical hourly rainfalls are used, named as mean, standard deviation (SD), autocorrelation lag-1h and proportion of dry days. In general, the Hyetos model using the parameters from ABC and PSO was able to capture the observed rainfall. In term of SD, both algorithms were slightly able to show a good agreement between the observed and disaggregated rainfall. However, the study found that some stations were unable to perform well in capturing the autocorrelation lag-1h and proportion of dry days. The stations in Kuantan and Melaka were able to capture all rainfall statistical properties very well. However, the studied approaches slightly overestimated the autocorrelation lag-1h and proportion dry for the most months in the Alor Setar and Johor Bahru stations. Nonetheless, the results can still be accepted because the range of differences is not large. Studies by Hanaish et al. (2011), Hanaish et al. (2013), Abdellatif et al. (2013), and Yusop et al. (2014) also provided similar results. Like this study, findings of those studies were also not able to fit the autocorrelation lag-1hour and proportion of dry days perfectly.

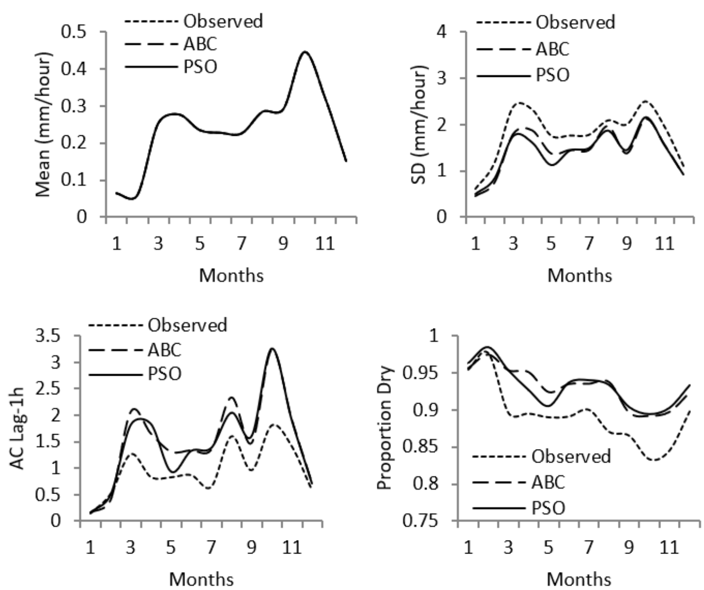

Figure 4. Properties of hourly rainfall for Alor Setar

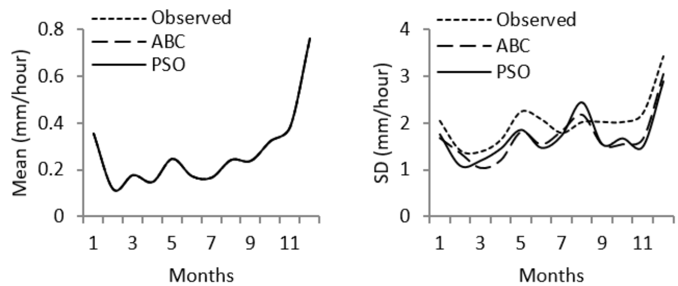

Figure 5. Properties of hourly rainfall for Kuantan

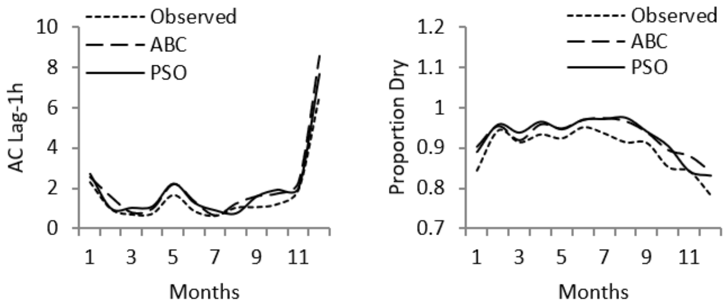

Figure 5. (Continued)

