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Multi-objective calibration of a distributed hydrological model (WetSpa) using a genetic algorithm

M. Shafii and F. De Smedt

Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel, Belgium

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Correspondence to: M. Shafii (mshafiih@vub.ac.be)

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Abstract

A multi-objective genetic algorithm, NSGA-II, is applied to calibrate a distributed hydrological model (WetSpa) for predicting river discharge. The evaluation criteria considered are the model bias (mass balance), the model efficiency (Nash-Sutcliffe efficiency), and a logarithmic transformed model efficiency (to emphasize low-flow values). The concept of Pareto dominance is used to solve the multi-objective optimization problem and derive Pareto-optimal parameter sets. In order to analyze the applicability of the approach, a comparison is made with another calibration routine using the parameter estimator PEST to minimize the model efficiency. The two approaches are evaluated by applying the WetSpa model to the Hornad River (Slovakia) for which observations of daily precipitation, temperature, potential evapotranspiration, and discharge are available for a 10 year period (1991–2000). The first 5 years of the data series are used for model calibration, while the second 5 years for model validation. The results revealed that the quality of the solutions obtained with NSGA-II is comparable or even better to what can be obtained with PEST, considering the same assumptions. Hence, NSGA-II is capable of locating Pareto optimal solutions in the parameter search space and the results obtained prove the excellent performance of the multi-objective model calibration methodology.

1 Introduction

Genetic algorithms (GA) have become increasingly popular for solving complex multi-objective optimization problems because of their better performance compared to other search strategies (Fonseca and Fleming, 1995; Valenzuela-Rend'on and Uresti-Charre, 1997). After the first pioneering studies on evolutionary multi-objective optimization in the mid-1980s (Schaffer, 1984; Fourman, 1985), these algorithms were successfully applied to various multi-objective optimization problems (e.g. Ishibuchi and Murata, 1996; Cunha et al., 1997; Valenzuela-Rendón and Uresti-Charre, 1997;

Fonseca and Fleming, 1995). There have also been significant contributions on application of GAs for multi-objective optimization in water resources research (Ritzel et al., 1994; Cieniawski et al., 1995; Reed et al., 2001; Reed and Minsker, 2004).

Conceptual rainfall-runoff (RR) models, aiming at predicting streamflow from the knowledge of precipitation over a catchment, have become basic tools for flood and drought forecasting, catchment basin management, spillway design, and flood protection. Calibration of RR models is a process in which parameter adjustment are made so as to match (as closely as possible) the dynamic behaviour of the RR model to the observed behaviour of the catchment. Because of the multi-objective nature of RR calibration processes, automatic calibration methodologies have been shifted from single-objective towards multi-objective formulation in recent years. Gupta et al. (1998) discussed for the first time the advantages of multiple-objective model calibration and showed that such schemes are applicable and desirable. Subsequently, more research has been focused on multi-objective approaches for calibration of RR models (Yapo et al., 1998; Seibert, 2000; Cheng et al., 2002; Boyle et al., 2000; Madsen, 2000; Vrugt et al., 2003).

Over past recent years, population-based search algorithms have shown to be powerful search methods for multi-objective optimization problems and have been applied for multi-objective RR calibration, especially when there are a large number of calibration parameters (Boyle et al., 2000; Madsen, 2000; Vrugt et al., 2003; Khu et al., 2005). Tang et al. (2006) comprehensively assessed the efficiency, effectiveness, reliability, and ease-of-use of three multi-objective evolutionary optimization algorithms (MOEAs) for hydrologic model calibration. Moreover, some researchers have applied MOEAs to develop automatic multi-objective calibration strategies for distributed hydrological models (Madsen, 2003; Ajami et al., 2004; Muleta and Nicklow, 2005a, b; Vrugt et al., 2005, Bekele and Nivklow, 2007).

