Review of Hydrological Model for Simulating Precipitation-Runoff Process

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Abstract— **The review contains the study of diverse advance methodologies of developing hydrological models for estimating runoff. The use of water budgeting was found feasible with the availability of the digital computers. The methodology of developing hydrological model explained the parameter identifiability, modelling the parameters, calibration, verification, advantages and its limitations. The methodologies studied was Rational Hydrograph Method, Geographical Information System method, Artificial Neural Method, Genetic Algorithm Method and Dynamic Identifiability Method. The objective was to compare their models with respect to the simulation performed for precipitation-runoff process in the catchment.**

Keywords— **Hydrological model, Rainfall- runoff process, Rational Hydrograph Method, Geographical Information System method, Artificial Neural Method, Genetic Algorithm Method and Dynamic Identifiability Method**

I. INTRODUCTION

The flowing off precipitation from given catchment area through the surface channel was called as *runoff.* The determination of runoff using hydrologic water-budget equation demands enormous calculation efforts. With the availability of the digital computers, the use of water budgeting had become feasible. This technique of predicting the runoff (catchment response to the given precipitation) was termed as *deterministic watershed simulation.*

The first watershed model was developed by *Crawford and Linsley* in 1959 and named as Standard Watershed Model (SWM). This underwent several modifications until SWM-IV was proposed in 1966. Based on this logic, many models and better versions like *HSP (1966), SSARR (1968) and KWM (1970)* were developed during late 1960s. In the late 1980s, there were at least 75 hydrologic simulation models that were available and deemed appropriate for small watershed. In the past two decades, considerable effort had been directed towards the development of process based, spatially explicit and physically based hydrological model such as *GSSHA* [1].

The objective of many field experiments was to gain knowledge about *runoff generation process*. Using evidence from such field experiments, simulation models had been developed and used to consider the impact of vegetation cover, soil properties and morphological parameters etc. on runoff generation process in the catchment.

There were few model studies, compared to number of model applications where spatial and temporal data on hydrological response had been calculated to gain comprehensive knowledge of runoff generation process and ultimately characterise the state of hydrological system in the catchment.

The field observations and measurements should be necessary requirement for a hydrological model application, typically catchment outflows of stream gauges located downstream of study area were the only available data. Such data were of little use for quantifying individual catchment process.

Hydrological models accounted for storage, flow of water and water balance in the catchment. This included exchange of water and energy between ground, atmosphere and ocean. In the absence of measured process properties, model used *parameter* to characterise process behaviour. The parameters referred to some form of average behaviour in terms of both spatial and temporal variability and were generally model definite. The mathematical relationships describing the interdependencies of various parameters in the system were first prepared. This was called *model.*

The parameters were seldom directly measurable and were frequently inferred from iterative calculation using catchment outflows, an operation called *model calibration.* Here model was calibrated i.e. the numerical values of various coefficients determined by simulating the known precipitation-runoff records.

The researchers founded that calibrated models performed poorly when data from non-calibration period (another time) that had diverse forcing conditions, a process called *model verification*. Here the accuracy of the model was further checked by reproducing the results of another string of precipitation data for which runoff values were known. After this, model was ready for the use [2].

The reliability of model prediction outside of calibrations was questionable and was subjected to uncertainties. The uncertainty in calibration occurs due to alternations in input data between diverse periods such as wet and dry periods.

Often the outputs of hydrological models were compared with observed data by plotting model estimates against observed data. These comparisons frequently fail to recognise serious model deficiencies.

To build confidence in hydrological model prediction, it was necessary to evaluate if it could realistically reflect the natural behaviour of hydrological system. Following were the conclusions of some of the recent hydrological models developed which marked the improvements in producing precise results w.r.t. given observations. This became possible because of some definite considerations as [1,2]:

1). The *process constraints* contained more beneficial information than *parameter constraints*, thereby having beneficial impact on model performance.
2). The *distributed model structure* performed better than a *lumped model structure* in producing dynamics of hydrograph.
3). The process of representation of hydrological model could be made better by using *temporal parameter sensitivity*.

The present review was based on the study of diverse advance methodologies of developing hydrological models for estimating runoff. The methodology provided the information about the modelling, its calibration, verification, advantages and its limitations with respect to the simulation of the precipitation-runoff process. The difference was in true identification of the parameter, calibrating methodology augmented and its result analysis with the observed data. These approaches marked the difference in the processing of a hydrological model. The parameter identifiability, modelling the parameters, calibrating and validating were some of the fundamental approach for the development of watershed models that was taken into account for the study.

II. RATIONAL HYDROGRAPH METHOD

Despite the simplicity of rational method, it was the most popular method to design drainage facilities. Rational method is strongly favoured by engineers, as it demands few parameters, all of which were physical and easily obtained from site surveys.

A. *History*

The rational hydrograph formula was developed by *Rossmiller* in 1982 and was based on assumption of rational formula to compute hydrograph using constant precipitation-intensity deduced from intensity-frequency-duration curves.

The rational hydrograph method was developed by *Smith and Lee* in 1982 that could simulate runoff corresponding to variable precipitation-intensity. The method appeared to be limited by grimy of accurately computing the time of concentration and runoff coefficient.

The better rational hydrograph method was introduced by *Gua* in 2001. A new formula was given to calculate the time of concentration. Unfortunately, the formula for time of concentration was derived from the limited data and therefore could not be used with confidence.

B. *New Runoff Simulation Model for Small Urban Catchment* [3]

The goal of the present note was to offer engineers a better rational hydrograph method by having following considerations:

- Capacity to use variable intensity precipitation.
- An alternative to lumped runoff coefficient by introducing infiltration for pervious areas including abstraction.
- Methodology for sequential calibration of parameters involved.

1). Rational Hydrograph Method

The Improved Rational Hydrograph (IRH) method was based on Linear System theory as shown in Fig. 1 and Fig. 2. The runoff at time 't' due to variable precipitation intensity was obtained by convolution product between precipitation intensity and impulse response function given by the following equation:

$$Q(t) = \int_0^t [(I(\tau) - dp(\tau))u_{\text{imp}}(t-\tau)]d\tau + \int_0^t [(I(\tau) - f(\tau))u_{\text{per}}(t-\tau)]d\tau$$

Q: runoff (m^3/s); *I*: precipitation intensity(mm/h); U_{imp}: Impulse response function of impervious area; U_{per}: for pervious area; *Dp*: initial abstraction(mm/h); *f*: infiltration capacity(mm/h).

