31002

Uzoigwe, l. O and Mbajiorgu, C.C/ Elixir Civil Engg. 80 (2015) 31002-31008

Available online at www.elixirpublishers.com (Elixir International Journal)



Civil Engineering

Elixir Civil Engg. 80 (2015) 31002-31008



Development of an Autocalibration Capability for Watershed Resources Management (WRM): A Processed Based Model Application

Uzoigwe, l. O^1 and Mbajiorgu, C.C²

¹Faculty of Engineering, Department of Agricultural Engineering, Imo State University Owerri, Imo State, Nigeria. ²Faculty of Engineering, Department of Agricultural and Bioresources Engineering, University of Nigeria Nsukka, Enugu State, Nigeria.

ARTICLE INFO

Article history: Received: 11 January 2015; Received in revised form: 25 February 2015; Accepted: 7 March 2015;

Keywords

Genomes (Mann1, Mann2, Mann3 And Kret), Optimization, Autocalibration, WRM. Genetic Algorithm, Graphic User Interface (GUI).

ABSTRACT

The watershed resources management (WRM) model is a basin-scale model for continuous simulation. It is applicable in planning, forecasting and operational hydrology. Hydrological simulation requires calibration to match reality. In automatic calibration, optimization is carried out using selected model parameters. WRM model originally calibrated heuristically in FORTRAN for Curley's and Mayne's sub-watersheds Canada was converted to C# (C sharp) to allow flexibility in programming and to enable Graphic User Interface (GUI) creation, and autocalibrated for tropical watersheds. The WRM model was repackaged to run in normal and autocalibration mode. Two software programs, WRMGA and WRMGUI, were successfully developed, tested and applied. Genetic algorithm (GA) was employed as optimization technique. Four parameters (genomes) namely, the Manning roughness coefficient for land surface (MANN1), Manning roughness coefficient for stream surface (MANN2), Manning roughness coefficient for terrace surface (MANN3) and surface retention parameter (KRET) with high sensitivity were used to adjust the four input files (FOR001.DAT, FOR003.DAT, FOR005.DAT, optimized.dat and WRM.DAT.optimized.dat) for the autocalibration. Genomes were generated using a random number generator within specified ranges. The generated values were stored in a file, Optimized.dat, which the program calls up and uses to compute the best fit. For MANN1, MANN2, MANN3 and KRET, minimum values of 0.10, 0.01, 0.00 and 0.01 and maximum values of 0.18, 0.05, 0.05 and 0.05 respectively were set and used for optimization process. The optimization process with up to 1000 trials using these sets of minimum and maximum values gave optimized values of 0.1272, 0.0214, 0.0201 and 0.0102 for MANN1, MANN2, MANN3 and KRET respectively, with a best fitness test of 0.9998. Hydrograph plots of both the originally heuristically calibrated simulations for the watersheds and the autocalibration simulations for the same watershed were compared with measured hydrographs and statistically validated. WRM originally calibrated to the watersheds gave a regression coefficient (R) of 34.8% while the autocalibrated model gave 37% showing an improvement in the autocalibration scheme. The WRM model was successfully repackaged for autocalibration in this paper and could be employed by non-expert in hydrologic modelling.

© 2015 Elixir All rights reserved.

Introduction

Simulation of complex hydrological response in large watersheds for decades has prompted the need for procedures for autocalibration. The commonly available models of watershed hydrology are of the event type applicable on a basin scale or continuous models applicable on a field scale. But the watershed resources management (WRM) model is a basin-scale model for continuous simulation. It is generally applicable in planning, forecasting and operational hydrology, to the study of environmental impacts of land-use change and to soil and water conservation planning. Empirical equations, derived from relating physical quantities experimentally and validated independently, are employed. In every hydrological simulation, there is always a need for optimization and the optimization is carried out by best possible technique that will yield perfect or near perfect values for selected calibration parameters.

Calibration is the process of determining the optimal or best solution corresponding to the most accurate representation of a

Tele: E-mail addresses: luzoigwe@yahoo.com

real system by simulation. Calibration is not a simple task as there are quite a few model parameters that can be adjusted and many of them seem to affect the simulated hydrograph. The purpose of autocalibration is to simplify this task in an objective manner and it deals with systems and sub-systems analysis that can be extended to water resources planning and development (Lindstrom, 1997). Autocalibation is a computer-based procedure for simplifying this task i.e. a complete data processing by computer from a prepared program instruction in machine form for immediate use. Certainly, the model calibration problem could be programmed without difficulty through formulation of calibration and optimization problems. A multi-objective function measuring the closeness between the observed and simulated hydrographs with an optimization algorithm to search for the parameter values that minimize the objective function with some reasonable mathematical conditions is required in finding the optimal solution.