In this paper, one of the famous MOEAs named “Non-dominated Sorting Genetic Algorithm II (NSGA-II)” (Deb et al., 2002) is applied for multi-objective RR calibration of a distributed hydrological model (WetSpa; Wang et al., 1997). In order to investigate the

HESSD
6, 243–271, 2009

M. Shafii and F. De Smedt

impacts of multi-objective calibration formulation on quality of solutions, the obtained results are subsequently compared to results obtained with the more classical Parameter ESTimator software (PEST; Doherty and Johnson, 2003). PEST has shown to be a proper calibration routine for WetSpa (Liu et al., 2005), but in a single objective framework. Therefore, this comparison may give an insight into applicability of our multi-objective formulation for WetSpa calibration.

This paper is organized as follows. Description of the multi-objective optimization routine, developed and applied in this study, is presented in Sect. 2. Section 3 provides material and methods used in this paper, i.e. the WetSpa model, the multi-objective formulation of the model calibration, and the study area. Section 4 describes the model application, comparison between single and multiple objective strategies for calibration, and discussion of the obtained results. Finally, conclusions are presented in Sect. 5.

2 Material and methods

2.1 Non-domination Sorting Genetic Algorithm II (NSGA-II)

Multi-objective genetic algorithms (MOGAs) and the Pareto optimality concept (Pareto, 1896) have been widely applied in water resources studies. MOGAs are search algorithms based upon the mechanics of natural selection, derived from the theory of natural evolution. They represent the solutions using strings (also referred to as chromosomes) of variables, which are comprised of a number of genes (decision variables). The fitness of each chromosome is an expression of the objective function value. A MOGA starts with a population of initial chromosomes, which through genetic operators such as selection, crossover, and mutation produce successively better chromosomes.

NSGA-II is one of the most commonly used MOGAs, proposed by Deb et al. (2002) as a significant improvement to the original NSGA (Sirinivas et al., 1993) by using a more efficient ranking scheme and improved selection to capture the Pareto front. Zitzler et al. (2000) and Deb et al. (2002) have shown that NSGA-II performs as well as or better than other algorithms on difficult multi-objective problems. In NSGA-II, the selection process at various stages of the algorithm toward a uniformly spread-out Pareto optimal front is guided by assigning fitness to chromosomes based on domination and diversity. Domination is determined by ranking all chromosomes in the population. The dominating solutions in the Pareto front receive the highest rank and the next dominating chromosomes receive one rank less, and so on. Obviously, chromosomes with higher rank are considered to have better fitness. Chromosomes with the same rank are compared based on their diversity. A crowding measure for each chromosome is calculated in the objective function space as the distance between its nearest neighbouring solutions with the same rank. Chromosomes with larger values of crowding distance are preferred to be selected for next generations.

The algorithm starts with a random generation of a parent population and this population is sorted based on domination and crowding distance. The algorithm proceeds by creating an offspring population through selection process. First, chromosomes are selected randomly in pairs from the parent population and the chromosome with better fitness (having higher rank or larger diversity) is placed in the offspring population until the offspring population has the same size as the parent population. Next, a certain percentage of the offspring generation is changed by another genetic operator, called crossover. Crossover is the process of switching genes of some selected individuals (parents) to produce offspring with better fitness. To do so, parents are selected randomly in pairs, one from the parent population and the other one from the offspring population. Genes are switched randomly to reproduce a new chromosome which replaces the parent in the offspring population. Next, the chromosomes in the offspring population are mutated by changing their genes. Mutation is altering one or more gene values in a chromosome from its initial state, which may result in better solutions and helps to prevent the population from stagnating at any local optimum. Genes are selected randomly within a particular chromosome and replaced by new randomly generated genes within their preset range of feasibility. The crossover and mutation probabilities, used in this paper, are 90% and $1/s$, respectively, where s is

HESSD
6, 243–271, 2009

M. Shafii and F. De Smedt

the number of genes (decision variables). Finally, the offspring population is combined with the parent generation, and the chromosomes are ranked based on domination and diversity and the top half best chromosomes become the next parent generation. This process is continued till termination criteria are met. Interested readers may refer to Deb et al. (2002) for a detailed description of the algorithm.

