Stream flow forecasting by artificial neural network (ANN) model trained by real coded genetic algorithm (GA) — A case study when role of groundwater flow component in surface runoff is small —

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Abstract
Runoff analyses are important to efficiently manage the watersheds such as the precise prediction of discharge. Runoff is mainly composed of surface and groundwater flow components, therefore hydrological conditions should be well described before any runoff analysis. In this study, runoff analyses were performed for two small sub-basins of a mountainous catchment of Tono area Japan with the aim to forecast runoff after 1 and ½ hours by using 3 different numerical models and performances of these models were compared to each other. The runoff and other meteorological data have been collected in these sub-basins over the last 14 years. The effect of the basin area on the prediction time of runoff and the seasonal data impacts were also investigated. For the analyses, a new approach of training artificial neural network model (ANN) with real coded genetic algorithm (GA) named as GAANN model is proposed. The results of this model were compared with famous back propagation artificial neural network (BPANN) model and with multivariate autoregressive moving average model (MARMA). It was found that for very small catchments, seasonal effect on the runoff is dominant and this effect should be considered for obtaining better forecasting estimates. It was also found that estimation by ANN models was better than MARMA model for analyzing the responses to intense rainfalls in summer, whereas the results were almost similar for the light rains of winter season. The accuracy of the forecasts after several time periods in future was also investigated and found to decrease as the time period is increased. The results showed that GAANN and BPANN models almost provided similar prediction estimates in a very small mountainous watershed when precisely measured dataset was used. Modelling advantages of using genetic algorithm instead of backpropagation for the training of ANN models are also highlighted.

Key Words: Tono test field; Artificial neural network; Genetic algorithm; Rainfall—runoff process; Small watersheds; Rainy and dry seasons; ARMA models; Runoff analysis

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1. Introduction

One of the key factors in the water resources management is the forecasting of runoff for the flood control and design of hydraulic structures. Rainfall runoff (R-R) process is a complex phenomenon and is a function of many parameters among which, groundwater and soil conditions significantly affect the generation of surface runoff. The rate of rainwater seepage as groundwater is different at different instances during a rainfall event, and largely depends upon the saturation conditions of soil and underground geology. However, when the soil is saturated, large amount of rainwater is available as surface runoff and base flow, with little percentage percolating as groundwater. It is therefore necessary to understand the role of base flow and groundwater in the generation of surface runoff during a rainfall event. This role further becomes highly important when we are dealing with small steep mountainous watersheds, and should be studied in detail to better understand the R-R process, and for more exact predictions of runoff. For the reason, a brief account of the site geological conditions is provided in this paper, to understand the contribution of shallow and deep groundwater, in the generation of rapid runoff observed during the rainfall event.

Traditionally, the modelling approaches applied to forecast runoff can be classified as lumped conceptual models, distributed physically based models and black-box or system theoretical models (Dooge, 1977; Tingsanchali and Gautam, 2000). Conceptual and physically based models, although try to account all the physical processes of rainfall runoff (R-R) phenomena, but their successful use is restricted by a need for catchment specific parameters, and simplifications involved in solving the governing equations (Hsu et al., 1995; Maria et al., 2004). On the other hand, ANNs, which belong to time series category and are system theoretical models, offer a relatively flexible and quick means of modelling with equally reliable results, and is one of the reasons that applications of artificial neural network models (ANN) in hydrology increased during the last decade, and was also
used in this study.

Most of ANN applications to R-R simulation used feed forward artificial neural networks trained by error back propagation (BP) method and named as BPANN models (Atiya et al., 1999; Campolo et al., 1999; Dawson & Wilby, 1998; French et al., 1992; Gautam et al., 2000; Hsu et al., 1995; Minns & Hall, 1996; Shamseldin, 1997; Todini, 1988). Although, ANN models have been used successfully in these studies, but various difficulties in the applications of BPANN models have been reported, like selection of appropriate values of learning rate and momentum factor, starting values of synaptic weights, number of hidden nodes etc.

To overcome these problems, several architectures and numerous algorithms for the training of the ANN models have been proposed by different researchers, which have their own merits and demerits. For example, Daliakopoulos et al. (2005) used feed forward neural network (FNN), recurrent neural network (RNN) and radial basis function (RBF) and trained these models with three different algorithms i.e. Gradient descent (GD), Levenberg-Marquardt (LM) and Bayesian regularization (BR) for the forecasting of groundwater levels in Greece. He concluded that the FNN model trained with LM was most effective.

In this paper, a relatively new approach of training ANN model with real coded genetic algorithm (GA), named as GAANN model, is proposed and compared with the frequently used BPANN technique. In hydrology, it was only during recent years that some researchers used GA than BP to train the ANN models. The general unawareness about GAANN in hydrology community might be due to the reason that BP algorithm is much simpler than GA in usage and in comprehension. Secondly to use GAANN, one must understands the concepts of both the technologies of GA and ANN. Therefore, until now only a few studies exist in literature using GA to train ANN models (Shamseldin et al., 2002; Rao and Jamieson, 1997; Abrahart et al., 1999; See and Openshaw, 1999; Morshed and Kaluarachchi, 1998; Jain and Srinivasulu, 2004). This insufficient availability of studies gave rise to conflicting results about the importance of one model over the other. For example, Morshed and Kaluarachchi (1998) reported that BP is better than GA for training an ANN model, but on the contrary, Jain and Srinivasulu (2004) claimed that GA is better than BP for training an ANN model to predict daily flows. Therefore, to understand the conditions in which one model is preferable to other, extensive field applications of both these models are required, under different geological and hydrological conditions with good quality data. In Tono research field, the meteorological and runoff data have been measured with 10 minutes time period and is ideal to check the suitability of both these models to a very small mountainous watershed.

This study thus signifies two important aspects of ANN modelling. First, it checks the comparative performance of both BPANN and GAANN models in a very small mountainous watershed for the first time. Secondly, it helps to understand the accuracy of results obtained by ANN models as compared with traditional stochastic models using good quality data from a small catchment. Multivariate autoregressive moving average models (MARMA) have been used as the traditional stochastic models. Moreover, to understand the seasonal data effects on the R-R response major rainfall events from two extreme seasons, summer and winter, are also considered separately.

