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Parameters Optimization using Fuzzy Rule Based Multi-Objective Genetic Algorithm for an Event Based Rainfall-Runoff Model

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Abstract The calibration of an event based rainfall-runoff model for steam flow forecasting is challenging because, it is difficult to measure the parameters physically on the field for each rainfall event. In the present study, Fuzzy rule based Multi-objective Genetic Algorithm (MGA) is developed to optimize the infiltration and roughness parameters of an event based rainfall-runoff model. Nash Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2) and transformed volume difference ($f(V)$) are used as the objective functions of the MGA and all Pareto optimal solutions are identified using Nondominated Sorting method. As three objective functions are included in the calibration, the number of Pareto optimal solutions are also increases and hence, the optimization problem now becomes a decision making problem. Therefore, to select the best solution from all Pareto optimal solutions, a Fuzzy Rule-Based Model (FRBM) is developed to get alternative values of each Pareto optimal solution. First, the Fuzzy rule based MGA is developed by integrating the FRBM with the MGA. Then the Fuzzy rule based MGA is integrated with an event based runoff model. The developed Fuzzy-MGA based runoff model is tested on three different watersheds and the simulation results of

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Fuzzy-MGA based runoff model are compared with observed data and previous study results. From the simulated events of three watersheds using Fuzzy-MGA based runoff model, it is observed that the mean percentage error in any criteria (i.e. volume of runoff, peak runoff, and time to peak) of the developed model for a watershed is less than 16.33%. It is also noted that the developed Fuzzy-MGA based runoff model is able to produce hydrographs that are much closer to the measured hydrographs.

Keywords Event based rainfall-runoff model · Fuzzy Rule-Based Model · Multi-objective Genetic Algorithm · Optimization

1 Introduction

Water resource management and design of hydraulic structures in a watershed are primarily based on hydrological modeling of watershed. In particular, rainfall runoff models have been widely used for flood forecasting as basic tools for watershed management. In recent years, the demand for timely and accurate forecasts has increased in hydrology. However, the major difficulty of rainfall runoff model calibration is that these models generally have a large number of parameters that cannot be directly obtained from measurable quantities of catchments characteristics, and the accuracy of runoff simulation depends on how the relevant parameters are defined (Wang et al. 2012; Sankar and Kumar 2012). Therefore, it is very important to calibrate those parameters efficiently. Calibration of the parameters is a crucial step in the rainfall-runoff models and it can be carried out either by manual methods or using automatic calibration methods. In the past, manual methods of calibration were commonly used and they were tedious and time consuming processes (Cheng et al. 2002; Reshma et al. 2015). Moreover, calibration result will vary with respect to person and there is need for local hydrology expert.

To overcome the difficulties of manual method, the computer based automatic calibration approaches have been developed and they received a great deal of attention. A lot of research is available on the application of traditional optimization methods for automatic calibration of rainfall-runoff model (only some parts have been listed here; Harpa et al. 2006; Pinheiro and Naghettini 2013). However, some important hydrograph characteristics, i.e. peak runoff, volume of runoff and time to peak are difficult to estimate with traditional optimization methods and it is not an easy task to get global optima using traditional optimization methods. Moreover, calibration based on a single objective function is often inadequate to simulate all the important characteristics of the observed data. Recently soft computing techniques like Genetic Algorithm (GA) (Khu et al. 2001; Cheng et al. 2006; Fang and Ball 2007; Chaid and Sujin 2009; Lio et al. 2011; Wu et al. 2012; Amir et al. 2013; Khazaei et al. 2014; Krebs et al. 2014; Yang et al. 2014), Artificial Neural Networks (ANN) (Kermani et al. 2013) and fuzzy methods (Pesti et al. 1996; Kayastha et al. 2013) have become most widely used techniques for solving a number of hydrology and water resource problems. In combination techniques, two or three soft computing tools are coupled to get the advantages from both of them (Yu and Yang 2000; Nayak et al. 2004; Rajesh and Michael 2008; Regulwar and Raj 2008; Talei et al. 2010; Zahraie and Hosseini 2010; Dorum et al. 2010; Alexandre et al. 2012; Kamali and Mousavi 2014).

Many researchers adopted these soft computing techniques (i.e. GA, fuzzy logic and ANN) to calibrate model parameters of continuous (daily or monthly hydrometric data) watershed models (Yu and Yang 2000; Cheng et al. 2002, 2006; Nayak et al. 2004; Harpa et al. 2006; Rajesh and Michael 2008; Lio et al. 2011; Wu et al. 2012; Kayastha et al. 2013; Pinheiro and Naghettini 2013) and more

recently by Khazaei et al. (2014) and Yang et al. (2014). However, very few studies attempted to calibrate the model parameters of event based (hourly or sub-hourly hydrometric data) watershed models (Talei et al. 2010; Sankar and Kumar 2012; Kamali and Mousavi 2014; Reshma et al. 2015). But, for watershed management activities and for designing of hydraulic structures in small and micro watersheds (where the overland flow is the main contributor to peak runoff/flow), there is a need for an event based rainfall runoff model with proper automatic calibration methodologies.

Therefore, in the present study, an automatic calibration method for an event based rainfall-runoff model is developed using Fuzzy Rule-Based Model (FRBM) and Multi-objective Genetic Algorithm (MGA). In particular, FRBM is developed to select the optimal solution of MGA and it is integrated with MGA. Subsequently the FRBM based MGA is integrated with an event based rainfall-runoff model for parameter optimization. GA is computerized search and optimization algorithm based on the mechanics of natural genetics and natural selection (Rajasekaran and Pai 2012). The advantage of GA is that, it is adaptive and one can learn from experience and it is efficient for solving complex problems. GA based automatic approaches can be carried out by considering single objective or multi objective problems. As mentioned before, calibration with a single objective is often insufficient to satisfy the event based analysis and catchment characteristics. Therefore, in this study, MGA with three objective functions is used to optimize the parameters. Moreover, selecting an optimal solution in MGA is difficult using traditional methods because of multiple objective functions (i.e. when many objective functions are included in the calibration, the number of Pareto optimal solutions also increases, then the optimization problem becomes a decision-making problem). Therefore, in the present study, FRBM is developed to select the best solution of MGA that is integrated with MGA.