2.2 WetSpa hydrological model

WetSpa is a grid-based distributed hydrologic model for water and energy transfer between soil, plants and atmosphere, which was originally developed by Wang et al. (1997) and adapted for flood prediction on hourly time step by De Smedt et al. (2000, 2004), and Liu et al. (2003, 2004, 2005). For each grid cell, four layers are considered in the vertical direction, i.e. the plant canopy, the soil surface, the root zone, and the groundwater zone (Fig. 1). The hydrologic processes considered in the model are precipitation, interception, depression storage, surface runoff, snowmelt, infiltration, evapotranspiration, interflow, percolation, and groundwater drainage. The model predicts peak discharges and hydrographs, which can be defined for any numbers and locations in the channel network, and can simulate the spatial distribution of basin hydrological variables. Interested readers may refer to Liu et al. (2003) and De Smedt et al. (2004) for detailed information about WetSpa and its methodology to predict stream flow.

The WetSpa distributed model potentially involves a large number of model parameters to be specified during the model setup. Most of these parameters can be assessed from field data, e.g. hydrometeorological observations, maps of topography, soil types, land use, etc. However, comprehensive field data are seldom available to fully support specification of all model parameters. In addition, some model parameters are of a more conceptual nature and cannot be directly assessed. Hence, some parameters have to be determined through a calibration process. The choice of parameters to calibrate is based on earlier studies of the WetSpa model (Liu et al., 2003; Liu and De Smedt, 2005, Bahremand et al., 2007). The model parameters that have to be determined through calibration are listed in Table 1 and their impact on the different model components of WetSpa is schematically depicted in Fig. 1. All other model parameters are automatically derived using GIS tools and need not to be calibrated.

2.3 Formulation of multi-objective calibration problem

For calibration the following objectives are usually considered (Madsen 2000): (1) good agreement between average simulated and observed catchment runoff volume (i.e. a good water balance); (2) good overall agreement of the shape of the hydrograph; (3) good agreement of the peak flows with respect to timing, rate and volume; and (4) good agreement for low flows. In general, trade-offs exist between these different objectives. For instance, one may find a set of parameters that provide a very good simulation of peak flows but a poor simulation of low flows, and vice versa. Hence, in order to obtain a successful calibration, it is necessary to formulate performance measures in a multi-objective framework. The following evaluation criteria are used in the present study:

$$CR_1 = \left| 1 - \sum_{i=1}^{N} Qs_i \Big/ \sum_{i=1}^{N} Qo_i \right| \tag{1}$$

$$CR_2 = 1 - \sum_{i=1}^{N} \left(Qs_i - Qo_i \right)^2 \Big/ \sum_{i=1}^{N} \left(Qo_i - \overline{Qo} \right)^2 \tag{2}$$

$$CR_3 = 1 - \sum_{i=1}^{N} \left[\ln(Qs_i) - \ln(Qo_i) \right]^2 \Big/ \sum_{i=1}^{N} \left[\ln(Qo_i) - \overline{\ln(Q_0)} \right]^2 \tag{3}$$

where, Qo_i is the observed discharge at time i, Qs_i the simulated discharge, the bar stands for average, and N is the total number of time steps in the calibration period. The first criterion, CR_1, is the model bias, for which the value zero represents a perfect simulation of the observed flow volume. The second criterion, CR_2, is the model efficiency (Nash and Sutcliffe, 1970) which evaluates the ability of reproducing all stream flows but is known biased for peak flows. The third criterion, CR_3, is a logarithmic transformed model efficiency, giving more emphasize to low-flow values. Therefore, the goal is to minimize CR_1 along with maximization of CR_2 and CR_3 at the same time. However, the result of the optimisation will not be a single unique set of parameters but will consist of Pareto front solutions.

The optimisation procedure starts with identifying feasible parameter values. Global model parameters ranges are chosen according to the basin characteristics, as discussed in the documentation and user manual of the WetSpa model (Liu and De Smedt, 2004) and a previous study on the same area by Bahremand et al. (2007). The preset feasible parameter ranges are given in Table 1. Next, initial values of the parameters for the NSGA-II algorithm have to be selected. A Latin Hypercube Sampling (LHS) (Iman and Conover, 1980) technique is used to explore the full range of all feasible parameter values. Thousand parameter sets are generated using the LHS technique and WetSpa is run to evaluate the objective criteria. The solutions are subsequently ranked based on the concept of Pareto dominance and the top 40 parameter sets are selected to be the initial parent population for NSGA-II.