It should be noted that even though ANN can be well adopted, hydrological conditions of watershed should be well defined. Some researchers (Dawson et al., 2002) also recommended that ANN should not be applied blindly to a catchment, but a complete understanding of the catchment characteristics and hydrological
processes should be developed, to decide factors like lead time selection and input parameters.

2. Description of Study Area and Data Used

2.1 Tono basin and the data acquisition system

Figure 1 illustrates the location and the topographic map of the Tono basin that is the research field of the Tono Geoscience Centre of JAEA (Japan Atomic Energy Agency).

The Tono basin is located at the central part of Japan, and the total area is about 71.63 hectares. The whole basin is subdivided into 4 sub-basins, which are denoted as sub-basin I, II, III and IV as displayed in Fig. 1. The topogra-

Fig. 1 Location map of Tono area and sub-basins detail. Topographic contours are shown as solid lines with elevation (m) shown. Schematic layout of sub-basins in Tono area are also shown.
phy of every sub-basin is classified as the steep hill slopes (slope gradient: 25-35%) and the areas and maximum, minimum elevations of these sub-basins are summarized in table 1.

Numerous instruments for measuring meteorological and hydrological data are installed in the basin, and Parshall flumes at four gauging stations IPU, SPU, TPU and SPD are used to measure discharge from four sub-basins at 10 min. time interval (Fig. 1). The data is measured automatically, and sent to a central computer where it is stored in a database. Although the data has been measured at four stations but the complete data of 14 years of only two stations SPU and SPD was available. The data of other two stations was available for only a few years that too contained a lot of missing rainfall events. Therefore, the calculations in this study are based on the data obtained at SPD and SPU. It can be observed from Fig. 1 that the flow data at SPD basically represents the accumulated runoff from 3 sub-basins, I, II and IV (shaded portion in Fig. 1) whereas data at SPU represents data from sub-basin II only. Meteorological station is located in sub-basin I (Fig. 1) and measures data related to temperature, pressure, humidity, evaporation, wind speed, wind directions etc at 10 min. interval.

### Table 1 Tono area catchment characteristics (Sub-basin I, II, III, IV are shown in Fig. 1)

<table>
<thead>
<tr>
<th>Sub-basin</th>
<th>Gauging station</th>
<th>Sub-basin area (ha)</th>
<th>Max/Min elevation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>IPU</td>
<td>0.985</td>
<td>317/270</td>
</tr>
<tr>
<td>II</td>
<td>SPU</td>
<td>11.4</td>
<td>328/256</td>
</tr>
<tr>
<td>III</td>
<td>TPU</td>
<td>6.36</td>
<td>317/257</td>
</tr>
<tr>
<td>IV</td>
<td>SPD*</td>
<td>52.88</td>
<td>328/224</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>71.625</strong></td>
<td></td>
</tr>
</tbody>
</table>

* The SPD gauging station shows accumulated discharge from three sub-basins namely I, II & IV

2.2 Geology and surface conditions of basin:

The Tono basin is geologically composed of two types of rocks; granite forming the basement of the area and Tertiary sedimentary rocks overlaying the basement. The average thickness of the Tertiary sedimentary rock is around 150m, and is further divided into two geological units, the Seto group and the Mizunami group from the top. The Toki ignimbrite formation is locating at the bottom of Mizunami group. The schematic geological cross-sections of the area are illustrated in Fig. 2(a).

The Seto group, mainly composed of poorly consolidated conglomerate layer, lies beneath the surface soil layer. Some portions of rainwater may infiltrate into the Seto group and flows down as a base flow (Gautam et al., 2000; Watanabe, 1993). The rock of the Mizunami group, below the Seto group, is mainly composed of low permeable silt and clay layers except for the Toki formation, and the groundwater in this group may not contribute much in the rapid runoff process. The Toki ignimbrite formation is composed of sand and conglomerate, and the hydraulic conductivity is larger than the Mizunami group. Some tunnels of the Tono uranium mine (Fig. 1 & 2) were excavated in this layer and in granite rock at the depth of 130m-150m, and have been used for the research of groundwater flow. By
the continuous pumping from the tunnels, the groundwater table of deep aquifer may be lower than the invert level of Parshall flumes and also due to the low hydraulic conductivity of the Mizunami group, the deep aquifer does not contribute to the rapid runoff response of the area significantly. The groundwater contained in the granite may also not contribute to the runoff. Fig. 2(b) schematically illustrates the surface layer covering the weathered conglomerate and the landslide deposit in the small valley. The thickness of landslide deposit is less than 1 meter and the hydrological conditions of the surface soil layer, such as the permeability, porosity and so forth, are almost the same on both the weathered rock and the landslide deposit. Rainwater mainly flows through high permeable surface layer having roots and decomposed leaves.

Figure 3 illustrates three vertical profiles of hydraulic conductivity distributions, measured at three different locations in sub-basin III. Hydraulic conductivity was measured in laboratory using undisturbed specimens of soil. It can be concluded that high permeable surface soil layer exists from the ground surface to 50-60 cm depth and the hydraulic conductivity is in the order of $10^{-4} - 10^{-3}$ cm/s. This almost corresponds to the decomposed leaves layer and the root

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**Fig. 2** The schematic presentation of hydro-geological conditions of site.
The low permeable clay rich layer exists below this surface layer having thickness of about 1.0 – 1.2 m. Under the clay rich layer, a little weathered conglomerate layer of the Seto group having hydraulic conductivity in the range of $10^{-5} - 10^{-4}$ cm/s is locating. Due to the hydrogeological features, the runoff process can be described as follows:

i) Rainwater is mainly flowing through the high permeable surface layer.

ii) A little portion of rainwater may infiltrate into the deep ground after passing through the low permeable layer.

iii) Infiltrated rainwater discharges as the groundwater runoff component through the fresh part of Seto group.

It can be said that the R-R analysis was performed on the basis of small component of deep groundwater flow.

2.3 Meteorological conditions and runoff data

Meteorological and runoff data have been measured continuously from April 1990 to March 2004 with 10 min. time interval. Fig. 4 displays the meteorological conditions of the basin.