Years back, the approach to runoff calculation involved a systematic error, resulting in an under or over-estimation of runoff amount, a hazard associated with manual calibration which is computationally inefficient with rough scaling results. Review of continuous simulation and autocalibration in hydrologic modelling for the past decade, revealed search techniques for model optimization, thus allowing for multiple-criteria concept on alternative parameter sets that are optimal on the basis of multi-objective global optimization. This technique has been applied to models developed by Betson and Ardis (1978), Abbott et al., (1986) and Hodge et al., (1988).

Mbajiorgu (1991, 1995a and b) developed the WRM model in relation to continuous simulation of agricultural watershed hydrology and conservation hydraulics structures which was then applied to two sub-watersheds (Curley's and Mayne's) in Canada. The WRM model was heuristically optimized and there was a need to develop automatic calibration for the same model which also could be applicable to the tropical watersheds.

The focus of this work therefore, include: development and application of an automatic calibration procedure to an existing watershed hydrologic model developed by Mbajiorgu (1991, 1995a and b); application of a suitable optimization procedure for automatic calibration of the WRM model; validation of the developed WRM models in relation to existing normal models for predicting the hydrograph pattern of the Nigerian watersheds; repackaging the WRM model with modified graphic user interface (WRMGUI) and genetic algorithm (WRMGA) software programs for user-friendliness and autocalibration capability in modelling of the same model that could be applied in the modelling of tropical watersheds.

It is important to note here that hydrological simulations require calibration to match reality. The confidence that can be ascribed to the model simulation depends on the model uncertainty remaining after the model has been calibrated. Due to the fact that calibration process is different and complex, there is need for robust and reliable automatic calibration procedures. Extensive literatures (Duan et al., 1992; Luce and Cundy, 1994; Gan and Biftu, 1996; Freedman et al., 1998; Abdulla et al., 1999) reveal that there exists no general algorithm for the solution of optimization problems. The choice of method depends on the characteristics of the system, the availability of data and the objectives and constraints specified (Knox et al., 2001). The GA is recommended for use in the model autocalibration scheme, in the sense that the choice of a set value for model responses to specific study base is encouraging. Methodology

The Watershed Resources Management (WRM) model developed for Canadian conditions in FORTRAN programming language was converted to C# (C Sharp), an object oriented programming language developed by Microsoft. The choice of C# is to allow flexibility in programming and to enable GUI creation, in order to directly input data for an application rather than creating an input file. The FORTRAN version of WRM model used subroutines, while the C# version of the model makes use of void functions to implement the same sub-programmes.

The WRM model was repackaged in such a way that it can be directly accessed from GUI. In order to implement the automatic calibration feature, the WRM model is programmed to run in two modes (normal and autocalibration modes). When the WRM is running in normal mode, no optimizable parameter values are needed but when it is running in autocalibration mode, the values of selected calibration parameters are needed. In order to achieve this, an input data file WRM.DAT was introduced to the main program. The WRM.DAT stores a value that tells the WRM Model the mode to run. When 0 is stored in the WRM.DAT, the WRM model runs in normal mode and when 1 is stored in it, the model runs in autocalibration mode. In order to make the model run in autocalibration mode, an additional subroutine called READOV (READ Optimizable Values) was introduced. READOV subroutine reads the values of the preselected parameters from a file called optimized.dat. Four input files (FOR001.DAT, FOR003.DAT, FOR005.DAT, optimized.dat and WRM.DAT. Optimized.dat) were used by the model to achieve the autocalibration.

Genetic algorithm which is intelligence based nonmathematical, non-deterministic but stochastic process or algorithm for solving optimization problems was adopted as the technique for autocalibration. Two software programs, genetic algorithm watershed resources management (WRMGA) and watershed resources management graphic user interface (WRMGUI) were successfully developed. WRMGA handles the autocalibration operation.

Processed response/program development

Three main classes Population, Genome and ListGenome, Figure 1, control the genetic algorithm. The processes involved were handled using these classes and the WRMGA interface which calls the population class.



Figure 1. Unified modelling language (UML) class diagram of the WRMGA

Computed responses/WRM model repackaging for GUI and automatic calibration

The computed response/WRM model repackaging for GUI and automatic calibration was achieved using Figure 2.