2.4 Study area

The WetSpa model is applied to the Hornad River, located in Slovakia. The drainage area of the river up to the Margecany gauging station is 1.131 km^2. Figure 2 shows the Hornad catchment, the topography until Margecany, and the location of gauging and meteorological stations. The basin is mountainous with elevations ranging from 339 to 1556 m. The basin has a northern temperate climate with distinct seasons. The highest amount of precipitation occurs in the summer period from May to August while in winter there is usually only snow. The mean annual precipitation is about 680 mm, ranging from 640 mm in the valley to more than 1000 mm in the mountains. The mean temperature of the catchment is about 6°C and the annual potential evapotranspiration about 520 mm. About half of the basin is covered by forest, while the other half consists mainly of grassland, pasture, and agriculture areas. The dominant soil texture is loam, which covers about 42% of the basin, and sandy loam and silt loam about 24% and 23% respectively. Detailed information about the study area along with the methodology to extract required data for the WetSpa model has been provided by Bahremand et al. (2007). Observations of daily precipitation, temperature, potential evaporation, and discharge are available for the period 1991–2000. The first 5 years of the 10-year period is chosen for model calibration and the second 5 years for model validation.

3 Results and discussion

3.1 Model evaluation criteria

NSGA-II is run to calibrate the WetSpa model, starting with the 40 initial solutions already obtained through LHS, for a total of 100 generations. As a result, 27 Pareto front solutions are obtained, of which the corresponding objective function values for the calibration and validation periods are given in Table 2. As it is observed for the calibration period, the model bias (CR_1) ranges between 0.001 and 0.051, the model efficiency (CR_2) between 0.708 and 0.758, and the low flow model efficiency (CR_3) between 0.574 and 0.718. Values for the validation period are similar with respect to bias, somewhat lower for model efficiency, but generally better for the low flow efficiency. In order to show the results more comprehensively, bi-criterion plots for the calibration period are shown in Fig. 3.

All NSGA-II solutions listed in Table 2 are Pareto optimal for the calibration period, i.e. no solution dominates any other solution in the list. For instance, solution no. 27 performs best for model efficiency criterion (CR_2), but all other solutions are either better for model bias criterion (CR_1) and/or low flow efficiency criterion (CR_3). Hence, all solutions are worthy candidates for model calibration depending upon the preferences of the user and the goals of the model application. Notice that for the validation period only solutions no. 4, 12, 13, 16, 17, 18, and 20 are Pareto optimal, while all other solutions are dominated by at least one of these.

The obtained results of the multi-objective calibration are compared to the single-objective calibration procedure with the parameter estimator (PEST) software (Doherty and Johnson, 2003). PEST is a search algorithm to minimize a single objective function, i.e. minimization of a weighted least squares objective, in this case the model efficiency criterion CR_2. In practice, the quality of the optimal solution produced by PEST is highly dependent upon the number of parameters as well as their initial values. To make a comprehensive comparison between NSGA-II and PEST, all 40 initial parameter sets of NSGA-II along with their same preset feasible range were used as starting values for optimisation with PEST. Among the 40 resulting optimal solutions obtained with PEST, the best solution (highest CR_2 value) was selected for comparison with the solutions obtained with NSGA-II. The best criteria values obtained by PEST are given in the first value row (PEST solution no. 1) in Table 2, also depicted in Fig. 3. It should be noted that PEST only calibrates the model based on the second objective function (CR_2) and the other objective function values are subsequently evaluated from the simulated discharges.