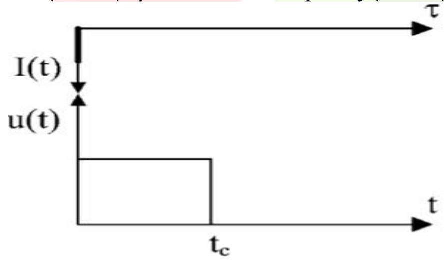


Fig. 1: Impulse Response Function

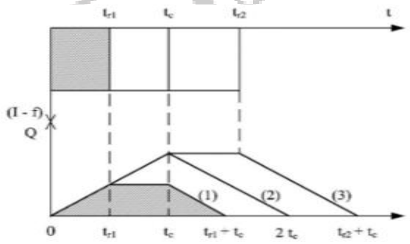


Fig. 2: Runoff Hydrograph of the IRH Method for Various Rainfall Duration

2). Calibration Procedure

A calibration procedure in three sequential steps was proposed to fit simulated runoff to the measured runoff. Process were augmented to both non-linear reservoir model (NLR) and IRH method. (see Table I).

Step:1 Impervious area (*IMP*) and D_p Calibration

Fraction of directly connected impervious areas (*IMP*) and initial abstraction depth (D_p), were calibrated using precipitation event of low intensity and short duration.

IMP was initially taken equal to fraction of impervious areas. After first runoff simulation using equation of convolution product, value of IMP was updated using:

IMP (2) = IMP (1) ÷ R

Then a default value of D_p could be estimated using SCS-CN method. The initial value of D_p was adjusted to fit beginning of simulated runoff to the beginning of measured runoff.

Step:2 Time of Concentration (t_c) and Catchment Width (W) Calibration

Initial value of W and t_c could be estimated using various formulae proposed in the literature of [3]. The values were adjusted manually or with optimisation process.

Step:3 Horton Model Parameters Calibration

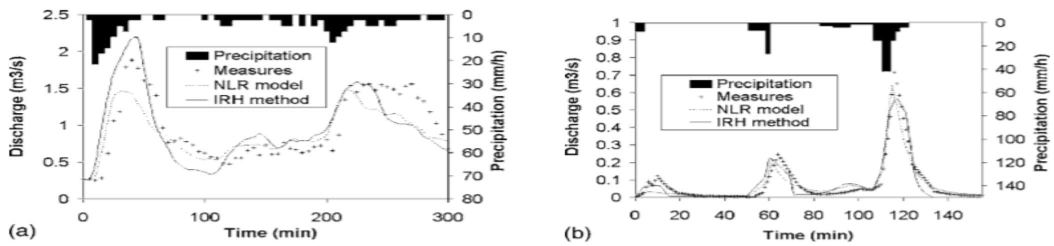
A sensitivity analysis conducted on NLR model of SWMM had showed that initial abstraction capacity (f_o) of the Horton's model was far sensitive than final infiltration (f_∞) and decay rate (K). Calibration started with the use of an initial value of f_o which was then adjusted in order to equalise simulated runoff volume to measure runoff volume (see Fig. 3).

TABLE I
CALIBRATED PARAMETER OF THE NLR MODEL OF THE IRH METHOD

Catchment	A (ha)	IMP (%)	t_c (min)	W (m)	S_o (m/m)	n_{imp}	n_{per}	D_p (mm)	f_o (mm/h)	f_∞ (mm/h)	K (h^{-1})
Verdun	177.0	0.41	37	2,700	0.005	0.014	0.025	0.7	55	15	2
Malvern	23.3	0.35	11	1,100	0.020	0.014	0.025	0.5	50	15	2

3). Model Calibration and Verification

The NLR model and IRH method were calibrated with 2 precipitation events for each catchment studied, the 4 precipitation events used for calibration and parameters obtained after calibration for each catchment were obtained in the Table I.



(a) Runoff Calculated during Heavy Precipitation (b) Runoff Computed during Light Precipitation
Fig. 3: Runoff Computed with NLR Model and IRH Method for Precipitation

The calibrated IRH method and NLR model were used to compute 6 precipitation events. The error in the simulated runoff volume is less than 10% for 4 events, which means model give accurate forecast of runoff volume as shown in Fig. 3. However, the peak flow error is greater than 10% for 5 events, which underlines the accuracy limits of 2 hydrologic models.

The improved rational hydrograph method showed satisfactorily covenant between simulated and observed runoff hydrograph. Moreover, runoff derived with the proposed method were equivalent to those computed with the non-linear reservoir model (NLR model). Practically, the IRH method could easily be executed with an excel spreadsheet or with a computer based programming languages. Following attributes could be concluded from their hydrological model:

a). IRH method represents the urban catchment as linear system where impulse response function was rectangular shaped with duration equal to time of concentration. Runoff was premeditated with convoluted multiplication between precipitation intensity (variable intensity) and impulse response function of catchment.

b). IRH method overtly assumed the contribution of pervious and impervious areas, the variability if precipitation intensity as well as losses due to infiltration and initial abstractions. Verification of IRH method and NLR model signposted that IRH method gives equivalent results to those of more erudite NLR model.

III. Geographical Information System Method

As most field measurements were point measurement, while hydrological modelling was a catchment or sub-catchment level, one of the biggest challenge in comparing modelled value with observed was accounting for alternations in scale of comparator variable. For comparison of semi or distributed hydrological models, one or more spatial pattern should be used to supplement single point measurement of variable under investigation. Geographical Information System (GIS) based approach using digital maps, topography of soil type and vegetation could be beneficial methodology for simulating hydrological models.

A. *Inter-Comparison of Catchment Data and Hydrological Modelling* [2]

The purpose of the paper was to access and potentially improve the ability of physically-based, semi-distributed hydrological model *Topnet* in modelling the hydrological process-flows and fluxes-within a headwater catchment of the Waipara river in South Island of New Zealand, using spatially (space) and temporally (time) comprehensive set of field measurements of catchment responses to diverse types of weather.

1) Hydrological Model Details

Topnet was a physically based semi-distributed hydrological model which simulates catchment water balance and flow as shown in Fig. 4. It was developed using TOPMODEL for parametrisation of soil moisture deficit using a topographic index to model the dynamics of various source areas contributing to saturation excess runoff.