Figure 2. WRM genetic algorithm flow chart

From Figure 2, the initial generation of Genomes was produced using a random number generator. The fitness of the genomes was determined and the best solution obtained. The genomes that can reproduce were crossed-over in the allowable population. The fittest genomes of the two parent and two children resulting from the crossover were added to the next generation and random mutations through the next generation population was produced before looping back to step 2.

The genomes here are the four parameters to be optimized. These parameters: MANN1; MANN2; MANN3 and KRET were used for autocalibration. These parameters were chosen for the autocalibration due to their sensitivity.

WRM autocalibration process

The autocalibration initial progress trial was set to zero and allowed to undergo a total trial set to 1000. The genomes (MANN1, MANN2, MANN3 and KRET values) were generated using random number generator with specific ranges. The generated values were stored in a file called optimized.dat so that the FORTRAN program (WRMGA) read up the values and use them to compute runoff values. The computed runoff values were stored in a file called tmp.dat and then used in fitness test for best result. Figure 3 shows the WRM autocalibration process flowchart.



Figure 3. Wrm Autocalibration Process Flowchart

To run the heuristically calibrated model, there are seventyseven (77) input parameters stored in the following input data files (Figures 4 to 6): FOR001.DAT (for vegetation and watershed elements information); FOR003.DAT (for rainfall values); and FOR005.DAT (for pan evaporation values).

In running the model in autocalibration mode, importing data from external file involves the minimum and maximum values of the autocalibration parameters (MANN1, MANN2, MANN3 and KRET). A random number to produce random numbers distributed uniformly between 0 and 1 for WRM and WRMGA as normal and autocalibration modes respectively. Each run consisted of 1000 function r generator was adopted evaluation (iterations) for model optimization.



Figure 4. Watershed elements input data file (FOR001.DAT)



Figure 5. Rainfall input data file (FOR003.DAT)



Figure 6. Pan Evaporation input data file (FOR005.DAT) The WRM.DAT file instructs the FORTRAN WRM model to run in normal mode showing a Console Window WRMMODEL output screen (FORTRAN version) in Figure 7

C:\Users\UCCINC\Doo	uments\Visual Studio 20	10\Projects\WRM\WRM\bir		EXE X
42780	66.74	0.0038	56	-
42900	47.86	0.0013	27	
43020	36.44	0.0005	14	
43080 43140	32.48 29.33	0.0003 0.0003	11 9	
43200 43260	26.78 24.72	0.0002 0.0002	7	
43320 43380	23.03 21.63	0.0001 0.0001	5 4	
43440 43500	20.46	0.0001 0.0001	4 3	
43560 43620	18.65 17.94	0.0001 0.0001	3	
43680	17.34	0.0001	22	
43800	16.36	0.0000	22	
43920	15.62	0.0000	22	
44040	15.04	0.0000	2	
44160	14.59	0.0000	1	

Figure 7. WRMMODEL output screen (FORTRAN version)

Figure 8 shows the autocalibration WRM output model with the minimum and maximum values of the autocalibration parameters.WRMGA was introduced as an engine to compute different values of runoff. The computed runoff values were compared with the observed runoff values. Equation (1) was used to determine the fitness of the genomes.

$$R^{2} = \frac{\left[\left((\text{sum of RHS})\right]^{2} - (\text{sum of difference})^{2}\right)}{(\text{sum of RHS})^{2}}$$
(1)

Auto Calibration using Genetic Algorithm (uzoigwe.wrm)									
	#	Runoff		^	Parameter	Min va	lue	Max value	
•	1	43.96		Ξ	MANN1	0.1		0.18	
	2	26.06			MANN2	0.01		0.05	
	3	14.21				0.0		0.05	
	4	21.42			MAINING	0.0		0.05	
	5	19.74			KRET	0.01		0.05	
	6	18.34			Input the obs	erved runoff	with at leas	t 58 values.	
	7	17.19			Finally, input the minimum and maximum values of MANN1, MANN2, MANN3 and KRET				
	8	16.26							
	9	130.74		-					
Generation	n 1 N		MANNE	_		D			
0.00381	- 6	03406	0 15947	_	0 01241	1 999406288	3023469	_	
0.0161	6	.04925	0.13081		0.01304	0.999536486	6486842	_	
0.01867	D	.04244	0.14656		0.01235	0.999676959	0659127		
0.03106	þ	.02541	0.13767		0.01898	0.995871278	360004		
0.01045	p	.01891	0.11659		0.04803	0.986218187	7208082		
0.04245	D	.02675	0.11713		0.01473	0.996508661	1530101		
0.00331	D	.04205	0.17616		0.01525	0.995218321752729			
0.04668	D	.03358	0.10045		0.0268	.992033729924537		_	
0.02005	D	.02142	0.12717		0.01019	0.999746481216065		_	
0.04685	D	.02913	0.1539		0.01745	996157943563492		_	
0.04099	6	01087	0 12828		04469	989904813	989904813616997		
0 00894	6	02759	0 11211		02211	994475955009516			
0.03979	- 6	03812	0 13685	_	01282	999518830400723			
0.02351	- 6	02844	0 13014	_	001115	998802737787879			
0 03221	ĥ	01444	n 1252	-	101139	36855666	7046995		
AutoCalibrated Parameters Optimum Values									
1. Manning roughness coefficient for land surface - MANN1 0.12717									
2. Manning roughness coefficient for stream surface - MANN2 0.02142					-				
Marining roughness coefficient for terrace surface - MANN3 Surface retention parameter - KRET					0.0200				
Ready Fitness: 0.999746481216065:									