2 Event Based Rainfall-Runoff Model: Structure and Calibration Parameters

The present study uses an event based rainfall-runoff model developed by Reddy et al. (2011). In this model, Green–Ampt Mein Larson (GAML) method is used to estimate the infiltration and kinematic wave equations are solved for a channel network using the finite element method to estimate the surface runoff. Governing equations and model formulation for this event based rainfall - runoff model can be seen in Reddy et al. (2007, 2011). In Reddy et al. (2011) model, with other inputs, calibration was carried out by interactively changing the infiltration parameters like saturated hydraulic conductivity (K_s), average capillary suction at the wetting front (S_{av}), initial water content (θ_i) and saturated water content (θ_s) within physically realistic limits. The present paper focuses on the calibration of infiltration and roughness parameters of the event based rainfall-runoff model using Fuzzy-MGA approach. The Fuzzy based MGA integrated runoff model consists of hourly and sub hourly based rainfall data as an input and the output runoff is simulated for 30 s each.

In the present study to estimate infiltration rate GAML (Mein and Larson 1973) method is used which is as follows:

$$f_p = K_s \left[1 + \frac{Ms_c}{F} \right] \tag{1}$$

where f_p is infiltration capacity (cm/h), K_s is saturated hydraulic conductivity (cm/h), M is initial moisture deficit, s_c is capillary suction at the wetting front (cm), F is cumulative infiltration (cm). Initial moisture deficit M can be expressed as follows:

$$M = \theta_s - \theta_i \tag{2}$$

where θ_s is saturated water content and θ_i is initial water content. The basic equation for continuity and momentum equations for kinematic wave are given in Reddy et al. (2011) and Reshma et al. (2015).

The final form of the Finite Element Method (FEM) equation for a kinematic wave equation, which is used to simulate the overland flow is as follows (Reddy et al. 2011):

$$[C]\{h\}^{t+\Delta t} = [C]\{h\}^t - \Delta t [B]\{(1-\omega)q^t + \omega q^{t+\Delta t}\} + \Delta t\{f\}\left((1-\omega)(r_e)^t + \omega(r_e)^{t+\Delta t}\right) \tag{3}$$

where h is the depth of flow (m), q is the unit width flow (m^2/s), r_e is excess rainfall rate (m/s), superscripts t and t + Δt indicate the variables at the previous time step and the current time step. ω is the factor that determines the type of finite difference scheme involved. Crank–Nicolson scheme with $\omega = 0.5$ is used in this study. [C], [B] and {f} are global matrices. The one-dimensional kinematic equation for channel flow was considered by Reddy et al. (2011). The continuity and momentum equations for channel flow has been discussed and given in Reddy et al. (2011) and Reshma et al. (2015).

The final matrix form of the FEM equation, which is used for the simulation of the channel flow, is as follows (Reddy et al. 2011):

$$[C]\{A\}^{t+\Delta t} = [C]\{A\}^t - \Delta t [B]\{(1-\omega)Q^t + \omega Q^{t+\Delta t}\} + \Delta t\{f\}\left((1-\omega)q^t + \omega q^{t+\Delta t}\right) \tag{4}$$

where A is area of flow in the channel (m^2) and Q is discharge in the channel (m^3/s).

3 Fuzzy-MGA Methodology for Parameter Calibration

Infiltration, overland and channel Manning's roughness parameters are the main parameters determining runoff generation process. The GAML model infiltration parameters K_s, S_{av}, θ_i, and θ_s and Manning's roughness parameters of overland flow (n_o) and channel flow (n_c) are optimized with MGA. Manning's roughness, n_o and n_c are land use variables and they vary within the watershed for each rainfall event. The initial values of Manning's roughness, n_o and n_c are assigned based on land use (Vieux et al. 2004). Multiplication scale factors are used to optimize these two parameters (range of multiplication scale factor is restricted based on physical realistic limit of the roughness parameter).

The percentage error of peak runoff, volume of runoff and time to peak runoff are important performance measures to evaluate the real-time flood forecasting and flood simulation (Cheng et al. 2002). An appropriate objective function is essential for successful calibration schemes. To compare the performance of model calibration, two conventional objective functions, Nash Sutcliffe Efficiency (NSE) and Coefficient of Determination (R^2), and one transformed volume difference $f(V)$ are considered to calibrate Fuzzy based MGA integrated runoff model and they are given by Eq. (5), Eq. (6), and Eq. (7) respectively.

$$NSE = \left(1 - \frac{\sum\limits_{i=1}^{n}(Q_i - S_i)^2}{\sum\limits_{i=1}^{n}\left(Q_i - \overline{Q}\right)^2}\right) \tag{5}$$

$$R^2 = \left(\frac{\sum\limits_{i=1}^{n} \left(Q_i - \overline{Q}\right)\left(S_i - \overline{S}\right)}{\sqrt{\sum\limits_{i=1}^{n} \left(Q_i - \overline{Q}\right)^2}\sqrt{\sum\limits_{i=1}^{n} \left(S_i - \overline{S}\right)^2}} \right)^2 \tag{6}$$

$$f(V) = \frac{1}{1 + \Delta V} \tag{7}$$

where, Q_i is observed runoff, $\overline{Q}$ is the mean of observed runoff values, S_i is simulated runoff, $\overline{S}$ is the mean of simulated runoff values, ΔV is volume difference and given as $\Delta V = |V_o - V_s|$, V_o is the total volume of observed runoff, and V_s is the total volume of simulated runoff. The range of NSE value varies from $-\infty$ to 1 and the R^2 value varies from 0 to 1. The range of ΔV varies from 0 to ∞, however, $f(V)$ value varies from 1 to 0. All three objective functions are maximized to optimize six calibration parameters.