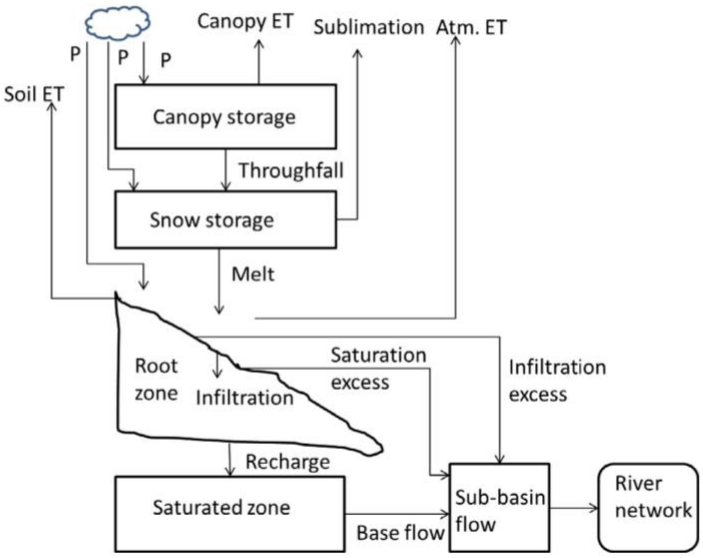


Fig. 4: Schematic Representation of Topnet Model Structure

As Topnet model was distributed at catchment scale but lumped at sub-catchment scale for each sub-catchment model, there was a separate interception components based that controls the production of net precipitation. Table II provides the catchment details.

TABLE II
STUDY AND CATCHMENT INFORMATION

Catchment	**Langs Gully**
Area	0.7 km^2
Period of analysis	24 January 2012 to 23 August 2013
Mean elevation	500-723
Mean slope	17^0
Mean annual precipitation	945 mm
Mean annual discharge	151 mm
Mean rainfall runoff ratio	0.16

2). Modelling and Calibration

The Topnet model used 31 parameters to characterise the hydrological process of catchment as observed from the satellite image as shown in Fig. 5, where possible, parameters values were determined from physical catchment properties.

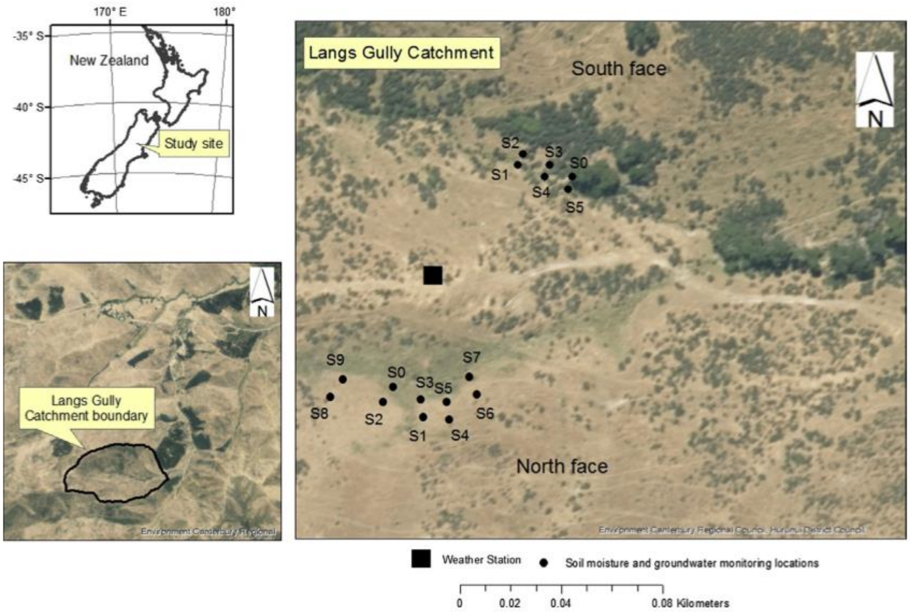


Fig. 5: GIS Based Langs Gully Catchment Image

Model inputs were precipitation and temperature-time series, relative humidity, solar radiation, maps of elevation, vegetation type, soil type and long term precipitation isohyetal pattern as shown in Table III.

TABLE III
MODEL PARAMETERS OF THE TOPNET MODEL

Parameter	Description	Range	
		Min	Max
Topmodf	TOPMODEL f parameter (m^{-1})	0.001	2
Hydcono	Saturated hydraulic conductivity (ms^{-1})	0.01	9999
Swater1	Drainable water (m)	0.05	20
Swater2	Plant – available water(m)	0.05	20
Dthetat	Soil water content (m)	0.1	10
Overvel	Overland flow velocity (ms^{-1})	0.1	10
r_man_n	Manning's n (-)	0.1	10

3). Model Verification

The observed data were analysed to gain insight about the flow generation process from study area as shown in Table IV. They found from the data, the poor correspondence between precipitation and runoff i.e. catchment had considerable storage potential, mainly in the form of groundwater storage so that it takes the time to get saturated and started producing the runoff. The percentage of total runoff that was likely to be the base flow was around 75%. Hence, to model this type of catchment, any model need a detail groundwater and soil moisture component.

Author classified the study area into north and south face. For each monitoring location, the temporal variation of soil moisture at 2 measurement depth 30cm and 60cm were obtained. Clearly the soil moisture for north slope was more variable than the south facing slope with many more occurrences of low moisture values. Despite their alternations for both slope, the largest soil moisture content generally occurred at 60cm depth. This was consistent with the notion that catchment had considerable groundwater storage.

TABLE IV
CORRELATION BETWEEN MODEL SOIL MOISTURE AND OBSERVED SOIL MOISTURE

	Correlation coefficient	
	Soil moisture at 30 cm	Soil moisture at 60 cm
North face	0.84	0.80
South face	0.81	0.71

4). Comparison of Observed and Model Fluxes

The comparison of model simulations against measured data was often dependent on determining the correct correspondence between the measured and model fluxes. This was made grimmer because field data were at the point scale while model simulations were at the catchment scale.