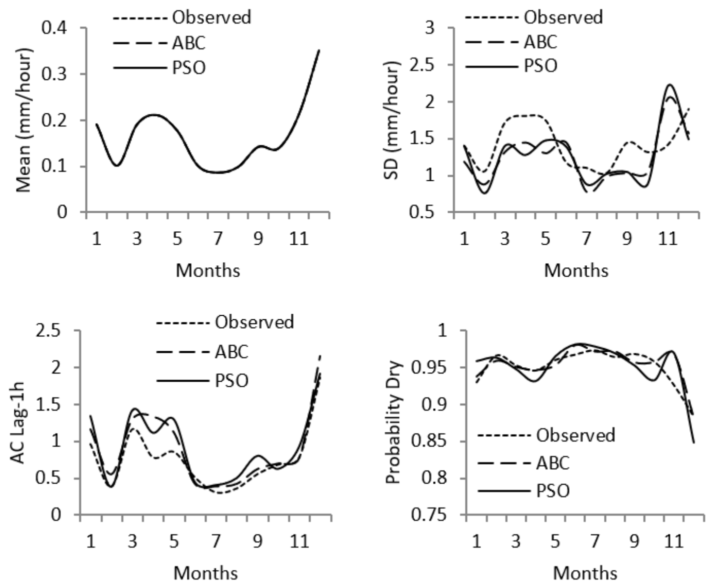

Figure 6. Properties of hourly rainfall for Melaka

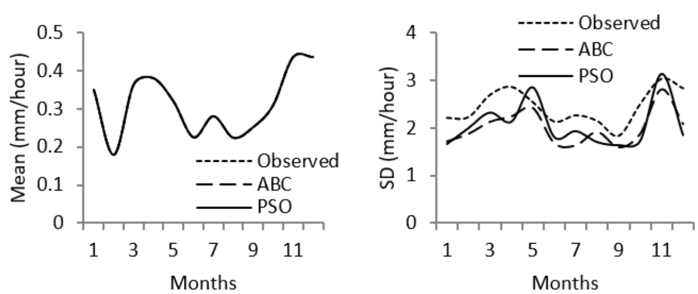

Figure 7. Properties of hourly rainfall for Johor Bahru

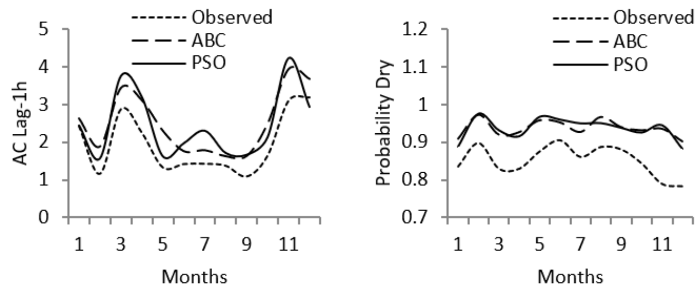

Figure 7. (Continued)

Performance of ABC and PSO to Disaggregate Extreme Rainfall. Figure 8 illustrates the evaluation of the capability of BLRP to replicate the observed extreme values of rainfall. An hourly annual maximum (*AM*) as the extreme rainfall indices is applied and fitted with the Gumbel's distribution. The relationship between *AM* intensity and return period (*T*) can be defined as:

$$x_T = \bar{x} + K_T s \qquad (20)$$

where, x_T is *AM* intensity at *T*, $\bar{x}$ is the average of *AM* data series, K_T is the frequency factor, and *s* is the standard deviation of *AM* data series. Since this study applied Gumbel's distribution, K_T values are calculated for different return periods using this distribution. Therefore, K_T can be written as:

$$K_T = -\frac{\sqrt{6}}{\pi}\left\{0.5772 + ln\left[ln\left(\frac{T}{T-1}\right)\right]\right\} \qquad (21)$$

In general, it is suggested that the BLRP model optimized using ABC and PSO is not able to capture well the observed extremes at the hourly scale. However, in Melaka and Johor Bahru, the approaches were able to capture slightly the observed extremes value. For the Alor Setar station (Figure 8a), it showed that both optimization methods were unable to provide fitted parameters to be used by the BLRP model in order to give a satisfactory result in capturing the extreme rainfall. This situation may happen due to the tropical regions of the rainfalls in Malaysia, which is mainly convective and the rains are produced by a sudden burst with high intensities of rainfall and the duration of rainfall is short. In terms of optimization algorithms, the PSO seems to perform slightly well by replicating near to the observed extremes value as compared to the ABC algorithm. Although both models are able to give a similar optimum possible solution, the converged towards it is different. The ABC algorithm is poor in the aspect of exploitation ability to reach the optimum solution as compared to PSO. The study also found that the search for the optimal parameters of the optimization methods requires most efforts for ABC, in which needs a large exploration of the search space (maximum of number of iterations) to find optimum solutions. Those converged results are similar with other research, which applied the ABC and/or PSO within their own case study such as Zhu and Kwang (2010), Jia et al. (2011), and Hossain and El-shafie (2013).