As mentioned before, unlike single objective problem, selecting the best solution in multi objective problem is complex because of the involvement of multiple objective functions. In the present study, the Pareto optimal solutions (i.e., on the Pareto front) are identified in MGA using Nondominated Sorting method. In this, fitnesses of the separate objectives are treated independently and never combined. Solutions are ranked into 'non-dominated' order (i.e. feasible solutions), with the fittest being solutions dominated the least by others (Goldberg 1989; Srinivas and Deb 1994). As the Pareto optimal solutions are superior to other solutions and the number of Pareto optimal solutions will increase for the consecutive higher generation, the alternative value is calculated only for Pareto optimal solutions using FRBM. The best solution among all Pareto optimal solutions is identified based on alternative values of Pareto optimal solutions (Srinivas and Deb 1994). For this study, a FRBM is developed in C language to calculate the alternative value for the corresponding objective function values of Pareto optimal solutions of the MGA and it is integrated with the available MGA code (Srinivas and Deb 1994) and the event based rainfall-runoff model (Reddy et al. 2011). The methodology flowchart for integrated Fuzzy-MGA based runoff model is shown in Fig. 1.

General steps in the integrated runoff model for calibration of six parameters using Fuzzy based MGA are as follows:

Step 1: Initially, the required GA and runoff model inputs are given to the integrated model. The detail information about the integrated runoff model inputs is discussed in Reshma et al. (2015). For this study, the calibrated parameter values for Harsul and Khadakohol watersheds obtained from Reddy et al. (2011) are used as base values to fix the upper and lower boundary limit of MGA (Vieux et al. 2004; Reddy et al. 2011), such that the optimal value will achieve with a limited number of generation and populations. Hence, the generation and population size has been fixed for 100 and 12 respectively. Three objective functions NSE, R^2 and $f(V)$ have been used to optimize six variables for calibration of the model. The upper and lower boundaries of parameters of Walnut Gulch watershed have been fixed for each rainfall event with the available information (Keefer et al. 2008). Roulette wheel selection and uniform crossover have been considered with 0.9 cross over probability and 0.2 mutation probability.

Step 2: For generation zero, a set of initial population (12 sets of 6 variables) is created in MGA based on given inputs, especially lower and upper boundaries of variables. Each set of variable is transferred to rainfall-runoff model. With other inputs, the rainfall-runoff model is simulated for runoff. The objective function values are calculated between observed and simulated runoff and these values are transferred
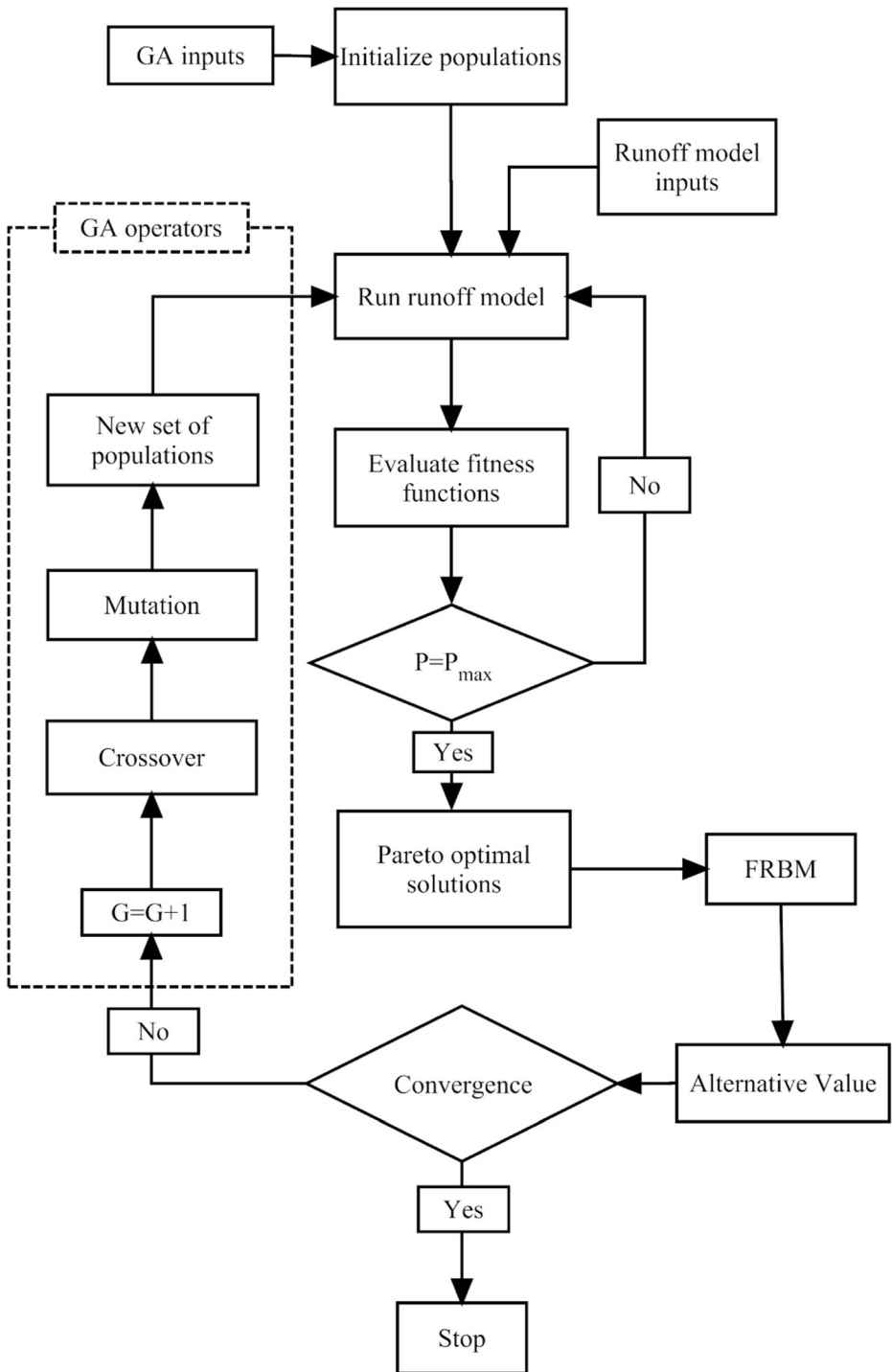
Fig. 1 Methodology flowchart of Fuzzy-MGA based runoff model