Figure 8. Autocalibration output window showing minimum and maximum values of the autocalibration parameters (genomes)

Where **R** is the fitness and **RHS** is right hand side (i.e. the observed runoff values). The sum of difference was obtained as the difference of the observed runoff and the calculated runoff. The values of R^2 ranged between 0.0 and

The values of \mathbb{R}^2 ranged between 0.0 and $1.0(i.e.\ 0.0 \le \mathbb{R}^2 \le 1.0)$; and the fitness values that are closer to 1.0 imply a good fitness while a fitness value of 1.0 gives a better fitness that produces the accurate solution to the equation. A well fitted set of generation forms the initial population for the next generation and subsequently until the stopping criterion of fitness of 1.0 or very close to 1.0 is obtained or the maximum generation indicated in the program has been reached.

Results

The results of the autocalibrated, simulated and the heuristically measured runoffs data generated were statistically analysed. Considering n pairs of measurements or observations of (X_i, Y_i) , the degree of correlation or the goodness of fit $(\mathbf{R}\mathbf{Y}\mathbf{X})$ (i.e. the correlation coefficient) of the regression of Y on X, Equations (2 to 5) were found useful for this application.

$$\mathbf{R}_{\mathbf{Y}\mathbf{X}} = \frac{\mathbf{S}_{\mathbf{Y}\mathbf{X}}}{\sqrt{\mathbf{S}_{\mathbf{Y}}^2 \cdot \mathbf{S}_{\mathbf{X}}^2}} \tag{2}$$

Where the terms in Equation (2) are obtained from Equations (3 to 5):

$$S_{X}^{2} = \sum_{i=1}^{n} X_{i}^{2} - n(\overline{X})^{2}$$
(3)

$$\mathbf{S}_{\mathbf{Y}}^2 = \sum_{i=1}^{n} \mathbf{Y}_i^2 - \mathbf{n}(\overline{\mathbf{Y}})^2 \tag{4}$$

$$\mathbf{S}_{\mathbf{Y}\mathbf{X}} = \sum_{i=1}^{n-1} \mathbf{X}_i \mathbf{Y}_i - \mathbf{n}(\overline{\mathbf{X}})(\overline{\mathbf{Y}})$$
(5)

The Regression Equation of \mathbf{Y} on \mathbf{X} is obtained using Equation (6):

$$\mathbf{Y} = \mathbf{a} + \mathbf{b}\mathbf{X} \tag{6}$$

Where a and b are constants to be determined from the data, and are respectively obtained from Equations (7 and 8):

$$a = Y - bX$$
(7)
$$b = \frac{S_{YX}}{S_{Y}^{2}}$$
(8)

Where $\mathbf{\overline{Y}}$ and $\mathbf{\overline{X}}$, are mean of the dependent and the independent variable, respectively.

The analysis of linear regression was extended to cover situations in which the dependent variable Y_{\bullet} is affected by several controlled variables, X_1 and X_2 (i.e. independent variables). In such case, a linear multiple regression equation (LMRE) of the form expressed in Equation (9) was used to obtain the regression equation of Y_{\bullet} or X_{\bullet} and X_{\bullet}

obtain the regression equation of
$$\mathbf{1}$$
 on $\mathbf{A}\mathbf{1}$ and $\mathbf{A}\mathbf{2}$.

$$\mathbf{Y} = \mathbf{a}_1 + \mathbf{b}_1 \mathbf{X}_1 + \mathbf{b}_2 \mathbf{X}_2$$
(9)