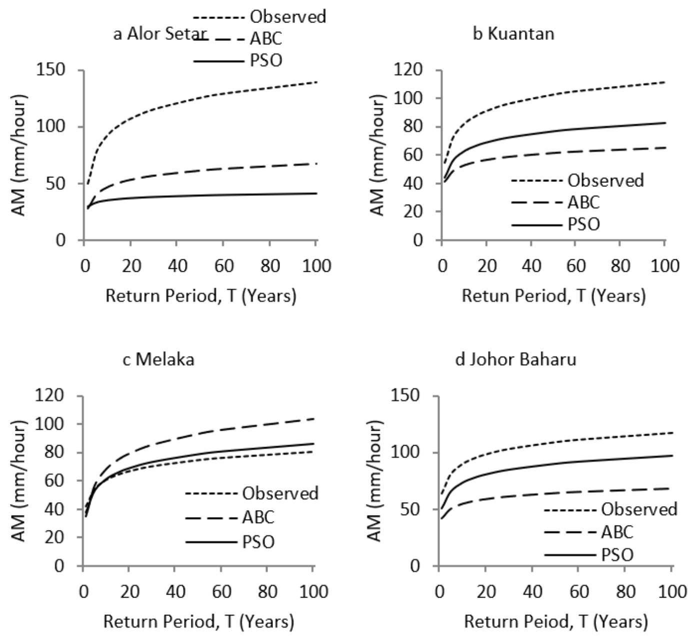

Figure 8. Return level plots of the annual maximum (AM) intensity of hourly rainfall series in a) Alor Setar, b) Kuantan, c) Melaka, and d) Johor Bahru

CONCLUSION

This study proposed a further improvement on the calibration process of the Bartlett-Lewis rectangular pulse (BLRP) with applications of the artificial bee colony (ABC) and particle swarm optimization (PSO). Historical rainfall data from four selected stations in Peninsular Malaysia were used for this study.

In the calibration of the BLRP model, estimation of the BLRP parameters was addressed. Those parameters were obtained by using a combination of different moments generated from four statistical properties of hourly and daily rainfalls. The optimized parameters obtained from the ABC and PSO algorithms were discovered that the different combinations of parameters were directed to identical results. Both models are also able to match the rainfall properties. Although ABC is claimed to much reliable in finding optimal solutions (Karaboga & Akay, 2009; Akay & Karaboga, 2012), the result is different with the application of the BLRP model with the PSO, in which it is able to find the optimal solution much better as compared to the ABC algorithm.

Hyetos was used to regenerate the statistical and extreme properties by utilizing the optimized BLRP parameters. In general, the statistical properties obtained from Hyetos with the parameters optimized by ABC and PSO are able to give a satisfactory agreement between the simulated and observed hourly data. The model does not have the ability to match the extreme rainfall. However, some stations namely Melaka and Johor Bahru are able to slightly match the extreme rainfall. In terms of optimization algorithm in matching extreme rainfall, the study found that the BLRP parameters optimized by PSO can nearly replicate the extreme rainfall as compared to the ABC algorithm.

Further study is required to improve the quality of the BLRP model especially for rainfall events model, which involves extreme rainfalls. Effect of the alternative function towards the performance of the model in reproducing the rainfall series and its extremes can be applied in the future study.

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REFERENCES

Abdellatif, M., Atherton, W., & Alkhaddar, R. (2013). Application of the stochastic model for temporal rainfall disaggregation for hydrological studies in north western England. *Journal of Hydroinformatics, 15*(2), 555-567.

Akay, B., & Karaboga, D. (2012). A modified artificial bee colony algorithm for real-parameter optimization. *Information Sciences, 192*, 120-142.

Cowpertwait, P. S. P., O'Connell, P. E., Metcalfe, A. V., & Mawdsley, J. A. (1996). Stochastic point process modelling of rainfall. I. Single-site fitting and validation. *Journal of Hydrology, 175*(1-4), 17-46.

Cowpertwait, P. S. P., Isham, V., & Onof, C. (2007). Point process models of rainfall: developments for fine-scale structure. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 463*(2086), 2569-2587.

Debele, B., Srinivasan, R., & Parlange, J. Y. (2007). Accuracy evaluation of weather data generation and disaggregation methods at finer timescales. *Advances in Water Resources, 30*(5), 1286-1300.

Eberhart, R. C., & Yuhui, S. (2001). Particle swarm optimization: developments, applications and resources. *Evolutionary Computation, 1*, 81-86.

Hanaish, I. S., Ibrahim, K., & Jemain, A. A. (2011). Stochastic modeling of rainfall in Peninsular Malaysia using Bartlett Lewis rectangular pulses models. *Modelling and Simulation in Engineering, 2011*, 1-6.

Hanaish, I. S., Ibrahim, K., & Jemain, A. A. (2013) On the potential of Bartlett Lewis rectangular pulse models for simulating rainfall in Peninsular Malaysia. *Hydrological Sciences Journal, 58*(8), 1690-1703.