Their Topnet model was set up for whole study area and sub-catchment resolution based on Strahler-1 classification system. The uncalibrated model was run for the period of 24th January to 23rd August 2013. Comparison of soil moisture values obtained from Topnet model with average observed soil moisture shows that:

- Observed temporal variation of soil moisture was reasonably well represented by both slopes of study area.
- For spatial and temporal comparison between both model results and observations, they calculated temporal correlations for each pixel (topographic index value). They concluded that highest correlations occur during spring and winter as evaporation rates were lower. While autumn and summer had weather correlation as evaporation rates rises during summer that results into deterioration of spatial correlation.
- Topnet model was validated for saturated area representation. The normalised percentage of saturated area along with soil moisture and precipitation had observed for short period in winter of 2012 when it appeared the whole catchment quickly become saturated and the following winter, the extent of saturation was less.
- The final comparison was to look at the depth of the groundwater table. As there was no conceptual connection between observed depth to water table and normal depth to groundwater table an offset was inevitable. Temporal patterns of model were compared with observed depth to water table. The best agreement in terms of range of values was with Bore S6, while Bore S0 had a similar temporal profile but with greater range of values. Comparison with other bores were highly variable.

As most field measurements were point measurement, while hydrological modelling was a catchment or sub-catchment level, one of the biggest encounter in comparing simulated value with observed was accounting for alterations in scale of comparator variable. For comparison of semi or distributed hydrological models, one or more 3-D pattern should be used to supplement single point measurement of variable under examination. The GIS overcomes this challenge well. Following attributes could be concluded from their hydrological model:

a). The Topnet model was set up using Geographical Information System based approach using field observation and the measurement data into the form usable by the model.

b). The simulations obtained from this model provide a truthful representation of what was happening in the catchment, notwithstanding with some exceptions. The total amount of simulated runoff from Topnet model showed judicious agreement with observations in terms of time-based variations.

The soil moisture variation calculated by this model were reasonable and the timing for production of saturation excess runoff was unswerving with observation. The correlation on seasonal basis between spatial pattern of observed and modelled soil moisture values designated that the best correlations occurs when evaporation instabilities were anticipated to be small and vice-versa. Following were the limitation identified in the study:

a). Alternations in altitudinal scales of observed and simulated quantities were coupled with few measurement points to model the locations, mades it awkward to compare observed data with model outcomes.

b). Though total amount of modelled runoff from the Topnet model showed rational agreement, however there was incongruity in the total volume measured from the catchment.

c). Topnet model was restricted to guesstimate under low flow conditions. Model result for high flows were generally driven by precipitation and thus were more associated to data ambiguity.

d). Vegetation effects may well need more comprehensive knowledge of rooting depth of diverse species under diverse soil conditions.

e). Attention needs to be focussed on the dynamics of the vegetation driven extraction of soil moisture.

IV. ARTIFICIAL NEURAL NETWORK METHOD

The Artificial Neural Networks (ANNs) had been in existence since 1940s but current logarithm had overcome the restrictions of those early neural networks, prodigious interest in the practical applications of ANN had arisen in current decade**.** Encouraged by the functioning of brain and biological nervous system, ANN had been applied to various hydrological problems in recent years. An ANN was described as an information processing system that was self-possessed of many non-linear and densely interconnected processing elements or neurons. ANNs had been proven to provide better resolution when applied to:

- Complex system that may be poorly described
- Problems that deals with noise and involve pattern recognition, diagnosis, abstractions and generalisations.
- Situation where input is incomplete or ambiguous by nature.

ANN could extract patterns in phenomena and overcome complications, due to assortment of the models from such as linear, power or polynomial. It could model the precipitation-runoff associations due to its skill to generalise in noisy and ambiguous input data and to synthesise a complex model without the preceding knowledge or probability distributions.

A. *Precipitation - Runoff Modelling Using Artificial Neural Network and Conceptual Models* [4]

An ANN was an information processing system that was composed of processing elements (or neurons) analogous to biological neurons and interconnection or weights between these elements that imitate the synaptic strength in biological nervous system as shown in Fig. 6.

IJCRT Publish Paper record is available at DOI: http://doi.one/10.1727/IJCRT.17132

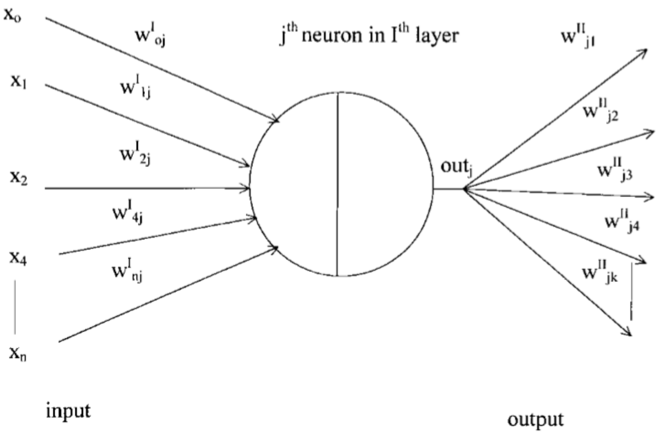


Fig. 6: Artificial Neuron Transfer Function

In an ANN architecture, the neurons were arranged in groups called layers. Each neuron in a layer operated in the logical parallelism. Information was transmitted from one layer to another in serial operations**.** A network could had several layers. The basic structures of network usually consist of 3 layers:

- *Input layer(s):* data were introduced to the network.
- *Hidden layer(s)*: data were processed.
- *Output layer***:** results for given inputs were produced.

1). Training ANN

The most idiosyncratic characteristics of an ANN was its ability to learn from examples. Learning or training was defined as self-adjustment of the network weights to approximate the target output based on certain algorithm. Learning ANN consists of 3 elements:

- Weights between neurons that defines the relative importance of the input.
- A transfer function that controls the generation of the output from the neuron.
- Learning laws that describes how the adjustment of weights were made during training**.**

During learning, a neuron receives inputs from input or previous layers, weights each input with a pre-assigned value, and combined these weighted inputs. The net_j (summation of weighted input for say j neuron) was either compared to a threshold or passed through a transfer function to determine the level of activation. If the activation was strong enough, it produced an output which was sent to other neuron in successive layers. The hyperbolic tangent or sigmoid were often employed as *transfer function* in the training of the network.

2). Modelling Precipitation-Runoff Process

The Little Patuxent River was in Maryland was the study area of the author. General information of the basin used in the case study was shown in Table V. It was the precipitation dominated stream exhibiting the behaviour of the stable groundwater and perennial runoff stream type**.**

ANN technique was used to model daily precipitation-runoff in the watershed network defined by various combinations of precipitation, temperature and discharge at present and previous time were trained and tested to simulate stream flows using diverse ANN configurations.