Where a_1 , b_1 and b_2 are constants (estimators) obtained respectively as follow:

$$\mathbf{a}_{1} = \mathbf{a}_{0} - \mathbf{b}_{1}\overline{\mathbf{X}}_{1} - \mathbf{b}_{2}\overline{\mathbf{X}}_{2}[(\text{where } \mathbf{a}]_{0} = \overline{\mathbf{Y}})$$
(10)
$$(\mathbf{S}_{\mathbf{X}_{2}}^{2})(\mathbf{S}_{\mathbf{X}_{1}\mathbf{Y}}) - (\mathbf{S}_{\mathbf{X}_{1}\mathbf{X}_{2}})(\mathbf{S}_{\mathbf{X}_{2}\mathbf{Y}})$$

$$\mathbf{b}_{1} = \frac{(\mathbf{x}_{2})(\mathbf{x}_{1}) - (\mathbf{x}_{1}\mathbf{x}_{2})(\mathbf{x}_{2})}{(\mathbf{s}_{X_{1}}^{2})(\mathbf{s}_{X_{2}}^{2}) - (\mathbf{s}_{X_{1}X_{2}})^{2}}$$
(11)
$$\mathbf{b}_{2} = \frac{(\mathbf{s}_{X_{1}}^{2})(\mathbf{s}_{X_{2}Y}) - (\mathbf{s}_{X_{1}X_{2}})(\mathbf{s}_{X_{1}Y})}{(\mathbf{s}_{X_{1}Y}) - (\mathbf{s}_{X_{1}X_{2}})(\mathbf{s}_{X_{1}Y})}$$
(12)

$$\frac{\left(\mathbf{S}_{\mathbf{X}_{1}}^{2}\right)\left(\mathbf{S}_{\mathbf{X}_{2}}^{2}\right) - \left(\mathbf{S}_{\mathbf{X}_{1}\mathbf{X}_{2}}\right)^{2} }{\left(\mathbf{S}_{\mathbf{X}_{1}}^{2}\right)\left(\mathbf{S}_{\mathbf{X}_{2}}^{2}\right) - \left(\mathbf{S}_{\mathbf{X}_{1}\mathbf{X}_{2}}\right)^{2} }$$

Where the terms of Equations (11 and 12) are obtained from Equations (13 to 18):

$$\mathbf{S}_{\mathbf{y}}^{2} = \sum_{i=\underline{1}}^{-} \mathbf{Y}_{i}^{2} - \mathbf{n}(\overline{\mathbf{Y}})^{2}$$
(13)

$$S_{X_1}^2 = \sum_{i=1}^{n} X_{1i}^2 - n(\overline{X_1})^2$$
(14)

$$S_{X_2}^2 = \sum_{i=1}^{n} X_{2i}^2 - n(\overline{X_2})^2$$
(15)

$$\mathbf{S}_{\mathbf{X}_{1}\mathbf{Y}} = \sum_{\substack{i=1\\n}}^{n} \mathbf{X}_{1i} \mathbf{Y}_{i} - \mathbf{n}(\overline{\mathbf{X}_{1}})(\overline{\mathbf{Y}}) \tag{16}$$

$$\mathbf{S}_{\mathbf{X}_{2}\mathbf{Y}} = \sum_{\substack{i=1\\n}}^{-} \mathbf{X}_{2i}\mathbf{Y}_{i} - \mathbf{n}(\overline{\mathbf{X}_{2}})(\overline{\mathbf{Y}})$$
(17)

$$\mathbf{S}_{\mathbf{X}_{1}\mathbf{X}_{2}} = \sum_{i=1}^{n} \mathbf{X}_{1i} \mathbf{X}_{2i} - \mathbf{n} \left(\overline{\mathbf{X}_{1}} \right) \left(\overline{\mathbf{X}_{2}} \right)$$
(18)

Using Equations (10 to 18), the degree of correlation or the goodness of fit $({}^{R_{Y}, X_{1}X_{2}})$ of the regression of Y on X_{1} and X_{2} , as found from Equation (19) is:

$$\mathbf{R} = \sqrt{\frac{(\mathbf{b_1})\left(\mathbf{S}_{\mathbf{X}_1\mathbf{Y}}\right) + (\mathbf{b}_2)\left(\mathbf{S}_{\mathbf{X}_2\mathbf{Y}}\right)}{\mathbf{S}_{\mathbf{Y}}^2}}$$
(19)