back to MGA. Once the fitness function values for all populations are calculated, the populations are sorted using Nondominated Sorting method and all Pareto optimal solutions are assigned to rank one. For all other generations, except for generation zero, the populations are created based on previous generation populations (parent population) with MGA operations such as selection, crossover and mutation for a given crossover probability, mutation probability and selection method.

Step 3: FRBM is developed to calculate the alternative value for the corresponding fitness function values of Pareto optimal solutions of the MGA. Figure 2 shows the methodology flowchart of the developed FRBM. Each Pareto optimal solutions and corresponding fitness functions value obtained from MGA has been transformed to the FRBM one by one. The objective function NSE is transformed as an exponential function, given in Eq. (8), and used as first input of FRBM.

$$T_{NSE} = e^{(NSE)} = e^{\left(1 - \frac{\sum_{i=1}^{n}(Q_i - S_i)^2}{\sum_{i=1}^{n}\left(Q_i - \overline{Q}\right)^2}\right)} \tag{8}$$

Where T_{NSE} is the transformed NSE and its value varies from 0 to 2.718. The objective functions R^2, $f(V)$ are directly used as second and third inputs of FRBM.

The FRBM inputs are divided into a number of fuzzy sets with adequate overlap. The membership functions of three inputs are plotted in Fig. 3a, b, c. All fuzzy sets, except end sets, are represented by acute-angled triangle membership functions and
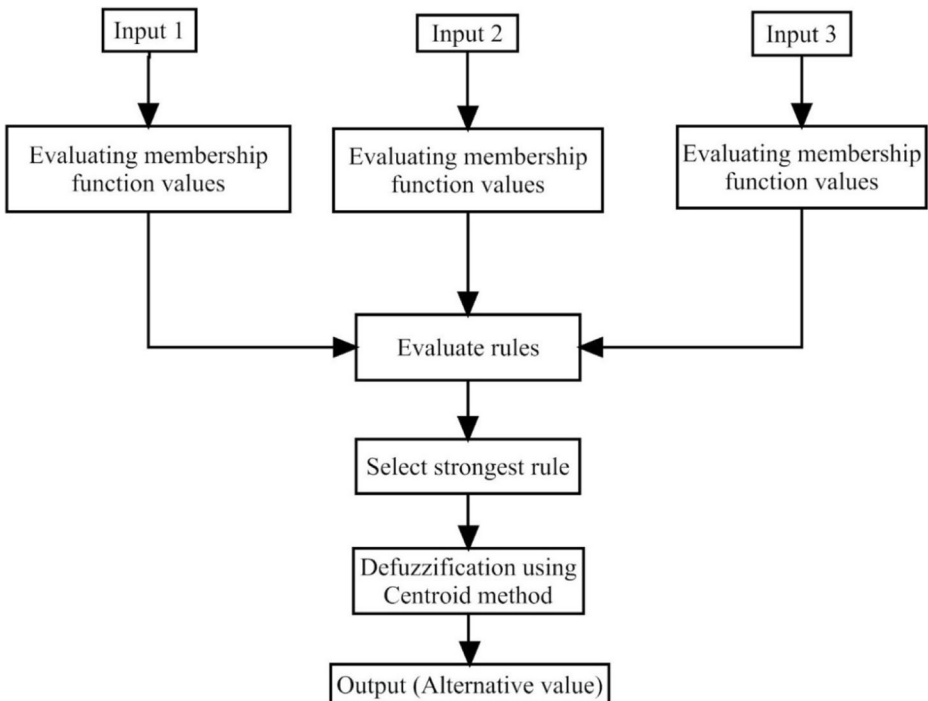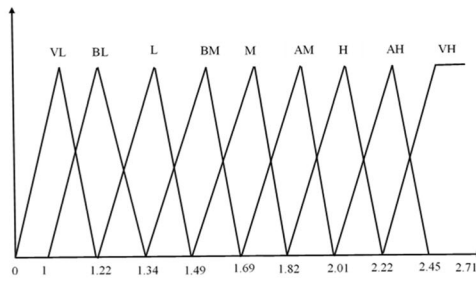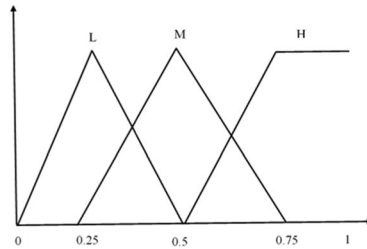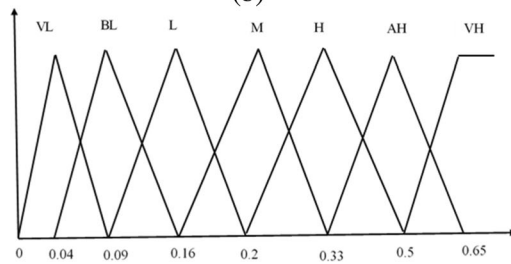