Comparing with the results provided by NSGA-II, it is concluded that several Pareto front solutions obtained with NSGA-II perform better with respect to criterion CR_2. Moreover, the solution obtained with PEST is not Pareto optimal because some of the NSGA-II solutions (no. 5, 10, 15, and 21) perform better for all three criteria. This clearly indicates that, compared to PEST, NSGA-II can search the parameter space more efficiently and find better solutions starting from the same initial parameter values. In order to investigate the capability of NSGA-II to locate optimal points in the parameter space, the 27 parameter sets obtained by NSGA-II were each considered as initial values for further optimisation with PEST to find out if better results can be obtained. The second value row for PEST in Table 2 (PEST solution no. 2) shows the best solution provided by PEST starting from the 27 Pareto optimal NSGA-II solutions. This solution is also shown in Fig. 3. The best solution provided by PEST is obtained starting from solution no. 18 of Table 2. Obviously the new CR_2 value obtained by PEST is better as before, but only slightly better than several other NSGA-II solutions. However, the final solution provided by PEST is Pareto optimal, because it performs best for criterion CR_2.

Figure 4 shows plot of minimum, average, and maximum of criteria values of Pareto optimal solutions versus number of NSGA-II iterations. One can notice that the values of different criteria stabilize in different iterations, as for CR_1, CR_2, and CR_3 in iteration 38, 40, and 18, respectively. To obtain these results with NSGA-II, around 4000 model evaluations have been made, while this number was more than 5000 for 40 PEST runs, i.e. separate runs with 40 different initial solutions (the parameter sets within the first population of NSGA-II).

Overall, it can be concluded that the quality of the solutions obtained with NSGA-II is very good, and comparable or even better as what can be obtained with PEST. Moreover, NSGA-II is capable of locating Pareto optimal solutions in the parameter search space. Furthermore, the slight differences between the final solution obtained with PEST and the Pareto solutions obtained by NSGA-II indicate the excellent performance of the NSGA-II searching methodology.

3.2 Model parameter values

The optimal parameter values obtained with NSGA-II and PEST are presented in Table 1. For NSGA-II only the range (minimum and maximum) of the 27 Pareto optimal values for each parameter is given. For the final solution obtained with PEST (no. 2 in the bottom part of Table 2), the mean estimate and 95% confidence limits are listed for each parameter. Notice that all except one of the parameter estimates obtained with PEST fall within the range predicted by NSGA-II.

Figure 5 gives a graphical comparison between calculated and observed daily flow at Margecany for the year 1991 of the calibration period, and Fig. 6 for the year 2000 of the validation period. The observed discharges are shown as a dashed line, the best hydrograph produced by PEST as a solid line, and the range of simulated discharges

HESSD
6, 243–271, 2009

Multiobjective rainfall-runoff calibration using GA

M. Shafii and F. De Smedt

obtained with the 27 Pareto front solutions obtained with NGSA-II as the grey shaded area. Comparing PEST and NSGA-II results reveals consistency between these two approaches. However, as can be clearly observed in these figures, both the stream flow estimations in the calibration period and the stream flow predictions in the validation period display systematic errors with respect to the observations. Because PEST and NSGA-II results do not differ very much, and the range of NSGA-II results do not contain all observations, it can be concluded that these deviations are due to inconsistencies associated with the model structure and/or the measurements. Hence, as well as improving the calibration routines, it is also required to improve the model structure or to provide suitable methods to quantify model uncertainty appropriately so that estimation and prediction bounds bracket the observations. Research aimed at improving the WetSpa model and development of a methodology to quantify model uncertainty is ongoing.

From Figs. 5 and 6 one can notice that the NSGA-II Pareto front predictions are fairly consistent such that the range of predicted flow values is rather narrow. Beven (1993) introduced the concept of equifinality, i.e. the fact that there may be different parameter sets equally suitable to reproduce the observed behaviour of the system. This has caused researchers to develop new strategies for model uncertainty analysis, such as GLUE (Beven and Binley, 1992) as the most famous methodology. The hydrograph ranges obtained in Figs. 5 and 6 by the NSGA-II Pareto front solutions can be interpreted as equifinality. Although it may be argued that this issue is not really a problem for practical model application, because any of these parameter sets may be applied (Lindstorm, 1997). In particular they also yield similar results for the evaluation period. Nevertheless, it is desirable to address the prediction uncertainty due to different parameter sets obtained by calibration. In order to investigate the identifiability of the model parameters, normalized values of the different parameters of WetSpa are depicted in Fig. 7 versus number of NSGA-II iterations, i.e., for each iteration all parameter values of the Pareto fronts solutions are shown. These values are normalized based on their initially preset feasible minimum and maximum values as given in Table 1.