Autocalibrated [(Y] _f)	Measured $[(X]_{i_1})$	Simulated $[(X]_{2_1})$	Y_i^2	$X_{1_1}^{2}$	X21 ²	$X_{1_i}Y_i$	$X_{2_i}Y_i$	$X_{1_{1}}X_{2_{1}}$
12.1	9.1	12.1	146.41	82.81	146.41	110.11	146.41	110.11
12.1	9	12.1	146.41	81	146.41	108.9	146.41	108.9
12.1	8.9	12.1	146.41	79.21	146.41	107.69	146.41	107.69
15.91	8.9	13.38	253.1281	79.21	179.0244	141.599	212.8758	119.082
39.93	8.9	39.58	1594.4049	79.21	1566.5764	355.377	1580.4294	352.262
41.96	8.9	42.5	1760.6416	79.21	1806.25	373.444	1783.3	378.25
49.56	8.9	48.86	2456.1936	79.21	2387.2996	441.084	2421.5016	434.854
50.3	8.9	48.82	2530.09	79.21	2383.3924	447.67	2455.646	434.498
51.59	8.9	50.75	2661.5281	79.21	2575.5625	459.151	2618.1925	451.675
51.02	8.9	51.4	2603.0404	79.21	2641.96	454.078	2622.428	457.46
50.1	8.9	50.89	2510.01	79.21	2589.7921	445.89	2549.589	452.921
52.98	8.9	53.19	2806.8804	79.21	2829.1761	471.522	2818.0062	473.391
54.15	8.9	54.85	2932.2225	79.21	3008.5225	481.935	2970.1275	488.165
56.44	8.9	56.71	3185.4736	79.21	3216.0241	502.316	3200.7124	504.719
55.39	8.9	56.18	3068.0521	79.21	3156.1924	492.971	3111.8102	500.002
51.57	8.9	52.87	2659.4649	79.21	2795.2369	458.973	2726.5059	470.543
40.95	8.9	41.9	1676.9025	79.21	1755.61	364.455	1715.805	372.91
38.13	8.9	39.08	1453.8969	79.21	1527.2464	339.357	1490.1204	347.812
13.75	11.5	13.77	189.0625	132.25	189.6129	158.125	189.3375	158.355
13.73	11.5	13.76	188.5129	132.25	189.3376	157.895	188.9248	158.24
\sum terms								
24002.16	22976.5	24009.3	3044490.35	1469018	2975132.9	1169716.2	2963480.97	1118903
$MEAN = \frac{\sum terms}{n}, where n = 862$								
27.84473318	26.65487239	27.85301624	3531.89135	1704.197	3451.4303	1356.9794	3437.91296	1298.032

Table 1. Regression analysis computation

Based on the statistical Equations (2 to 19), the statistical analyses of the runoff hydrographs generated in this work were carried out and their respective regression equations formulated. Also, the scatter diagrams were plotted to determine the degree of deviation of the dependent variable from the independent variable.

Representing the autocalibrated, heuristically measured and simulated runoff data as Y_{i} , $X_{\mathbf{1}_i}$ and $X_{\mathbf{2}_i}$ respectively as shown in Table 1, the followings were estimated:

i. Correlation coefficient of simulated runoff data on heuristically measured runoff data $({}^{R}X_{2}X_{1})$ and the regression equation;

ii. Correlation coefficient of autocalibrated on heuristically measured runoff data (R_{YX_1}) and the regression equation; iii. Correlation coefficient of autocalibrated on simulated

iii. Correlation coefficient of autocalibrated on simulated runoff data (R_{YX_2}) and the regression equation;

iv. Correlation coefficient of autocalibrated on heuristically measured and simulated runoff data $({}^{R}_{Y,X_{1}X_{2}})$ and the

regression equation. Regression analysis of heuristically simulated runoff data, X_2 , on measured runoff data, X_1

Using Table 1 and Equations (2 to 8), the correlation coefficient $R_{X_2X_1}$ and the regression equation of X_2 on X_1 can be obtained by putting $Y = X_2$ and $X = X_1$ in the respective equations so that the standard errors S² shows:

 $S_{X_2}^2 = 2975132.939 - (862 \times 26.65487239^2) = 2362697.263$ $S_{X_1}^2 = 1469017.85 - (862 \times 27.85301624^2) = 800286.4272$ $S_{X_2X_1} = 1118903.156 - (862 \times 27.85301624 \times 26.65487239) = 478938.3283$ $\mathbf{b} = \frac{478938.3283}{2362697.263} = 0.202708293$

a = 27.85301624 - (0.202708293 × 26.65487239) = 22.44985257

The regression equation of simulated runoff data (X_12) , on measured runoff data (X_11) , is given by Equation (20). $X_2 = 22.44985 + 0.202708X_1$ (20) The correlation coefficient $\underset{3283}{R_{X_2X_1}}$ is computed as follows:

$$x_{2X_1} = 478938. \frac{1}{\sqrt{800286.4272 \times 2362697.263}} = 0.348299483$$

 $\therefore \mathbf{R}_{X_2X_1} = \mathbf{0}.348 \text{ or } \mathbf{34.8} \text{ %}$

The scatter diagram for the regression analysis is shown in Figure 9.