Fig. 2 Flowchart of FRBM
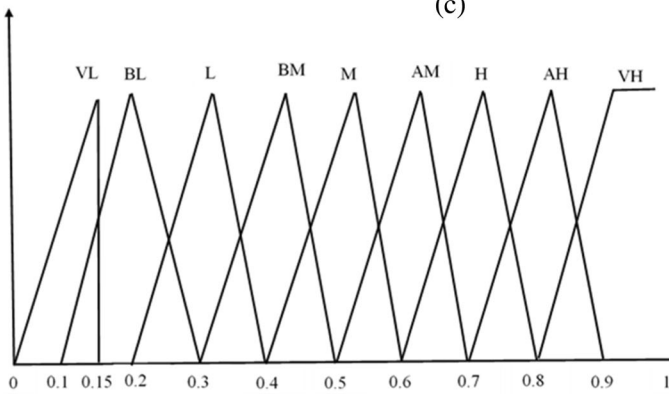
Fig. 3 Membership function of **a** e^NSE, **b** R², **c** *f(V)* and **d** output membership function

the end sets are represented by a combination of right-angled triangle and rectangle membership functions. The degree of membership ($\mu_A(x)$) for value x of a fuzzy set is calculated using Eq. (9).

$$\mu_A(x) = \min \begin{pmatrix} D1^*S1 \\ D2^*S2 \\ 1 \end{pmatrix} \tag{9}$$

where, S1, S2 are slopes, and D1, D2 are linear distances. The value of $\mu_A(x)$ is zero when x is larger than the upper limit (A_U) and lesser than lower limit (A_L) of the set A. The membership function values for fuzzy sets of each input, i.e. e^{NSE} (input 1), R^2 (input 2), $f(V)$ (input 3) are calculated using Eq. (9).

Based on all possible three input combinations (Refer Fig. 3a, b, c), a total of 189 rules are formulated and each rule strength is calculated using Eq. (10). The strength of each rule is the minimum degree of membership functions of the inputs.

$$Rule[i] = \min(mfvf1[j], mfvf2[k], mfvf3[l]) \ \ i < 190, j < 10, k < 4, l < 8 \tag{10}$$

where, $mfvf1$, $mfvf2$ and $mfvf3$ are the membership function value of input one, two and three respectively. For brevity, the 189 rules are not listed in this paper and the first rule is given below.

Rule-1: When e^{NSE} is very low, R^2 is low and $f(V)$ is very low then the output is very low (refer Fig. 3).

The 189 rules are then categorized into nine output fuzzy sets. After rules are evaluated, the strongest in each category is the output membership function value. The membership function values of nine output fuzzy sets are calculated using the following equations.

$$outputfuzzyset[1]value = \max(rule[1], rule[2], ..., rule[21]) \tag{11}$$

$$outputfuzzyset[2]value = \max(rule[a+1], rule[a+2], ..., rule[42]) \tag{12}$$

$$\begin{matrix} . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \end{matrix} \tag{13}$$
$$outputfuzzyset[9]value = \max(rule[h+1], rule[h+2], ..., rule[189])$$

In this study, the 189 rules are equally divided into 9 groups. The output membership function is graphically plotted in Fig. 3d. As this study uses the centroid method for defuzzification, where only very low fuzzy sets qualify, if we use an acute angle triangle for very low (VL) fuzzy set of output membership function, the output alternative value will be the same regardless of fuzzy set values. Thus, a right-angle triangle used for very low (VL) fuzzy set in the output membership function. In the event of more than one rule qualifying for the same fuzzy output, the stronger among them is chosen. The fuzzy outputs are then defuzzified using the centroid method which is given by Eq. (14).
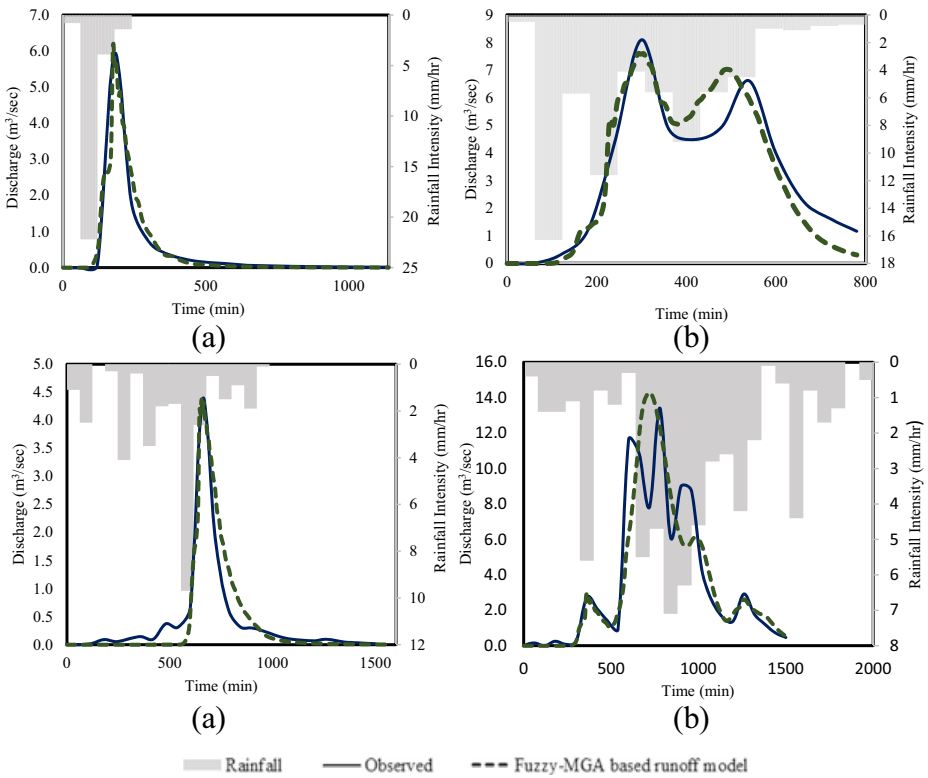
Fig. 4 Observed and simulated hydrographs generated by Fuzzy-MGA based runoff model for Harsul watershed **a** Sep 23, 1997 **b** Jul 26, 1997 **c** Aug 04, 1997 **d** Aug 24, 1997

$$x^* = \frac{\sum\limits_{i=1}^{n} x_i . \mu(x_i)}{\sum\limits_{i=1}^{n} \mu(x_i)} \tag{14}$$

here, n is the total number of sets in the output, $\mu(x_i)$ is the degree of membership function of ith set, and x_i is the centroid of set i. The defuzzified value is the alternative value of the corresponding Pareto optimal solution and it varies from 0 to 0.922.