3). *Model Training and Calibration*

The training of the network was accomplished using *back-propagation algorithm* of neural networks as shown in Fig. 7**.** Back propagation was the most commonly administered training algorithm in the multilayer feed forward network. Here the data was processed in the forward direction from input layers to the hidden layers and then to the output layer. The objective of the back-propagation network was to determine the weights that approximate target values of output with selected accuracy. The least-mean square method along with generalised delta rule was used to optimise the network**.**

TABLE V
GENERAL INFORMATION FOR BASIN USED IN THE CASE STUDY

Parameter	**Fraser River 1**	**Middle Raccoon River 2**	**Little Patuxent River 3**
Station	Near Granby, Colo.	Near Bayard, Iowa	Near Guiford, Md.
Latitude	$40^0$08’31”	$41^0$46’43”	$39^0$10’04”
Longitude	$105^0$056’31”	$94^0$29’33”	$76^0$51’07”
Drainage area (km^2)	458.2	960.0	98.4
Mean annual discharge (m^3/s)	6.2	7.4	1.32

Period of record	1948-94	1978-93	1968-93

The hyperbolic function was selected as an activation function in training of network. Based on average precipitation, 3 data sets representing average, dry and wet years was selected for training and testing to identify the precipitation-runoff behaviour in the study area, testing data was not used in the training; however, to avoid overtraining, network were tested using a test set. For diverse amalgamations of input variables, network was trained using one-hidden layer network.

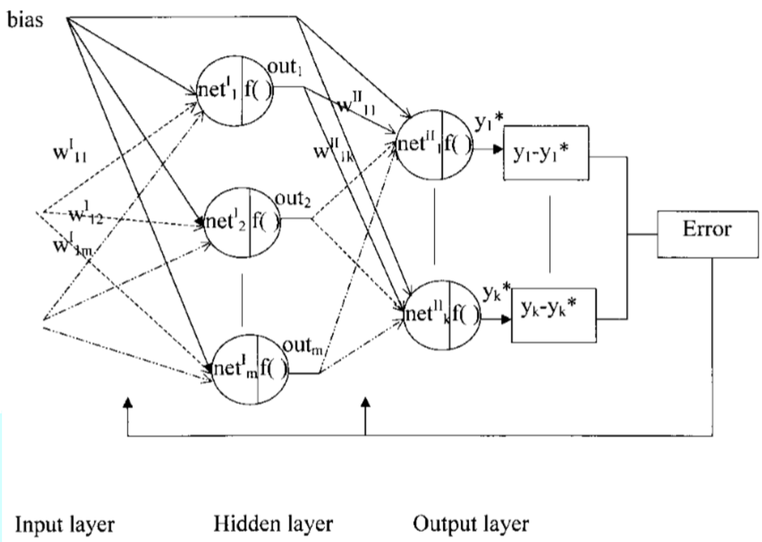


Fig. 7: Schematic of Back Propagation Network

4). *Model Verification*

Data obtained using ANN technique was compared with SCRR model. Simple Conceptual Precipitation- Runoff (SCRR) model was originally developed by *McCuen and Synder* in 1986. The SCRR model for Little Patuxent River Watershed as shown in Fig. 8 was calibrated under the supervision of R.H. McCuen. For conceptual model (root-mean square error (S_e) divided by standard deviation of observed discharge (S_y) values were 0.66 and 0.67 for calibration and verification respectively whereas ANN model obtained low values of 0.46 and 0.42 for training and testing respectively

The ANN model provided a significantly higher training accuracy for average and wet years compared to that of SCRR which illustrated better training accuracy for dry year. However, the ANN model demonstrated significantly higher testing accuracy for three years.

Following attributes could be concluded from their hydrological model:

a). The ANN practice has been explored to provide sensibly virtuous resolution for circumstances stated above.

b). It could accurately model non-linear relationship.

c). It has provided a methodical tactic and shortened time spat on training of models compared to the conceptual model.

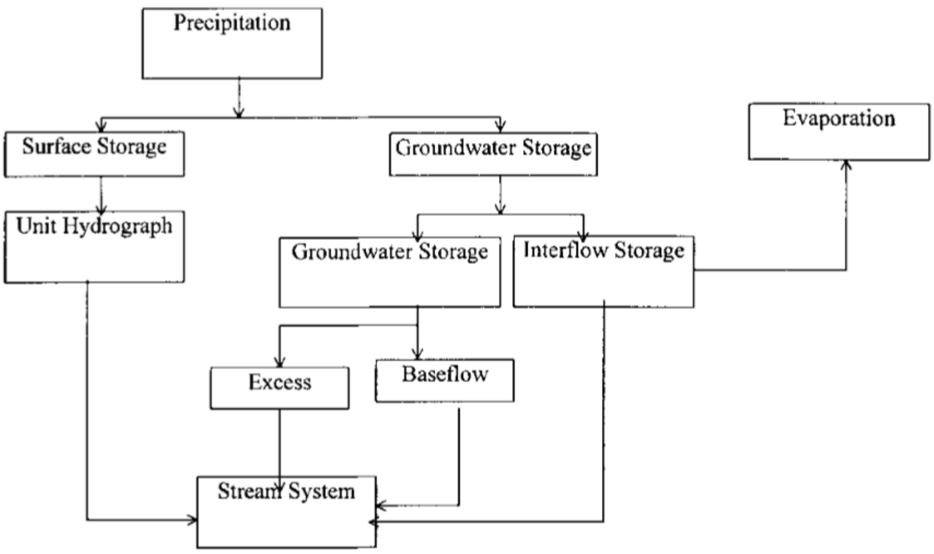


Fig. 8: Flowchart for SCRR

V. Genetic Algorithm Method

The manual calibration of a model by trial and error was a time-consuming method and the result may be subjective. This was particularly true when calibrating against more than 1 hydrological variable. Therefore, various automatic calibration method had been developed like Dynamic identifiability analysis method, genetic algorithm method etc. Evolution-based method had been found to be appropriate tool for the optimisation of conceptual models. Genetic algorithm was one of the class of these methods.

A. *History*

The idea of developing Genetic Algorithm was originally suggested by *Holland* was to mimic evolution parameters sets encoded to chromosome like string and diverse recombination operators were used to generate new parameters sets. The optimisation started with a population of randomly produced parameters sets. These were evaluated by running the model and those sets that give better simulation as per some objective function were given more chances to generate new sets that those sets that gave poorer results.