The monthly precipitation, temperature and humidity values averaging over 14 years (April, 1990–March, 2004) show that the precipitation from June to September (rainy season) is higher than rest of the year, and becomes minimum during December to February (dry season). The monthly averaged temperature reaches over 25°C in summer and drops below 2°C in winter. The monthly averaged humidity is above 85% in rainy season and 74% in dry season. Table 2

![Hydraulic Conductivity (cm/s)](image)

**Fig. 3** Hydraulic conductivity profiles measured at three different locations.
Fig. 4 The monthly (a) precipitation, (b) temperature and (c) humidity values averaging over 14 years.
shows the annual water budget information of SPD and SPU sub-basins for 14 years. The average runoff coefficients are 0.50 and 0.63 for SPD and SPU respectively.

Monthly average discharge values of SPD and SPU are graphically shown in Fig. 5.

The average discharge values in June, July and September are larger than the other months. The intense and heavy rainfalls are observed in these months mainly due to thunderstorms and typhoons. Although the average river discharge in August is not as high, intense rainfalls and corresponding high flood flows were commonly observed. For the reason, the period from June to September is defined as the rainy season in this paper, while the average discharge values in December, January and February are minimum and defined as the dry season.

Table 2 Annual water budget and runoff coefficients for SPD and SPU sub-basins

<table>
<thead>
<tr>
<th>Water year *</th>
<th>Rainfall (mm)</th>
<th>Runoff (mm)</th>
<th>Runoff Coefficient</th>
<th>Rainfall (mm)</th>
<th>Runoff (mm)</th>
<th>Runoff Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>1528</td>
<td>799</td>
<td>0.52</td>
<td>1528</td>
<td>908</td>
<td>0.59</td>
</tr>
<tr>
<td>1991</td>
<td>1814</td>
<td>1106</td>
<td>0.61</td>
<td>1814</td>
<td>1296</td>
<td>0.71</td>
</tr>
<tr>
<td>1992</td>
<td>1178</td>
<td>602</td>
<td>0.51</td>
<td>1178</td>
<td>772</td>
<td>0.65</td>
</tr>
<tr>
<td>1993</td>
<td>1616</td>
<td>978</td>
<td>0.61</td>
<td>1616</td>
<td>1153</td>
<td>0.71</td>
</tr>
<tr>
<td>1994</td>
<td>1030</td>
<td>369</td>
<td>0.36</td>
<td>1030</td>
<td>541</td>
<td>0.52</td>
</tr>
<tr>
<td>1995</td>
<td>1446</td>
<td>764</td>
<td>0.53</td>
<td>1446</td>
<td>1009</td>
<td>0.70</td>
</tr>
<tr>
<td>1996</td>
<td>1315</td>
<td>574</td>
<td>0.44</td>
<td>1315</td>
<td>740</td>
<td>0.56</td>
</tr>
<tr>
<td>1997</td>
<td>1872</td>
<td>1001</td>
<td>0.54</td>
<td>1872</td>
<td>1292</td>
<td>0.69</td>
</tr>
<tr>
<td>1998</td>
<td>2094</td>
<td>1156</td>
<td>0.55</td>
<td>2094</td>
<td>1458</td>
<td>0.70</td>
</tr>
<tr>
<td>1999</td>
<td>1640</td>
<td>764</td>
<td>0.47</td>
<td>1640</td>
<td>1036</td>
<td>0.63</td>
</tr>
<tr>
<td>2000</td>
<td>1377</td>
<td>735</td>
<td>0.53</td>
<td>1377</td>
<td>896</td>
<td>0.65</td>
</tr>
<tr>
<td>2001</td>
<td>1409</td>
<td>576</td>
<td>0.41</td>
<td>1409</td>
<td>746</td>
<td>0.53</td>
</tr>
<tr>
<td>2002</td>
<td>1373</td>
<td>540</td>
<td>0.39</td>
<td>1373</td>
<td>643</td>
<td>0.47</td>
</tr>
<tr>
<td>2003</td>
<td>2017</td>
<td>1074</td>
<td>0.53</td>
<td>2017</td>
<td>1358</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Year * = Each year is started from April to March of next year, the way year is characterized by JAEA during data collection.
Snowfall occasionally occurs in the area (once or twice in a year) but the snow usually melts in a relatively short time and its influence on the runoff is thought to be negligible. The effects of interceptions by canopy and litter are automatically accounted for by the stochastic nature of ANN models during the training phase.

Fig. 5 The average monthly discharge values based on 14 years.
(a) SPD
(b) SPU
3. Brief description of MARMA, BPANN and GAANN models

3.1 Multivariate autoregressive and moving average model (MARMA)

The ARMA (p,q) models proposed by Box and Jenkins (1976) are famous for their simplicity, easy use and acceptable results in many applications. The (p,q) notation refers to the autoregressive and moving average terms. The univariate ARMA(p,q) is mathematically written as follows:

\[ Z_t = \phi_0 + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \ldots + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \ldots + a_t \]  

(1)

Where, \( Z_t \) is the predicted value, \( z_{ts} \) are the historical values, \( a_{ts} \) are the residuals or shocks, and \( \phi \)s and \( \theta \)s are the weights associated with each previous observation and shock respectively. Box and Jenkins (1976) also discussed a bivariate version called as transfer function model and since then several multivariate extensions were introduced in literature. The multivariate ARMA model (MARMA) discussed by Master (1995) is used in this study and can be mathematically expressed as follows:

\[ Z_t = \phi_0 + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \ldots + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \ldots + a_t \]

+ \( \phi_{x,1} x_{t-1} + \phi_{x,2} x_{t-2} + \ldots + \theta_{x,1} a_{x,t-1} + \theta_{x,2} a_{x,t-2} + \ldots + \phi_{y,1} y_{t-1} + \phi_{y,2} y_{t-2} + \ldots + \theta_{y,1} a_{y,t-1} + \theta_{y,2} a_{y,t-2} + \ldots \)  

(2)

where, \( x_{ts} \) and \( y_{ts} \) are the time series observations from two different series with their shocks as \( a_{x,ts} \) & \( a_{y,ts} \) and \( \phi_{x,ts}, \phi_{y,ts} \) and \( \theta_{x,ts}, \theta_{y,ts} \) are the weights associated with previous observations and shocks of x and y series respectively. It is found that in the MARMA model linear relations are assumed among observed data.

3.2 Back propagation artificial neural network model (BPANN)

A typical feed forward artificial neural network (ANN) model optimized by back propagation equation is illustrated in Fig. 6.