If the alternative value satisfies the convergence or MGA generation reaches 100, then the processes are stopped, and runoff is simulated for the best ever solution.

4 Application Examples

The integrated model has been applied to two Indian watersheds and one experimental watershed located in USA and the figures of location map of Harsul, Kadhakohol and Walnut Gulch experimental watersheds are shown in Reshma et al. (2015). Harsul watershed is located in Nasik district, Maharashtra, India with an area of 10.929 sq.km. The major soil type in the watershed is gravelly loam. The watershed consists of three major Land Use/Land Cover (LU/LC) classes, i.e. agricultural land, forest land and waste land. Kadhakohol watershed is located

in Nashik district, Maharashtra, India. The watershed has an area of 5.89 sq.km. The major soil type in the watershed is sandy silt loam. The major LU/LC classes are cultivated land, forest land and fallow land.

The Walnut Gulch Experimental watershed is located in Arizona State of United State of America. Soils of the Walnut Gulch Experimental Watershed are pre-dominantly sandy and gravely loams. Major watershed vegetation includes the grass species and shrub species. The Walnut Gulch watershed consists of 42 major sub watersheds. The sub watershed, which is selected in the present study has an area of 7.8 sq.km. Digital Elevation Model (DEM), LU/LC, soil and rainfall data for this watershed have been downloaded from the USDA-ARS website (http://www.tucson.ars.ag.gov/dap/).

5 Results and Discussions

5.1 Harsul Watershed

For Harsul watershed, eleven rainfall events with varying duration of 120 min to 3060 min have been simulated using the developed integrated model. The Harsul watershed simulated results of Fuzzy-MGA based runoff model and observed hydrographs are given in Fig. 4.

From the hydrographs, it is evident that the Fuzzy-MGA based runoff model simulated hydrographs are very close to the observed hydrograph. Fuzzy-MGA based runoff model simulated results reveal that the volume of runoff has been simulated within the variation of 0 to 46.8%, and peak runoff has been simulated within the variation of 0.1 to 43%, and time to peak has been simulated within the variation of 0 to 12.7%.

5.2 Khadakohol Watershed

In case of Khadakohol watershed, seven rainfall events with varying duration of 180 min to 780 min, have been simulated using the developed Fuzzy-MGA based runoff model. The observed Fuzzy-MGA based runoff model simulated hydrographs of Khadakohol watershed are given in Fig. 5.

From the simulated results of Khadakohol watershed with integrated runoff model, it is seen that the volume of runoff has been simulated to within the variation of 0 to 43.5%, peak runoff has been simulated to within the variation of 4.2 to 37.8%, and time to peak has been simulated to within the variation of 1.58 to 8.8%. From the simulation results, it is observed that the Fuzzy-MGA based runoff model has better predicted the hydrographs.

5.3 Walnut Gulch Experimental Watershed

For Walnut Gulch Experimental watershed, four rainfall events (varying duration of 142 min to 235 min) have been simulated using the developed integrated model. The observed and simulated hydrographs from Fuzzy-MGA based runoff model are shown in Fig. 6.

From the simulated results of Walnut Gulch experimental watershed with integrated runoff model, it is noted that the volume of runoff has been simulated to within a variation of 0 to 6%, peak runoff has been simulated to within the variation of 2.9 to 16% and time to peak has been simulated to within the variation of 3.1 to 32%. Results of Walnut Gulch experimental watershed shows that the developed Fuzzy-MGA based runoff model has better performance.
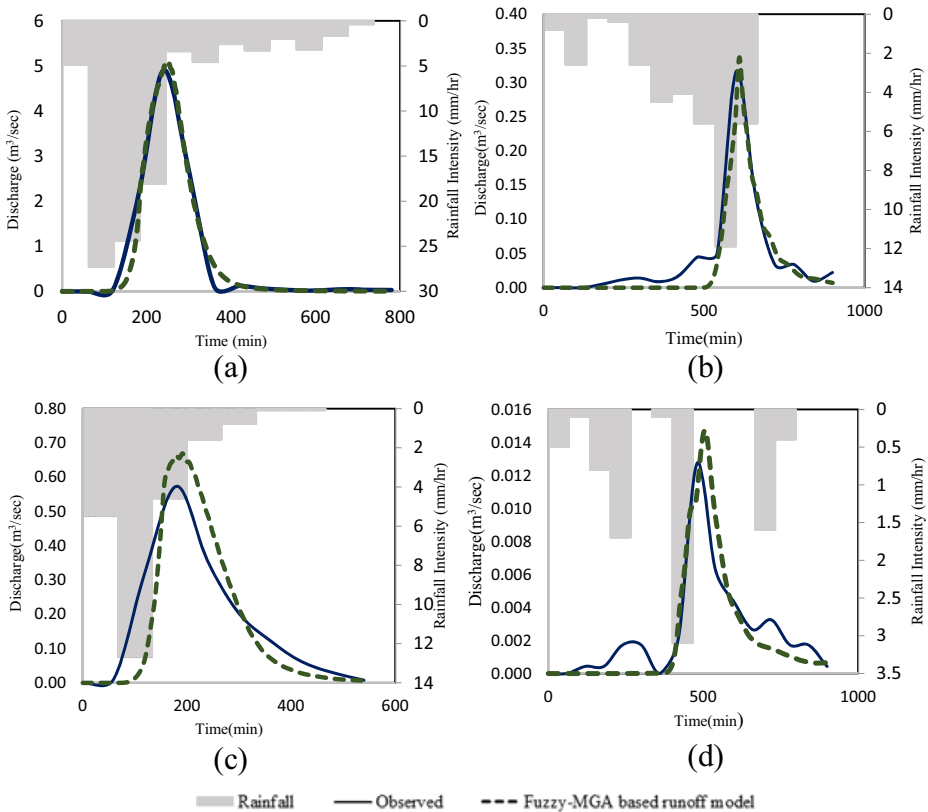
Fig. 5 Observed and simulated hydrographs generated by Fuzzy-MGA based runoff model for Khadakohol watershed **a** Aug 23, 1997 **b** Aug 25, 1997 **c** Jul 25, 1997 **d** Aug 07, 1997