In hydrology, genetic algorithms had been used for calibration of conceptual runoff models. In 1997, *Kuczera*, compared diverse probabilistic optimisation algorithm including the genetic algorithm and found that the Shuffled Complex Evolution (SCE-UA) algorithm to be superior to the genetic algorithm and pointed out that “better genetic algorithm performance is therefore possible”.

B. *Multi-Criteria Calibration of a Conceptual Runoff Model Using a Genetic Algorithm* [5]

In this study, a genetic algorithm was proposed for multi-criteria calibration of the HBV model. The HBV model was a conceptual model that simulated daily discharge using daily precipitation and temperature and monthly estimates of potential evaporation as input. The model comprised of diverse routines, where snowmelt was computed by degree day method, ground water recharge actual evaporation was the function of the actual water storage in a soil box, runoff formation was represented by 3 linear reservoir equations and channel routing was simulated by a triangular weighting functions.

Firstly, the model was calibrated to a synthetic runoff series engendered by the model. Thereafter 2 catchments with diverse geology were used to calibrate the model against both runoff and groundwater level observations. The aim was two-fold, a test of the capability of the genetic algorithm as a tool for multi-criteria calibration and an assessment of the worth of groundwater data for the calibration of the conceptual runoff model.

1). *Description of Genetic Algorithm* [3]

With a genetic calibration algorithm, optimised parameter sets were found by *evolution of parameter sets* using selection and recombination as shown in Table VI. Following was the description of the process:

An initial population of *n* parameters sets was produced randomly in the parameter space and the fitness of each set was evaluated by the value of objective function. From this population, a new population was produced by *n* times combining 2 of the parameter sets. The 2 sets were chosen randomly but the chance of being picked was associated to the fitness parameter sets, giving the highest probability to the set with the highest fitness. A new parameter set was produced from two parent set (set-A and set-B) using parameter by parameter generation by applying one of the following rule:

a). Value of set-A (p=0.41)

b). Value of set-B (p=0.41)

TABLE VI
MODEL PARAMETER AND FEASIBLE RANGE

Parameter	Explanation	Unit	Lower bound	Upper bound
Snow routine				
TT	Threshold temperature	^0C	-1.5	2.5
CFMAX	Degree-day factor	mm $^0C^{-1}d^{-1}$	1	10
SFCF	Snowfall correction factor	-	0.5	1.2
CWH	Water holding capacity	-	0	0.2
CFR	Refreezing coefficient	-	0	0.1
Soil routine				
FC	Maximum of SM (storage in the soil)	mm	50	500
LP	Threshold for reduction of evaporation (SM/FC)	-	0.3	1
BETA	Shape coefficient	-	1	6
Response routine				
K0	Recession coefficient (upper storage)	d^{-1}	0.1	0.5
K1	Recession coefficient (upper storage)	d^{-1}	0.05	0.3
K2	Recession coefficient (lower storage)	d^{-1}	0.001	0.1
UZL	Threshold for the k_0 – outflow	mm	0	50
PERC	Maximal flow from upper to lower	mm d^{-1}	0	4

	box			
MAXBAS	Routing, length of weighting function	d	1	7

c). Random value between set-A and set-B (alternatively if both values of set were equal, a random value close to p=0.16.

d). Random value within the limits given for the parameters (mutation)(p=0.02).

The first two rules preserved the values of the preceding generation, whereas the other 2 rules provided an amount of random search. Balance between these rules was important for the success of algorithm.

Subsequently the fitness of each set in the new population was evaluated and the new generation replaced the old one. The best set was retained if there was no better set in the proceeding generation.

2). Improvement of Genetic Algorithm Using Multiple Calibration

The authors mentioned that the combination of genetic algorithm with the local search method could improve the results. They used the 'parameter set' found by the genetic algorithm as a starting point for local optimisation. In this study, the idea of local search was implemented in a second way. At a small probability (p=0.02) a new parameter set was produced not by 'parameter by parameter' generation but by one-dimensional optimisation along the line determined by 2 parameter sets using Brent's method as shown in Fig. 9.

While other algorithms used the binary representation of parameters sets. In this study, real numbers were used. The advantage of the latter method was that the parameters were represented directly and it has been found to give faster, more consistent, more accurate results.

Furthermore, in all the three studies, one or two-point crossover had been used to combine 2 strings representing parameter sets. This means that values of several successive parameters were swapped jointly between the parent parameter set. This execution also called *uniform crossover* ensures independence on the location of parameter. This was assumed to make the algorithm more robust and made subjective ordering of the parameter sets unnecessary (see Fig. 9).

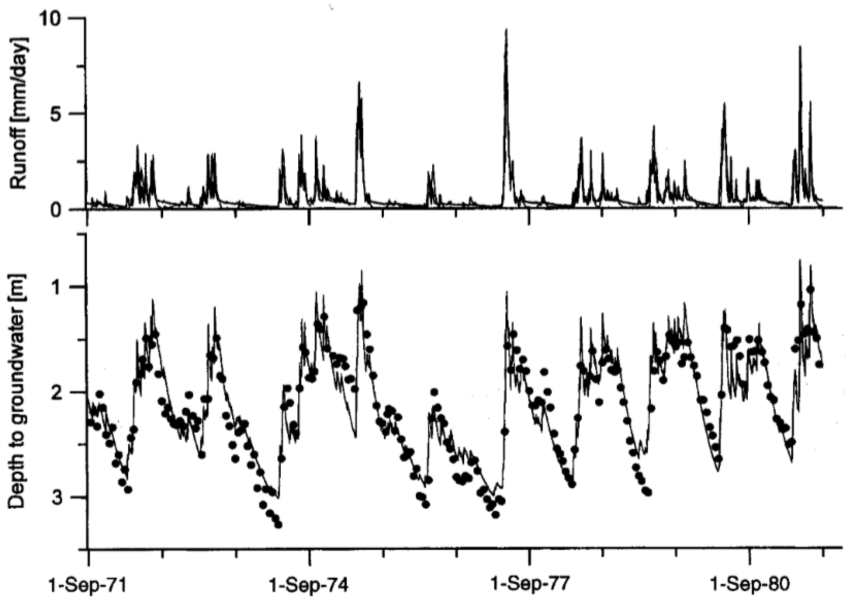


Fig. 9: Observation and Simulation of Runoff and Groundwater Level in the Study Area

The use of the multiple-population could improve genetic algorithm as shown in Table VII. Usually the same criteria were used to define fitness in the diverse population, but obviously, the use of the multiple-population provides a means to extent the genetic algorithm for multiple-calibration.