The input layer nodes (i) send input values
to all hidden nodes. At any particular hidden
node (h), the information received from all the
input nodes and bias node of the input layer
(i.e., i₁, i₂, i₃,...,iₙ,b₁) is summed up.

\[ xₜ = \sum_{j=1}^{n} w_{jh₁} + w_{hb₁} \]  (3)

where, \( w_{jh₁} \) = synaptic weight between hid-
ren and input node, \( w_{hb₁} \) = synaptic weight be-
tween hidden and bias node of input layer.

The summed up input \( (xₜ) \) is then proc-
essed using the commonly used sigmoid logistic
non-linear activation function, which yields the
output of \( Xₜ \) as follows:

\[ Xₜ = \frac{1}{1 + e^{-xₜ}} \]  (4)

In a similar manner, the processed values
\( (Xₜ) \) from the hidden layer nodes are conveyed
to the output layer nodes. At any output node
(o) the signals received from all the hidden
nodes and the bias node (i.e, h₁, h₂,...,hₙ, b₀) are
again summed up by a similar manner as eq.
(3), and processed by the activation function
similarly as eq. (4), and compared with the tar-
get values. Mean squared error (MSE) is calcu-
lated at the output layer, and if MSE is within
acceptable limit the process is terminated other-
wise the feed backward pass is carried out for
updating of synaptic weights by using the follow-
ing back propagation equation.

\[ w_{oh}(new) = w_{oh}(old) + \eta \delta_o p_o + \alpha[\Delta w_{oh}(old)] \]  (5)

where, \( \delta_o \) (Error signal term of output layer)
\( = (t_o - p_o) \cdot (p_o) \cdot (1-p_o) \)
\( \eta \) =learning rate, \( \alpha \) =momentum factor, \( w_{oh} \)
value of synaptic weight joining output layer and
hidden layer nodes, subscript “o” denotes a
node of output layer and subscript “h” denotes
a node of hidden layer, \( \Delta w_{oh}(old) \) =previous
weight change of respective synaptic weight, \( p_o \)
=computed value of output layer node and \( t_o \)=
measured or target value.

The synaptic weights between input layer
and hidden layer are also updated in an analog-
gous manner.

Fig. 6 shows the case of one hidden layer.
Additional hidden layers can also be used in
BPANN models, however most of the research-
ers like Masters (1993, p.174) recommended the
use of one layer, and suggested that more hid-
den layers may cause excess of parameters and
hardly improve the results (Shamseldin et al.,
2002). For the applications of BPANN models,
the dataset is usually divided into three por-
tions, training, validation and test sets. Training
set is used to optimize the synaptic weights,
validation set is used to generalize the BPANN
model and test set is used to check the accu-
rracy of a trained model.

3. 3 Artificial neural network model trained
by genetic algorithm (GAANN)

GA was invented by John Holland over the
course of 1960s and 1970s (Holland, 1975) and
was popularized by Goldberg (1989). The con-
cept of GA evolved from the biological evolution-
ary process. GA is based on the Darwinian-type
survival of the fittest strategy, and it operates
through its genetic operators like selection,
crossover and mutation to produce increasingly
stronger individuals. Each individual in the popu-
lation represents a potential solution to the prob-
lem that is to be solved, and is referred to as a
chromosome (Rooij et al., 1996). Chromosome is
assembled from a set of genes that can be bi-
nary digits, integers or real numbers (Mitchell
\( \chi \) can be thought of as a vector consisting of
l genes \( g_i \)

\[ \chi = (g_1, g_2,...,g_l), \quad g_i \in G \]  (6)

l is referred to as the length of the chromo-
some. The “g” represents the binary genes (G=
\{0,1\}), or integer genes (G={..., −2, −1,0,
1,2,...}) or real-value genes (G=R). In the last
case, the real values are stored in a gene by means of a floating point representation (Rooij et al., 1996). Fig. 7 displays the flowchart of a GAANN model showing all the primary operations of GA.

In GAANN, we used feed forward ANN model as the objective function. An initial population of chromosomes called population size (PS) is selected, and ANN calculates the fitness values of all chromosomes. The total number of genes i.e. \( l \) of each chromosome represents the total synaptic weights of ANN model.

\[
\{g_1, g_2, ..., g_l\} = \{w_{(i \rightarrow h)}, w_{(h \rightarrow o)}, w_{(o \rightarrow a)}, w_{(b \rightarrow a)}\}
\]

(7)

where, 'w' represents the value of a synaptic weight, subscript 'i' represents a node of input layer, 'h' is a node of hidden layer and 'o' represents the output layer node, 'f' is serial number of node which forwards the information (i.e. \( f=1,2,3,.... \)), 'r' is serial number of node which receives information (i.e. \( r=1,2,3,.... \)), 'ib' represent the bias node of input layer and 'hb' is bias node of hidden layer. The real values stored in the genes of chromosome are read as the respective weights of ANN model. Fig. 8 shows an example of translation of the genes of a chromosome into the respective synaptic weights of a simple ANN model.

The ANN performs only feed forward calculation with weights read from genes of forwarded chromosome as per equation (7), and calculates MSE (mean squared error). The inverse of MSE is regarded as the fitness value of forwarded chromosome. In GAANN the backward propagation of error is not allowed.

The selection operator (roulette wheel) randomly selects two chromosomes from the initial population, which are said the parent chromosomes. These parent chromosomes then crossover to produce two new chromosomes called children chromosomes. The concept of crossover is understandable from Fig 9, in which a crossover point is selected arbitrarily at the identical location in two parents, and the alternate halves of parents are recombined to form two children. After that, the mutation is carried out in the children to introduce changes in genes of a child chromosome. In the traditional GA, employing binary digits as the gene values (0 and 1), the value of selected gene is inverted in mutation i.e. if it has 0 value it is mutated as 1 or vice versa. However, in real coded GA, the two genes in a chromosome are selected and their positions are swapped to introduce mutation as shown in Fig. 9(b). The mutation keeps the diversity in the genes of a population and stops it from a premature convergence (Bowden et al., 2005).