The results of the developed integrated runoff model for three watersheds (i.e. Harsul, Kadakhoal, and Walnut-Gulch) are given in Table 1 and the statistics of the result is shown in Table 2. Average percentage error is the ratio between the sum of all events, absolute error percentage in a criteria and the total number of events in the watershed. From the previous study (Reshma et al. 2015) simulation results of Harsul watershed with Single-objective Genetic Algorithm (SGA) and Multi-objective Genetic Algorithm (MGA) integrated runoff model, for twelve rainfall events, the average percentage error for volume of runoff, peak runoff and time to peak are [44.76% 39.42%], [22.25% 17.96%] and [25.5% 25.19%] respectively. From the simulated results of Harsul watershed with Fuzzy based MGA integrated runoff model, for same rainfall events, the average percentage error of volume of runoff, peak runoff and time to peak are ±11.29%, ±14.26% and ±5.29% respectively. The model performance evaluator value, NSE, for Harsul watershed varies from +0.293 to +0.938 with an average value of +0.650 for the Fuzzy based MGA integrated runoff model.

From the simulation results of Reshma et al. (2015) study with SGA and MGA integrated runoff model of Khadakohol watershed, for seven rainfall events, it was observed that average percentage error of volume of runoff, peak runoff and time to peak are [39.83% 36.53%], [56.27% 22.02%] and [14.61% 12.06%] respectively. In Khadakohol watershed, from seven events, the results of the developed integrated rainfall-runoff model, the average percentage error of the volume of runoff, peak runoff and time to peak are 13.08%, 16.63% and 4.79%
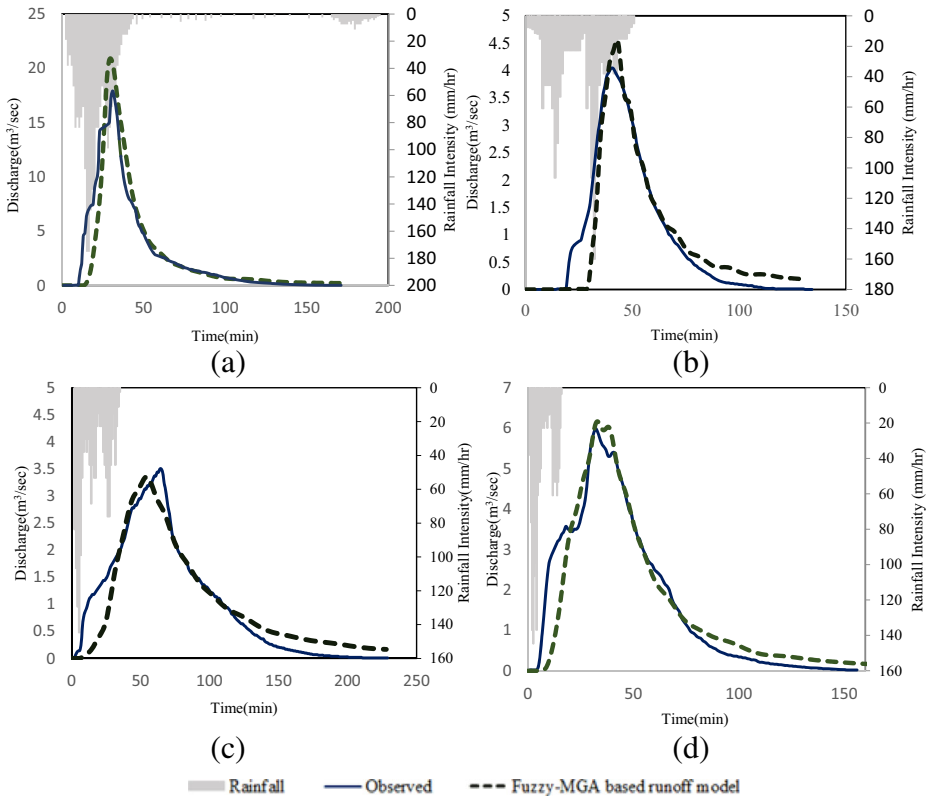
Fig. 6 Observed and simulated hydrographs generated by Fuzzy-MGA based runoff model for Walnut Gulch watershed **a** Jul 20, 2007 **b** Aug 23, 2009 **c** Aug 28, 2008 **d** Aug 28, 2010

respectively and the variation in NSE value is observed from +0.673 to +0.979 with an average NSE value of +0.848.

From the simulated results of SGA and MGA integrated runoff model of Reshma et al. (2015), it is observed that the average percentage error for volume of runoff, peak runoff and time to peak are [30.85% 30.17%], [10.61% 9.03%] and [36.68% 36.52%] respectively. With the Fuzzy based MGA integrated model simulated results, for same rainfall events, it is observed that average percentage error of volume of runoff, peak runoff and time to peak are ±1.19%, ±7.07%, and ±13.64% respectively and the NSE value varies from +0.791 to +0.935 with an average of +0.891.

The results of developed integrated model of all three watersheds show that the mean percentage error of all three aspects (volume of runoff, peak runoff, time to peak) is less than 16.63%. From the results it is evident that the developed integrated model is consistent and accurate in all aspects.