TABLE VII
PERFORMANCE OF SIMULATION AFTER CALIBRATION

Model application	**Runoff calibration**		**Groundwater level calibration**		**Multi-criteria calibration**	
	Runoff, R_{eff}	Groundwater Levels, r^2	Runoff, R_{eff}	Groundwater Levels, r^2	Runoff, R_{eff}	Groundwater Levels, r^2
Lilla Tivsjon	0.879	0.313	0.649	0.901	0.934	0.855
Tarnsjo	0.734	0.412	0.214	0.837	0.677	0.720
Taensjo (modified model structure)	0.762	0.521	0.435	0.845	0.713	0.787

In this study, the variation of parameter value found in diverse calibration trials were considerably smaller when calibrating to both runoff and groundwater level. Most significant was the reduction in the parameter uncertainty or some parameters of the response routine where the variation was only 10-30% of the variation of the singe-criteria calibration.

Following attributes could be concluded from their hydrological model:

a). In this study, an algorithm for single and multi-criteria calibration has been proposed for HBV model which could be implemented easily in other models.

b). It has been demonstrated that the use of the additional data (here groundwater level, local search parameter, multiple population) could help to constrain the range of parameter values.

c). Furthermore, the multi-criteria calibration motivated the modification of the model structure that provided a more realistic representation of the catchment hydrology.

d). The result obtained in this study designate that the genetic algorithm is capable of optimising the parameter of the conceptual-runoff model and that it could easily protracted for multi-criterion calibration as supported by *Seibert et. al. 1999.*

VI. DYNAMIC IDENTIFIABILITY ANALYSIS METHOD

Initially it was thought that the grimy in identification of an appropriate Conceptual Precipitation-Runoff (CRR) model for definite case i.e. a given modelling objective, catchment characteristic and data sets would disappear with better automatic search algorithm, capable of locating the global optimum on the response surface. However, a powerful global optimisation algorithm was available, but single-objective calibration procedure still failed to replace manual calibration completely. It was due to the fundamental problem that a single-objective automatic calibration was not sophisticated enough to replicate the several performance criteria implicitly or explicitly used by hydrologist in manual calibration. The problem was increased by indications that, due to structural inadequacies, one parameter set might not be enough to describe all response modes of hydrological system adequately. Therefore, there was a strong augment that the process of identification of dynamic, conceptual model must be rethought.

The efficient and objective automatic process were required to allow for the evaluation and discrimination between competing models, i.e. parameter set and model structure combinations and even competing model structures. *Dynamic Identifiability Analysis (DYNIA*) was an attempt to develop an approach to compliment traditional calibration methods to increase their discriminative power. The method was in testing stage and more case studies was required to be performed.

A. *Towards Reduced Uncertainty in Conceptual Precipitation-Runoff Modelling: Dynamic Identifiability Analysis* [6]

The paper presented a new approach to the identification and analysis of conceptual hydrological models called DYNIA derived from the well-known Regional Sensitivity Analysis. DYNIA was an attempt to avoid the loss of information through aggregation of the model residuals in time. This additional information could be used to analyse the working of the model, to found the amount of information available to identify a definite parameter, or to detect the failures of underlying model assumptions to assess adequacy of the selected model structure. The approach was applied to a conceptual model structure containing typical structural components and some initial results were presented.

1). Identifiability Analysis of Conceptual Precipitation-Runoff Models

The purpose of identifiability analysis of conceptual-rainfall-runoff (CRR) modelling was the identification of the model structure and a corresponding parameter set that were most representative of the catchment under investigation, while considering aspect such as modelling objectives and available data. This identifiability analysis could therefore be split into two stages:

a). Model Structure Identification

Evaluation of proper functioning of the model means questioning the assumptions underlying an individual model structure, such as Do the model components really represent the response modes they are intended to represent? Is the model structure capable of reproducing the diverse dominant modes of behaviour of the catchment with a single parameter set? A model structure was usually a combination of diverse hypothesis of the working of the natural system.

A test of performance was the assessment of whether the model structure was capable of sufficiently reproducing the observed behaviour of the natural system, considering the real quality data. It could be showed that the use of multiple objectives for single output models could give comprehensive information and allows the modeller to link model performance and model components**.** Additional information would also be available in case where the model produces other measurable output variables, e.g. groundwater level etc.

b). Parameter Identification

The second stage in the model identification process was the estimation of appropriate parameter set, i.e. the actual calibration of the model structure. The parameter of each model structures was adjusted until the observed system output and the model output show acceptable level of agreement. Manual calibration did this in a trial-error procedure, often using several diverse measures of performance and visual inspection of the hydrograph. It could yield virtuous results, but was time consuming, demands extensive experience with a definite model structure, and an objective analysis of parameter uncertainty was not possible.

Traditional single-objective automatic calibration, on the other hand, was fast and objective, but would produce result that reflect the choice of objective function leads to the neglect and loss of information about information response modes, and could result in a biased performance.

Author reviewed this problem in more detail and concluded that a multi-objective approach to automatic calibration could be successful. *Boyle et. al., (2000)* show how the process could be applied to combine the requirements of manual calibration with the advantage of automatic calibration.

2). Multi-Objective Calibration of Single Output Models

One-way of implementing automatic multi-objective calibration was by partitioning the continuous output time series into diverse response periods. A separate objective function could then be specified for this period, thus reducing the amount of information lost through aggregation of the residuals. Partitioning schemes proposed for hydrological time series include:

a). Experience with a definite model structure.

b). Hydrological understanding of the catchment.

c). Parameter sensitivity.

d). Grouping similar characteristics.

3). DYNIA

This was a novel approach for locating periods of high identifiability for individual parameters and to detect failures of the model structure in an objective manner. The basic steps could be seen in the flow chart as shown in Fig. 10. The approach here was protracted to assess the identifiability of parameters, not just their sensitivity.

a). Monte Carlo sampling based on a uniform prior distribution was used to examine the feasible parameter space.

b). The objective function associated with each parameter set was transformed into a support measure (they sumed to Fig.10a).