The four chromosomes (2 parents and 2 children) are compared with each other according to their fitness values. The best two are sent to a new pool and other two are destroyed. When the PS of new pool is same as initially selected, one generation cycle is said to be completed and model is checked for stopping conditions. The stopping criterion is simple and straightforward that when the variation in the genes of population becomes negligible the GA is converged and stopped, otherwise the maximum number of generations of 500 was selected to stop the GA (Muleta and Nicklow, 2004, Arthur and Rogers, 1995). When any of the two stopping criteria is fulfilled, the best chromosome selected through all the generations is identified, and the genes of best chromosome represent the optimized weights of ANN model.

4. Experiments and Methodology

4.1 Data treatment

As explained in section 2.1, the data obtained for sub-basins SPD and SPU were used in this study. In order to investigate the seasonal effects, the medium to high runoff events
Fig. 7 The flow chart of GAANN model applied to Tono test basin, Japan.
were selected from both rainy and dry seasons. The duration of each runoff event was considered from the start of the rainfall to the instant when the hydrograph comes down to the same position as observed before rainfall. The criterion for the selection of the runoff event was different for both seasons as explained below.

The daily runoff in the rainy season for SPD sub-basin was ranging from $8.35 \times 10^4$ m$^3$/day (17th August, 1994) to $5.96 \times 10^4$ m$^3$/day (12th September, 2000), and 44 rainfall events having daily runoffs greater than $9.00 \times 10^3$ m$^3$/day were selected from the 14 years data.

Similarly the fluctuation of daily runoff in dry season varied from $1.93 \times 10^3$ m$^3$/day (7th January, 1995) to $1.50 \times 10^3$ m$^3$/day (27th January, 2000), and 50 rainfall events having daily runoffs greater than $1.3 \times 10^3$ m$^3$/day were selected from 14 years data.

In order to compare the performance of runoff models for spatially two different sub-basins, the same rainfall events were selected for the flow data at SPU for both seasons, except for a few intense rainfall events in which data were missed.

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**Fig. 8** An example of assigning gene values of a chromosome to the respective synaptic weights of an ANN architecture during a GAANN model.
4.2 Identification and selection of BPANN model parameters

A successful model should be capable of making predictions after a sufficient time period in future relative to the present time. This time period is referred to as the lead time in this paper. Tingsanchali and Gautam (2000) used 1 and 2 day lead time predictions for two basins of 6250 km$^2$ and 2200 km$^2$ in Thailand. Dawson and Wilby (1998) used 6 hours lead time for two catchments in UK both having areas of 140 km$^2$. Dawson et al. (2002) used 48 hours lead time for the large catchment of 56000 km$^2$ (Three Gorges Project in China). The initial data analyses and the hydrological investigation of the Tono basin described in sections 2.2 and 2.3 showed that the R-R response is quick. For the reason, lead times of $\frac{1}{2}$ and 1 hour were

Fig. 9 (a) An illustration of Single-Point Crossover where "p" and "q" represent the real-value genes.
(b) Mutation in real-value chromosome. The 3rd and 9th gene values of 1st child are swapped to introduce mutation.

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chosen for the analyses in this study. Selection of the independent and dependent input variables greatly affects the performance of the model. In most previous studies, correlations between the variables and the discharge data were calculated to choose the best predictors (Shrestha et al., 2005; Dawson et al., 2002; Tokar and Johnson, 1999). The correlation values between observed discharge and selected predictors for SPD and SPU are listed in table 3. In this table, the lag time represents the time period in past.

For the forecasting of flow at 1 hour lead time in rainy season, current and antecedent flow, current and antecedent precipitation, and current humidity were selected as the suitable predictors. However, current temperature was an additional input in dry season. The other measured data resulted in very low or negative correlations with the discharge. The moisture content data was not available, therefore the antecedent discharge data used in the model at previous selected times was supposed to represent the catchment's moisture state indirectly.

Windowing approach (Hall and Minns, 1993; Abrahart and Kneal, 1997) involves the use of antecedent flows and rainfalls at times \( t, t_1, t_2, ..., t_n \) as direct inputs into the model, and was also adopted in this study. As presented in table 3, the correlation analyses showed a good correlation between the observed flow and antecedent flow and precipitation until 3 hours (lag times 60, 120, 180). The input data was thus selected as 12 antecedent values (current and past

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Lag time (minutes)</th>
<th>Correlation value</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Rainy season</td>
<td>Dry season</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>SPD</td>
<td>SPU</td>
<td>SPD</td>
</tr>
<tr>
<td>Discharge</td>
<td>60</td>
<td>0.885</td>
<td>0.818</td>
<td>0.885</td>
</tr>
<tr>
<td>Antecedent discharge</td>
<td>120</td>
<td>0.774</td>
<td>0.688</td>
<td>0.765</td>
</tr>
<tr>
<td>Antecedent discharge</td>
<td>180</td>
<td>0.679</td>
<td>0.574</td>
<td>0.656</td>
</tr>
<tr>
<td>Precipitation</td>
<td>60</td>
<td>0.287</td>
<td>0.258</td>
<td>0.339</td>
</tr>
<tr>
<td>Antecedent ppt.</td>
<td>120</td>
<td>0.232</td>
<td>0.209</td>
<td>0.273</td>
</tr>
<tr>
<td>Antecedent ppt.</td>
<td>180</td>
<td>0.183</td>
<td>0.164</td>
<td>0.212</td>
</tr>
<tr>
<td>Humidity</td>
<td>60</td>
<td>0.190</td>
<td>0.162</td>
<td>0.219</td>
</tr>
<tr>
<td>Temperature</td>
<td>60</td>
<td>-0.071 (not taken)</td>
<td>-0.040 (not taken)</td>
<td>0.203</td>
</tr>
</tbody>
</table>

(taken as input in dry season only)
11 values) of discharge and precipitation and 1 current humidity value to predict runoff after 1 hour in future in both seasons. However, an additional temperature input was also used in dry season. Thus, ANN models had 25 inputs for rainy season and 26 inputs for dry season. The models were called as BPANN, when back propagation equation was used for the training of the models, and GAANN when genetic algorithm was used.

The selection of an appropriate transfer function is an important factor in the success of an ANN model. A review by Maier and Dandy (2000) showed that hyperbolic and logistic transfer functions are most widely used in ANN applications. Imrie et al. (2000) investigated four different transfer functions for the output neuron, and suggested that a cubic polynomial transfer function or a similar shape transfer function may be useful to capture the extreme flood events with neural networks. In this study, as mentioned before, three layers ANN models were developed with logistic sigmoid function at the hidden and output layers (see Fig 6).