Regression analysis of autocalibrated runoff data, Y, on heuristically simulated runoff data, X_2 .Similarly from Table 1 and Equations (2 to 8), the correlation coefficient R_{YX_2} and the regression equation of Y on X_2 can be obtained by putting $X = X_2$ in the respective equations so that:

 $S_Y^2 = 3044490.346 - (862 \times 27.84473318^2) = 2376156.605$ $S_{X_2}^2 = 2975132.939 - (862 \times 27.85301624^2) = 2306401.516$ (21)



on heuristically simulated runoff data (X_1^2) , is given by Equation (21).

$$Y = 0.130029 + 0.99503X_2$$

The correlation coefficient R_{YX_2} is computed as follows:

$$R_{YX_2} = 2294948. \frac{421}{\sqrt{2376156.605 \times 2306401.516}} = 0.98032$$

: $R_{YX_2} = 0.98 \text{ or } 98 \text{ \%}$

The scatter diagram for the regression analysis is shown in Figure 10.



Figure 10. Scatter diagram of autocalibrated runoff data $({}^{Y})$ on heuristically simulated runoff data $({}^{X}{}_{1}{}^{2})$

Regression analysis of autocalibrated runoff data, $Y_{.}$ on measured runoff data, X_{1}

Also, from Table 1 and Equations (2 to 8), the correlation coefficient R_{YX_1} and the regression equation of Y on X_1 can be obtained by putting $X = X_1$ in the respective equations so that:

 $S_{Y}^{2} = 3044490.346 - (862 \times 27.84473318^{2}) = 2376156.605$ $S_{X_{1}}^{2} = 1469017.85 - (862 \times 26.65487239^{2}) = 856582.1745$ $S_{YX_{1}} = 1169716.243 - (862 \times 26.65487239 \times 27.84473318) = 529941.7311$ $\mathbf{b} = \frac{529941.7311}{25652245747} = 0.618670043$

 $a = 27.84473318 - (0.618670043 \times 26.65487239) = 11.35416212$

The regression equation of autocalibrated runoff data (\mathbf{Y}) , on measured runoff data $(\mathbf{X_{11}})$ is given by Equation (22)

$$Y = 11.35416 + 0.61867X_1$$
(22)

The correlation coefficient R_{YX_1} is computed as follows:

$$R_{YX_1} = 529941. \frac{7311}{\sqrt{2376156.605 \times 856582.1745}} = 0.3715$$

: $R_{YX_1} = 0.37$ or 37 %

The scatter diagram for the regression analysis is shown in Figure 11.



Figure 11. Scatter diagram of autocalibrated runoff data

(Y) on measured runoff data $(X_{\downarrow}1)$

The recorded hydrographs in graphical modes as time series for measured and heuristically simulated, measured and autocalibrated, heuristically simulated and autocalibrated, and measured, heuristically simulated and autocalibrated results are shown in Figures 12 to 15.



Figure 12. Measured and heuristically simulated hydrographs



Figure 13. Measured and autocalibrated hydrographs



Figure 14. Heuristically simulated and autocalibrated hydrographs



Figure 15: Measured, heuristically simulated and autocalibrated hydrographs

Discussion

From the result of the model simulated and measured, it remains the fact that hydrology is yet to evolve to expected science due to model assumptions, limitations in physical and operational representation as well as unavailability and accuracy of model testing data. The errors associated in the model structural representation and model parameters, led to the application of regression analysis for quantitative comparisons.

However, the statistically analysed measured and heuristically calibrated hydrographs which gave a regression coefficient (R) of 34.8 % compared with the autocalibrated hydrograph with measured hydrograph of 37 %, Figures 9 and 11 showing appreciable improvements of 2.2% with the autocalibration scheme. The heuristically calibrated hydrograph and the autocalibrated had R of 98 % which is much more similar with R of GA fitness test of 99 %, Figures 10 and 5.4 respectively. However, autocalibration involves a more objective procedure that can be employed in hydrologic modelling.