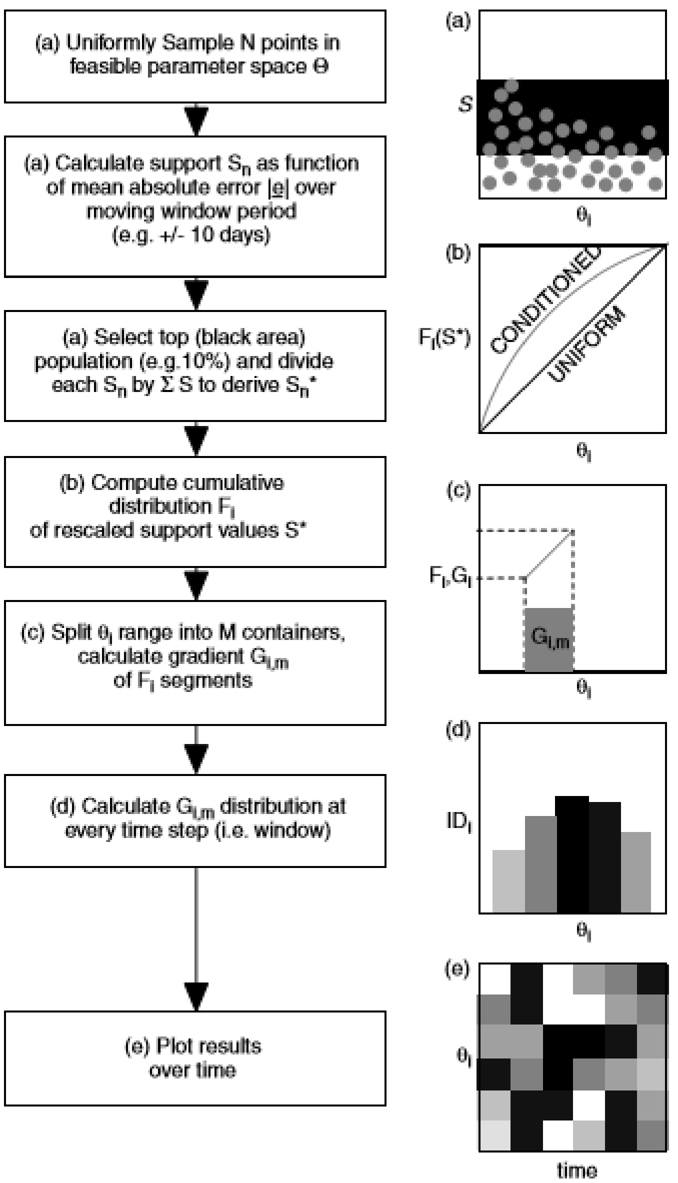


Fig. 10: The DYNIA Procedure

c). Best performing parameter values were selected and their cumulative support was calculated (fig. 10b). A straight line would designate a poorly identified parameter. Deviation from this straight line designates that parameter is conditioned by the objective function used.

d). Gradient of the cumulative support was calculated which was an indicator of strength and of the identifiability of parameter. The highest value designated by darkest colour, marked the location of greatest identifiability of the parameter.

e). The results were plotted for each parameter versus time using a colour coding, where a colour designated areas, in parameter space and time, of higher identifiability.

4). Applications

A list of possible areas of application of DYNIA were as follows:

a). To estimate parameters i.e. simple model calibration or identification.

b). To analyse model structures.

c). The algorithm associated model parameters and responses modes of the natural system.

d). To invest data outliers or anomalies.

The DYNIA provided a dimension for analysing the performance of the model in a dynamic manner resulting in a better use of available information. Model structures could be evaluated w.r.t the failure of individual components, and period of high information content for definite parameters identification.

The following attributes could be concluded from their hydrological model:

a). The identifiability of parameters of dynamic and conceptual precipitation-runoff model was a difficult operation and an automatic procedure overcoming these problems would, therefore, be extremely helpful. However, traditional, single-objective automatic calibration process often lead to many similarly performing parameter sets, and to biased and therefore unacceptable model behaviour.

b). DYNIA provided an approach for analysing the performance of the model in a dynamic fashion resulting in a better use of available information.

VII. CONCLUSION

In the present review, diverse methodologies for the development of hydrological models to simulate the precipitation-runoff process was studied. It was concluded that the parameter identifiability, modelling the parameters, calibrating and validating were the fundamental approach for the development of watershed models. The difference lies in the true identification of the parameter, calibrating methodology augmented and its result analysis with the observed data etc. These approaches mark the difference in the processing of a hydrological model. The following attributes could be concluded from this review:

1). The *Rational Hydrograph Method* presented a new runoff simulation model based on its improvement for developing hydrological model for the given catchment using rational method.

2). In *Geographical Information System* based approach of using digital maps, topography of the soil types, and vegetation marked the noticeable methodology of simulating hydrological models. Topnet model provides the future scope of refining the connection between spatial and temporal comparison even in season of summer and autumn

3). The *Artificial Neural Network* methodology had been researched to provide judiciously virtuous solution for situations having complex system that may be ill-defined or understood using mathematical equations, problem that deals with noise or involve pattern identification and input data that were unfinished and explicit by nature. The ANN could accurately model non-linear relationship between hydrological inputs, precipitation, snow water equivalent, temperature and output stream flow.

4). The *Genetic Algorithm method* had found to be appropriate for the optimisation of conceptual runoff models. This method provided an advancement in automatic calibration of the model instead of time consuming manual calibration. As an alternative of single-criteria calibration, author had stressed over the augmentation of multi-criteria calibration. This had resulted in the modification of the model structure that provided a more realistic representation of the catchment hydrology.

5). The *Dynamic Identifiability Analysis method* had been found to be beneficial where identifiability of parameters of dynamic and conceptual precipitation-runoff model was a grim task. Manual calibration could yield virtuous results, but the procedure was time consuming, demands experience, and did not allowed for the objective analysis of parameter ambiguity and interaction.

It can be concluded that the methods discussed in the review also founded limitations in their approaches which made their research incomplete and thus provided foundation for further research and analysis. The Genetic Algorithm method was considered better. This method was less tedious than ANN as genetic calibration algorithm provided a better optimisation of the *n* number of parameter sets. The result obtained in the study designated that the genetic algorithm was capable of optimising the parameter of the conceptual-runoff model and that it could easily protracted for multi-criterion calibration.

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