There is no rule for specifying number of neurons in the hidden layer. Dawson and Wilby (2001) pointed out from the literature review that some researchers used past experience, others used optimization algorithms such as cascade correlation, genetic algorithms and magnitude pruning to specify number of neurons in the hidden layer. However, most of the researchers selected the number by trial and error method. It is also recommended by Shamseldin et al. (2002) that for most practical applications, the number of hidden neurons can be estimated by hit and trial method in an iterative process. Many researchers like Masters (1993) noted down that too many number of neurons in the hidden layer has the risk of over-memorizing the data to the model whereas the too less numbers will result in poor training of the model. According to these recommendations in this study, 2, 4, 6, 8, 10, 12, 14 numbers of neurons, starting from 2 and incrementing by 2, were tried in the hidden layers and their errors were compared to each other. In most cases, the difference of MSE (mean square error) by using different numbers of neurons in the hidden layer was not so significant. Therefore, the principle of parameter parsimony was applied and models having the least number of neurons in the hidden layer with the minimum errors were chosen. The output in this study was only one i.e. the forecasted runoff at 1 hour lead time.

For the successful applications of the BPANN models to the available data, the parameters of learning rate (lr) and momentum factor (mf) are also needed to be adjusted in the trail runs of the BPANN models. The selection of appropriate values of lr and mf is one of the main difficulties encountered in the use of the BP algorithm, since the selection of inappropriate lr and mf values may lead to instability and slow convergence of BP algorithm (Shamseldin and O’Connor, 2001). In this study, it was observed that with 10 minutes temporal data the higher values of lr normally resulted in a saturation state of the model (Eberhart and Dobbins, 1990) showing the same values for outputs of all patterns i.e. either 0 or 1. Therefore, after trial calculations values of lr and mf as 0.001, 0.1 for the rainy season data and 0.01, 0.02 for the dry season data were selected for both SPD and SPU. The starting values of weight parameters also greatly affect the generalization capability of the BPANN models. Thus, depending on the selection of values for initial weights, several calibration trials of one ANN structure can lead to different results (Gaume and Gosset, 2003). Therefore, after the initial experiments, the random weight values were selected between ± 3 in rainy season data and ± 6 in dry season data for both SPD and SPU.

To achieve a desired level of accuracy during the training process of a BPANN model, the
appropriate stopping criteria is very important. The extended iterations beyond requirement in the training of a BPANN model may result in over-fitting of the model, behaving extra ordinarily well on the training data but poorly on the test data. Cross-validation approach has now become the standard technique for the generalization of BPANN models (Agarwal and Singh, 2004), and was used in this study. In cross-validation, it is customary to divide the data into three sets named as training, validation and test sets. The model is trained on the training data and error is monitored on the validation data after every certain number of epochs. In principle, monitoring of validation error should be performed after every iteration, however the monitoring of validation error after every 100 epochs was used due to large datasets (Dawson et al., 2002). After a certain level of training, although the training set error will be decreasing but error in validation set will start increasing or become stable. At this moment, the training is stopped and the network is said to be generalized. Generalization is dependent on the network structure and size, the training algorithm, training rate, quality and quantity of training and validation data domain (Fu, 1996).

The maximum range of the sigmoid logistic function is given between [0-1.0]. The available data is, therefore, to be standardized in between these two limits. In order to accommodate the extreme flood events having flows beyond the maximum flow of training data, some researchers have suggested using the limits of [0.1-0.9] (Imrie et al., 2000). The training data used in this study was therefore, rescaled in the effective range of [0-0.9]. C++ language was used to code the BPANN model.

4.3 Identification and selection of GAANN model parameters

In order to make the direct comparison between GA and BP algorithms, the architectures of the GAANN models were kept the same as selected for BPANN models in both seasons. Rooij et al. (1996) suggested keeping the population size (PS) in between 50 to 100 chromosomes for fast and reliable results. We experienced that small PS resulted in premature convergence, whereas large PS resulted in much longer time for optimization with no substantial gain in the accuracy of the results. After initial trials, the PS of 90 proved to be suitable for the present study. The gene values of chromosomes were taken as real numbers. We experimented with different range of numbers and for the present problem the range between 9.0 and 0.0009 was found to be suitable. The higher values than 9.0 and lower than 0.0009 did not improve the results. A code was written to generate 18 chromosomes in each range with 5 different ranges ±9, ±0.9, ±0.09, ±0.009, and ±0.0009 totaling to 90 PS.

The three genetic operators: selection, crossover (mating) and mutation in GA are primary powers to produce new and unique children. The selection operator is used to select parents from the pool. A number of selection techniques has been developed by various researchers like ‘roulette wheel’ (Holland, 1975), ‘stochastic universal sampling’ (Baker, 1987), ‘sigma scaling or truncation’ (Goldberg 1989), ‘boltzmann selection’ (de la Maza and Tidor, 1993), ‘rank selection’ (Baker 1985) and ‘tournament selection’ (Goldberg and Deb, 1991), however their success and utility depends upon the nature of problem in hand. The roulette wheel with elitism was used in this model. Elitism is a process in which the best chromosome of each generation is carried over to the next generation, to ensure that the best chromosome is saved during the evolutionary process.

Crossover (mating) operator is used to produce children from the selected parents. Various crossover techniques have been presented by different researchers, out of which the famous are
single-point crossover (simple crossover), two-point crossover and uniform crossover (Mitchell M., 1996). In GAANN, the uniform crossover was used with a crossover rate of \( p_c = 1.0 \), in which a toss is done at each gene position of child, and depending upon the result of toss the gene of 1\(^{st}\) or 2\(^{nd}\) parent is copied. The swap mutation with mutation rate of \( p_m = 0.8 \) was used.

We coded the GAANN model in C++ language, and some sub routines of LibGA package (Arthur and Rogers, 1995) were used with alterations to read and process the negative real values.

4.4 Identification and selection of multivariate ARMA models

The multivariate ARMA (MARMA) models have been used by many researchers for the simulation of R-R processes (Moore, 1999; Hsu et al., 1995). They are relatively easy to develop, and convenient to apply, and have been found to provide satisfactory results in many applications (Salas et al., 1980; Wood, 1980). The standard ARMA models require data to be stationary and normally distributed but the actual field data of R-R process rarely satisfies such requirements, and hence they may not be effective always. In this study, an iterative approach was adopted to find parsimonious and effective models (Masters, 1995, p. 229), in which plots of cross correlation and partial cross correlation were drawn to fit the MARMA models to available data. The models were computed, and the regular and partial cross correlations of the residuals (shocks) were monitored until all correlations appeared reasonably small.