The 37 % shown as correlation coefficient of the autocalibration may be attributed to the four parameters (MANN1, MANN2, MANN3 and KRET) employed in the heuristic calibration, which were used for automatic calibration. With more parameters included in the autocalibration model, a more reliable model performance is to be expected, bearing in mind that the simulated result is also acceptable in hydrology and related fields.

Conclusion

The results from the research into automatic calibration of WRM model as presented repackaged the original WRM FORTRAN model using WRMGA approach which computes and stores only runoff during optimization process and WRMGUI as an interface that brings together the integrated WRM/WRMGA.

Calibration was performed by adjusting parameters of initial simulation of Upper Wilmot watershed using Curley's and Mayne's sub-watersheds in Canada which was manual or heuristic calibration requires considerable expertise and could be time consuming. Adopting methodology for optimization and autocalibration repackaged the original WRM model to autocalibration mode. The WRM GUI software developed has about 14 window forms and 2 user controls and each has different functions applying GUI in the computation. The functions are direct conversions of already existing FORTRAN subroutine modules of WRM model into C# programming language. The WRM model been repackaged in autocalibration mode, considered the merits of optimization, calibration, validation and statistical analyses of simulated output, leading the way to an important aspect of water resources planning and development.

References

Abbott, M. B., Cunge, J. C., O'Connell J. A., and Rasmussen, P. E., (1986): An Introduction to the European Hydrological System – System Hydrologique European, "SHE", 87: pp.45 – 49.

Abdulla, F.A., Lettenmaier, D.P. and Liang, X, (1999): Estimation of the ARNO model baseflow Parameters using daily streamflow data. J. Hydrol. 222: pp. 37-54.

Betson, R. P., and Ardis, C.V. Jr., (1978): Implications for Modelling Surface Water Hydrology. Inc: M. J. Kirkby (ed.), Hillslope Hydrology. John Wiley and Sons Chichester.

Duan, Q., Sorooshian, S., and Gupta, V. K., (1992): Effective and efficient Global Optimization for Conceptual Rainfall-Runoff Models. Water Resour. Res., 24(7): pp.1163 – 1173.

Freedman V.L., Lopes, V.L., and Hernandez, M., (1998): Parameters Identifiability for Catchment Scale Erosion Modelling: A Comparison of Optimization Algorithms. J. Hydrol. 207: pp.83-97.

Gan, T.Y., and Biftu, G.F., (1996): Automatic Calibration of Conceptual Rainfall-Runoff Models: Optimization Algorithms, Catchment Conditions, and Model Structure. Water Resour. Res. 42(7), W07417, Doi: 10.1029/2005WR004528.

Hodge, W., W. L., and Goran, W., (1988): Linking the ARMSED Watershed Process Model the GRASS Geographic Information System. ASABE. Publ. 07/88. St. Joseph, M. I: pp.501 – 510.

Knox, J.W., Weatherhead, E.K., and Hess, T.M., (2001): Integrating Spatial data, GIS and a Computer Model to improve the Management and Planning of Water Resources for Irrigated Agriculture in England and Wales. In, Belward, A., Binaghi, E., Brivo, A., Lanzarone, G.A. and Tosi, G. (Eds.), International Workshop on Geo-spatial Knowledge Processing for Natural Resources Management. June 28-29, 2001. Varese, Italy. EU Joint Research Centre, Ispra, Italy: pp. 29-34.

Lindstrom, G., (1997): A Simple Automatic Calibration for the HBV Model Nordic Hydrol. 28 (3): pp.153-168.

Luce, C., and Cundy, T. W., (1994): Parameter Identification for a runoff Model for Forest Roads. Water Resour. Res. 30(4): pp.1057-1069.

Mbajiorgu, C. C. (1991): Watershed Resources Management Model I: A Process-Based, Continuous Distributed Parameter Mathematical Watershed Model. In corporating conservation structures unpul. Ph.D Thesis, Tech univ. of Nova Scotia Library (now Dalhousie Univ.), Halifax, NS, Canada: pp.367.

Mbajiorgu, C. C. (1995a): Watershed Resources Management (WRM) Model I. A Model Description. Computers and Electronics in Agriculture, Elsevier Science B.V. Vol.13, No.2: pp.195-216.

Mbajiorgu, C. C. (1995b): Watershed Resources Management (WRM) Model II. An Application to the Upper Wilmot Watershed. Computers and Electronics in Agriculture, Elsevier Science B.V. Vol.13, No.2: pp.217-226.