In the previous study, the optimization of parameters for event based rainfall runoff model is conducted using SGA and MGA integrated runoff model and HEC-HMS model for the same watersheds (Reshma et al. 2015). In that study, range of NSE values for study watersheds with integrated MGA, integrated SGA and HEC_HMS models are [−0.61 to 0.79], [−0.5 to 0.74] and [−3.37 to 0.82] respectively. For the present study, the range of NSE values obtained for all three watersheds using Fuzzy based MGA integrated runoff model is [0.29 to 0.93]. The

Table 1 Results of developed integrated model

Rainfall events	Volume of runoff (mm)		Peak runoff (m³/s)		Time to peak (min)	
	Obs	Sim_FRBM_MGA	Obs	Sim_FRBM_MGA	Obs	Sim_FRBM_MGA
Harsul Watershed						
22081997	11.01	14.85 (−34.90%)	16.56	11.27 (31.89%)	360	373.50 (−3.75%)
23091997	3.24	3.23 (0.31%)	5.93	6.20 (−4.65%)	180	176 (2.22%)
04081997	3.43	3.43 (0.00%)	4.38	4.37 (0.23%)	660	654.50 (0.83%)
27071997	21.81	22.75 (−4.31%)	8.50	6.82 (19.67%)	780	732 (6.15%)
30071997	205.10	205.16 (0.00%)	103.51	79.86 (22.85%)	1080	1080 (0.00%)
25081997	10.43	5.54 (46.88%)	7.05	7.80 (−10.70%)	600	549.50 (8.42%)
26071997	14.37	14.38 (−0.07%)	8.10	7.61 (6.05%)	300	271 (9.67%)
24081997	30.49	30.49 (0.00%)	13.41	14.29 (−6.56%)	780	723 (7.31%)
21081997	0.91	1.04 (−14.51%)	1.50	0.85 (43%)	600	589 (1.83%)
26091997	7.69	7.69 (0.00%)	4.22	4.86 (−15.28%)	240	209.50 (12.71%)
23081997	35.58	27.3 (23.27%)	20.40	20.38 (0.10%)	840	884.50 (−5.30%)
Khadakohol Watershed						
23081997	6.24	6.24 (0.00%)	4.90	5.11 (−4.29)	240	250.50 (−4.38%)
25081997	0.42	0.33 (21.88%)	0.32	0.33 (−5.00%)	600	609.50 (−1.58%)
24091997	6.16	3.48 (43.51%)	8.85	12.20 (−37.85%)	120	124 (−3.33%)
22081997	2.40	2.56 (−6.49%)	3.61	3.35 (7.08%)	180	172.50 (4.17%)
26091997	0.24	0.25 (−3.69%)	0.21	0.24 (−13.43%)	240	250.50 (−4.38%)
20091997	0.06	0.05 (11.78%)	0.01	0.02 (−32.09%)	480	522.50 (−8.85%)
25071997	1.04	0.97 (5.82%)	0.57	0.66 (−17.37%)	180	191.50 (−6.39%)
07081997	0.02	0.021 (11.52%)	0.01	0.014 (−15.98%)	480	505.50 (−5.31%)
Walnut Gulch Watershed						
20072007	3.80	3.80 (−0.21%)	17.90	20.90 (−16.81%)	31.00	29.50 (4.84%)
23082009	0.93	0.93 (0.00%)	4.04	4.55 (−12.62%)	52.00	42.50 (18.27%)
28082008	1.77	1.78 (−0.62%)	3.50	3.35 (4.17%)	81.00	54.50 (32.72%)
28082010	2.00	2.12 (−6.00%)	5.99	6.16 (−2.92%)	32.00	33.00 (−3.13%)

Obs Observed, *Sim* Simulated

comparison of the results reveal that the performance of Fuzzy based MGA integrated runoff model has significantly increased. The main limitations of the model are large amount of data and observed runoff. Reddy et al. (2011) event based model will simulate runoff for each 30 s and this is regard less of observed time step (rainfall). Thus, the Reddy et al. (2011) runoff model's percentage error includes the deviation in simulated runoff between each hour.

Table 2 Summary of results

Criteria	Watershed name	Fuzzy-MGA based runoff model	
		Range	Mean
Volume of runoff (mm)	Harsul	±0.00 to ±46.88%	11.29
	Khadakohol	±0.00 to ±43.51%	13.08
	Walnut Gulch	±0.00 to ±6.00%	1.70
Peak runoff (m³/s)	Harsul	±0.10 to ±43.00%	14.63
	Khadakohol	±4.29 to ±37.85%	16.63
	Walnut Gulch	±2.92 to ±16.81%	9.13
Time to peak (min)	Harsul	±0.00 to ±12.71%	5.29
	Khadakohol	±1.58 to ±8.85%	4.79
	Walnut Gulch	±3.13 to ±32.72%	14.74

6 Conclusions

In this study, which aims at optimizing parameters of an event based runoff mode, an FRBM has been developed and integrated with MGA to select the best solution from MGA. Further, the Fuzzy based MGA is integrated with an event based runoff model to optimize six parameters of the model. In addition, the developed Fuzzy-MGA based runoff model has been tested on three watersheds namely, Harsul watershed, Kadhakohol watershed and Walnut Gulch Experimental watershed. The simulation results from the Fuzzy-MGA based runoff model have been compared with the observed data. From the simulated events of three watersheds using the developed Fuzzy-MGA based runoff model, it is observed that the mean percentage error in any criteria (i.e. volume of runoff, peak runoff, and time to peak) for a watershed is less than 16.33%. From the SGA and MGA integrated runoff model simulated results (Reshma et al. 2015), it was observed that the MGA integrated runoff model has performed better than the SGA integrated runoff model results in all criteria. Even though the MGA integrated runoff model results are improved when compared to the SGA integrated runoff model results, it is difficult to select the optimal solution of MGA using traditional combining methods. Hence, FRBM model has been developed to select the alternative value from the Pareto optimal solutions. Therefore, Fuzzy –MGA based integrated model performed better for all three watersheds. It is also noted that the developed Fuzzy-MGA based runoff model is able to produce hydrographs that are much closer to the measured hydrographs.

Compliance with Ethical Standards

Conflict of Interest None.

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