The finally selected models were MARMA(2,2) and MARMA(2,0) for the rainy season and MARMA(3,0) and MARMA(3,0) for the dry season data of SPD and SPU respectively all having the multiple input parameters.

5. Results and Discussion

At first from 14 years data, 19025 patterns (a combination of input data and its respective output is called a pattern in this paper) were prepared from rainy season data, and 13015 from dry season data. These total data patterns were then divided into 3 sets namely, training, validation and test sets. The training set was used to train the network; validation set was used to check the accuracy of trained model after certain number of iterations, which is necessary to avoid the over-fitting of model. The test set was used to check the accuracy of fully trained model on an unseen data. The data sets of years 1990–1997 were used for the training, 1998–2000 for validation and 2001–2003 for testing of models. Thus, approximately 60\%, 18\%, and 22\% of total patterns were used for the training, validation and testing of models for each season (Dawson et al., 2002). Statistical characteristics of the flow data of three sets are summarized in table 4, and it can be seen that the data in all the three sets is statistically uniformly distributed in both seasons except rainy season data of SPU showing significant difference in the maximum discharges.

The performances of the models were checked by two different types of model evaluation criteria's; the goodness-of-fit and the absolute error measures that were recommended by Legates and McCabe (1999). Accordingly, three different performance measures, coefficient of efficiency (CE), the coefficient of determination \( r^2 \), and the root mean square error (RMSE) were used to determine the efficiencies of developed models (Nash and Sutcliffe, 1970). The values of these three statistics for SPD and SPU for the rainy and dry seasons are summarized in tables 5 and 6 respectively.

According to Shamseldin (1997), the models having CE values above 90\% are very satisfactory, in between 80–90\% are fairly good and be-
low 80% are unsatisfactory. Following this criterion, it can be clearly seen that in case of 1 hour rainy season results, the ANN models (both BPANN and GAANN) constructed for SPD are fairly good (CE values above 80%) but for SPU are unsatisfactory (CE values are below 80% in training and validation sets). Previous studies have noted that the accuracy of ANN model forecasts decrease as the lead time increase (Dawson and Wilby, 1999). For example,

<table>
<thead>
<tr>
<th>Data set</th>
<th>Mean discharge (m³/s)</th>
<th>Maximum discharge (m³/s)</th>
<th>Minimum discharge (m³/s)</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rainy Season</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPD Training set (1990-97)</td>
<td>6.66</td>
<td>91.82</td>
<td>0.15</td>
<td>8.63</td>
</tr>
<tr>
<td>Validation set (1998-00)</td>
<td>9.07</td>
<td>98.03</td>
<td>0.27</td>
<td>15.14</td>
</tr>
<tr>
<td>Test set (2001-03)</td>
<td>6.73</td>
<td>70.62</td>
<td>0.13</td>
<td>8.68</td>
</tr>
<tr>
<td>SPU Training set (1990-97)</td>
<td>1.48</td>
<td>67.60</td>
<td>0.008</td>
<td>2.04</td>
</tr>
<tr>
<td>Validation set (1998-00)</td>
<td>2.19</td>
<td>35.43</td>
<td>0.03</td>
<td>4.49</td>
</tr>
<tr>
<td>Test set (2001-03)</td>
<td>1.53</td>
<td>13.15</td>
<td>0.004</td>
<td>1.82</td>
</tr>
<tr>
<td><strong>Dry Season</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPD Training set (1990-97)</td>
<td>2.08</td>
<td>29.85</td>
<td>0.237</td>
<td>2.19</td>
</tr>
<tr>
<td>Validation set (1998-00)</td>
<td>3.32</td>
<td>24.37</td>
<td>0.244</td>
<td>3.90</td>
</tr>
<tr>
<td>Test set (2001-03)</td>
<td>2.46</td>
<td>37.07</td>
<td>0.242</td>
<td>3.50</td>
</tr>
<tr>
<td>SPU Training set (1990-97)</td>
<td>0.43</td>
<td>4.68</td>
<td>0.047</td>
<td>0.41</td>
</tr>
<tr>
<td>Validation set (1998-00)</td>
<td>0.69</td>
<td>4.28</td>
<td>0.064</td>
<td>0.76</td>
</tr>
<tr>
<td>Test set (2001-03)</td>
<td>0.06</td>
<td>5.46</td>
<td>0.056</td>
<td>0.58</td>
</tr>
</tbody>
</table>
Compolo et al. (1999) applied ANN models in the river Tagliomento (catchment area 2480 km²) with 1 hour temporal data and forecasted flows upto 10 hours ahead and reported deteriorating results after 5 hours. In this study, the hydrological investigation of the area suggested a highly quick R-R behavior during rainy season, and it was thought that most of the meaningful relationships between rainfall and runoff were lost at 1 hour lead time for SPU. The lead time was therefore reduced to 1/2 hour and the models were again trained to predict flows. Although the correlation values for 1/2 hour lead times were slightly different from the values shown in table 3 but the input variables were selected as the same, therefore the same 1 hour models were used for 1/2 hour predictions. The results of 1/2 hour lead time predictions are also summarized in tables 5 and 6 for both SPD and SPU. It was observed that the model efficiencies were considerable increased at both SPD and SPU in both seasons by decreasing the lead time. For example, the models for SPU in rainy season at 1/2 hour had CE values above 80% whereas at 1 hour the CE values were below 80% in training and validation sets.

By comparing the results obtained by the linear (MARMA) and by the nonlinear (ANN) approaches, we find that in rainy season results, the ANN models (BPANN and GAANN) generally performed better than MARMA models in the training sets, that may be due to the effects that are accounted by ANN models through the use of sigmoid function (Agrawal and Singh, 2004). In validation and test sets, the ANN models also performed better than MARMA models.
for SPD, but this trend was not observed at SPU, where MARMA models sometimes performed similar or even better than BPANN and GAANN models. This may have occurred due to statistically non-uniform distribution of data among three sets (see table 4). In dry season, the results show that ANN models were generally better than MARMA at SPD for all the three sets but at SPU, the two approaches appeared to be similar.