Hansen, L. P. (1982). Large properties of generalized method of moments estimators, *Econometrica, 50*, 1029-1054.

Hossain, M. S., & El-Shafie, A. (2013). Performance analysis of artificial bee colony (ABC) algorithm in optimizing release policy of Aswan High Dam. *Neural, Computing and Applications, 24*(5), 1199-1206.

Hutchinson, M. F. (1990). A point rainfall model based on a three-state continuous Markov occurrence process. *Journal of Hydrology, 114*(1-2), 125-148.

Jia, D., Zheng, G., Qu, B., & Khan, M. K. (2011). A hybrid particle swarm optimization algorithm for high-dimensional problems. *Computers and Industrial Engineering, 61*(4), 1117-1122.

Karaboga, D., & Akay, B. (2009). A survey: algorithms simulating bee swarm intelligence. *Artificial Intelligence Review, 31*(1), 55-68.

Karaboga, D. (2005). *An idea based on honey bee swarm for numerical optimization* (Technical Report-TR06). Computer Engineering Department, Engineering Faculty, Erciyes University, Turkey.

Karaboga, D., Gorkemli, B., & Ozturk, C. (2012). A comprehensive survey: artificial bee colony (ABC) algorithm and applications. *Artificial Intelligence Review, 2012*, 1-37.

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *Neural Network, 4*, 1942-1948.

Koutsoyiannis, D., & Onof, C. (2001). Rainfall disaggregation using adjusting procedures on a Poisson cluster model. *Journal of Hydrology, 246*(1-4), 109-122.

Pui, A., Sharma, A., & Mehrotra, R. (2009, July 13-17). A comparison of alternatives for daily to sub-daily rainfall disaggregation. In *Eighteenth World IMACS / MODSIM Congress* (pp. 3535-3541). Cairns, Australia.

Rodriguez-Iturbe, I., Cox, D. R., & Isham, V. (1988). A point process model for rainfall: further developments. *Proceedings of the Royal Society of London. A. Mathematical and Physical Sciences, 417*(1853), 283-298.

Rodriguez-Iturbe, I., De Power, B. F, & Valdes, J. B. (1987). Rectangular pulses point process models for rainfall: analysis of empirical data. *Journal of Geophysical Research: Atmospheres, 92*(D8), 9645-9656.

Salami, M., Sobhani, F. M., & Ghazizadeh, M. S. (2018). Short-term forecasting of electricity supply and demand by using the Wavelet-PSO-NNs-SO technique for searching in big data of Iran's Electricity Market. *Data, 3*(4), 43-68.

Sansom, J. (1998). A hidden Markov model for rainfall using breakpoint data. *Journal of Climate, 11*, 42-53.

Shamsudin, S., Dan'azumi, S., Aris, A., & Yusop, Z. (2013). Optimum combination of pond volume and outlet capacity of a stormwater detention pond using particle swarm optimization. *Urban Water Journal, 11*(2), 127-136.

Smithers, J. C., Pegram, G. G. S., & Schulze, R. E. (2002). Design rainfall in South Africa using Bartlett-Lewis rectangular pulse rainfall models. *Journal of Hydrology, 258*(1-4), 83-99.

Vanhaute, W. J., Vandenberghe, S., Scheerlinck, K., De Baets, B., & Verhoest N. E. C. (2012a). Calibration of the modified Bartlett-Lewis model using global optimization techniques and alternative objective functions. *Hydrology and Earth System Sciences, 16*(3), 873-891.

Vanhaute, W. J., Vandenberghe, S., Scheerlinck, K., De Baets, B., & Verhoest, N. E. C. (2012b, April 22-27). Improving the extreme value behaviour of Bartlett-Lewis rectangular pulse models. In *EGU General Assembly Conference Abstracts* (p. 2692). Vienna, Austria

Velghe, P. A., Troch, P. A., De Troch, F. P., & Van de Velde, J. (1994). Evaluation of cluster-based rectangular pulses point process models for rainfall. *Water Resources Research, 30*(10), 2847-2857.

Verhoest, N. E. C., Troch, P. A., & De Troch, F. P. (1997). On the applicability of Bartlett-Lewis rectangular pulses models in the modeling of design storms at a point. *Journal of Hydrology, 202*(1-4), 108-120.

Yusop, Z., Nasir, H., & Yusof, F. (2014). Disaggregation of daily rainfall data using Bartlett Lewis Rectangular Pulse model: a case study in central Peninsular Malaysia. *Environmental Earth Sciences, 71*(8), 3627-3640.

Zhu, G., & Kwong, S. (2010). Gbest-guided artificial bee colony algorithm for numerical function optimization. *Applied Mathematics and Computation, 217*, 3166-3173.