By comparing the efficiencies of two algorithms of training ANN models, we find that almost both the models BPANN and GAANN provided the similar forecasting estimates except at SPU during rainy season data at 1 hour lead time which may be data specific.

At both SPD and SPU, the results for dry season were generally better than that for rainy season. This result may have come from the fact that rainy season is generally more complex than that of dry season because of the high rain intensity. In general, the improvement in the results from rainy to dry season for the same lead time was more for SPU than that of SPD, for example in the training set of 1 hour lead time, results at SPD improved from CE 84% to 89% but at SPU from 71% to 94% (approx.). This result implies that seasonal data greatly affects the model performance for small catchments.

In general, from the examination of the graphs of the individual rainfall events it was observed that peak runoffs in rainy season were more accurately simulated by ANN (both BPANN and GAANN) models than MARMA models. However, in dry season, the simulation

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<table>
<thead>
<tr>
<th>Table 6</th>
<th>Comparative performances of BPANN, GAANN and MARMA runoff simulation models at 1-hour and 1/2-hour lead times for dry season</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model name</strong></td>
<td><strong>Model structure</strong></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>1-hour lead time</strong></td>
<td></td>
</tr>
<tr>
<td><strong>SPD</strong></td>
<td>BPANN</td>
</tr>
<tr>
<td></td>
<td>GAANN</td>
</tr>
<tr>
<td></td>
<td>MARMA</td>
</tr>
<tr>
<td><strong>SPU</strong></td>
<td>BPANN</td>
</tr>
<tr>
<td></td>
<td>GAANN</td>
</tr>
<tr>
<td></td>
<td>MARMA</td>
</tr>
<tr>
<td><strong>1/2-hour lead time</strong></td>
<td></td>
</tr>
<tr>
<td><strong>SPD</strong></td>
<td>BPANN</td>
</tr>
<tr>
<td></td>
<td>GAANN</td>
</tr>
<tr>
<td></td>
<td>MARMA</td>
</tr>
<tr>
<td><strong>SPU</strong></td>
<td>BPANN</td>
</tr>
<tr>
<td></td>
<td>GAANN</td>
</tr>
<tr>
<td></td>
<td>MARMA</td>
</tr>
</tbody>
</table>
by ANN and MARMA models appeared to be the same and in some cases, MARMA models gave slightly better results. This trend can be observed in the simulation graphs of individual rainfall events in Fig 10 and 11.

These figures show the comparative performances of BPANN, GAANN and MARMA models for rainy and dry seasons at SPD with 1 hour lead time. The better estimation by ANN models in rainy season is due to the inherent nonlinear architectures of ANN models, enabling them to better estimate the runoff from the complex and nonlinear intense rains of rainy season. This result also confirms the findings of Maria et al., (2004), who simulated runoff in Xallas River Spain and reported that the complex R-R relationships were better simulated by ANN models as compared with ARMA models. The delayed prediction of peak runoff was also observed with all the models and is lesser in case of ANN models than MARMA models.

The significant difference in the results of 1 and ½ hour lead times strongly suggest that the selection of an appropriate lead time for the model development is an important factor, especially for very small catchments. Therefore, in order to clarify the relationship between the lead time selection and the model performance, and catchment size, the rainy season data of SPD and SPU were analyzed at different lead times with all the three models. The lead time was varied from 10 to 180 minutes with 30 minutes interval. The training data results are shown in Fig. 12.

The declining trend in the forecasting ability with increasing lead time can be clearly observed in all the models. It can also be seen that the values for SPU are lower than that for SPD if the same lead time was used. This figure implies that an appropriate lead time for small catchments should be carefully selected with the experimental data before constructing a full scale model.

6. Conclusion

An approach of training ANN models with GA (genetic algorithms) is proposed and compared with the frequently used BP (back propagation) algorithm, in two very small sub-basins of Tono area watershed. Apparently, no significant difference was observed between the two techniques, either in the prediction of runoff volume or in the time of peak. The two approaches tend to be similar, with minor differences, when checked with a precisely measured dataset in a very small mountainous watershed. However, some researchers reported better results with GAANN than BPANN in bigger catchments (Jain and Srinivasulu, 2004). Which points to the fact that the catchment size and the underground geological conditions play a significant role, in the selection of the type of the model for the runoff prediction? The geological investigation of the site showed that only a small thickness of top soil is responsible for the infiltration of rainwater flowing as base flow, with little percolation of rain into the deep groundwater. This phenomenon appears to be one of the reasons, responsible for the rapid surface runoff observed in the basin. Therefore, based on our experience, we recommend that a detail investigation of the catchment geology and groundwater flow patterns should be carried out for deciding the lag time for input parameters and selecting lead time in ANN applications. This study will serve as a benchmark for comparing the similar studies carried out under different hydrological and geological conditions with different catchment sizes. In the modelling process, GA provides some advantages over BP algorithm, like there is no need to select learning rate or momentum factor by hit and trial method, which is one of the main problems in BPANN (Shamseldin and O’Connor, 2001), and there is no need to assign starting values to the synaptic weights. Local minimum trap is an-
Fig. 10 The comparative performances of BPANN, GAANN and MARMA models in the flow simulation of intense rainfall events at SPD with 1 hour lead time. Rainy season data. Small windows show close view around peak flow.

(a) Training data (b) Validation data (c) Test data
Fig. 11 The comparative performances of BPANN, GAANN and MARMA models in the flow simulation of light rainfall events at SPD with 1 hour lead time. Dry season data. Small windows show close view around peak flow.

(a) Training data (b) Validation data (c) Test data
Fig. 12 The declining trend in the forecasting capability of BPANN, GAANN and MARMA models at different lead times in future. Rainy season training data values are shown.

(a) SPD
(b) SPU
other potential danger in the application of BPANN model. In order to find global or near to global minimum, it is necessary to train the BPANN model with different combinations of starting values of synaptic weights by hit and trial method, which is a time consuming and frustrating method. On the other hand, GAANN algorithm searches a wide area of function surface and finds a global or near to global minimum before it settles for a more fine training. Thus, it can be said that training by GAANN model is more stable than that of BPANN. GAANN approximately consumes 4 to 5 times more time period than BPANN to find a good solution.

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