Initially, as there is no a priori information about optimal values for each parameter, the values were generated randomly within the feasible parameters space. But over the iterations, Pareto optimal solutions are obtained with better parameter values, located in optimal regions of the parameter space. As seen in Fig. 7, most WetSpa parameters (i.e. K_i, K_g, K_s, K_e, K_{gi} and K_{td}) are well identified because the range of values of the Pareto optimal solutions quickly become much more bounded compared to their initial range. However, some parameters are poorly identifiable (i.e. K_{gm}, K_t, K_{rd}, K_m, and K_p) exhibiting ranges that do not converge. Similar characteristics are noticeable in the confidence limits obtained with the PEST algorithm as given in Table 1. Table 3 gives the correlation between the different WetSpa model parameters for all Pareto front solutions of all iterations. The correlation between most of the parameters is typically low, further confirming that most of the WetSpa parameters are well defined. Hence, it can be concluded from the results presented in Figs. 7 and Table 3 that for this particular watershed and dataset, most WetSpa parameters can be reasonably calibrated using multi-objective formulation.

Finally, one can question whether the quality of the optimal solutions produced by NSGA-II is strongly dependable upon the initial starting values, which might also influence the identifiability of the model parameters. In order to investigate this, 10 different runs were made with different initial solutions. Hence, for each run 1000 parameter sets were generated randomly with the Latin Hypercube Sampling technique and the best 40 parameter sets were selected as starting values for NSGA-II. Figure 8 shows the obtained range of WetSpa parameters of the final Pareto front solutions resulting from the 10 runs. This figure clearly shows that most of the optimized parameters are located in the same range of their feasible space. This indicates that, firstly, NSGA-II has a good potential to search and find optimal parameter values and, secondly, most WetSpa parameters are well identifiable.

4 Conclusions

In this study, a multi-objective genetic algorithm, NSGA-II, was applied to calibrate a hydrological model (WetSpa). The evaluation criteria are the model bias (mass balance), the model efficiency (ability to reproduce all streamflows), and a logarithmic transformed model efficiency (to emphasize low-flow values). The concept of Pareto dominance was used to solve the multi-objective optimization problem. In order to analyze the applicability of the approach, a comparison was made with the Parameter ESTimator (PEST), which only minimizes the model efficiency. The two approaches were evaluated through application of the WetSpa model to the Hornad River located in Slovakia.

Based on the results obtained from the two calibration procedures, it can be concluded that our new approach for multi-objective calibration has performed favourably giving a set of results which are comparable or even superior to what is produced by PEST. Secondly, due to the variety of solutions spread over the Pareto front, all of which are good from the viewpoint of optimality, it is possible to select a parameter set that is most appropriate for a certain application based on existing priorities. Hence, multi-objective formulation can provide stake-holders with a proper decision support system. Moreover, when Pareto-optimal solutions were considered as initial parameter sets for PEST, calibration of the Wetspa model could not be improved, substantially. This reveals that NSGA-II is capable of locating Pareto optimal parameter values, and consequently, optimal model calibration for WetSpa.

The obtained results also clearly demonstrated that most of the WetSpa model parameters are well identifiable. For the parameters which are poorly identified, application of more efficient calibration strategies such as multi-population evolutionary algorithms or a combination of these search methods with mathematical local search procedures might be highly useful, as for instance the AMALGAM multi-objective evolutionary search strategy of Vrugt and Robinson (2007). Research aimed at further improvement of the optimization approach proposed in this study is also ongoing.

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Table 1. Global WetSpa model parameters to be calibrated: description symbols preset feasible range, range of Pareto optimal calibrated values obtained with NSGA-II, and estimated values and 95% confidence intervals obtained with PEST.

Description	Parameter	Units	Feasible range	NSGA-II Min	NSGA-II Max	PEST Estimate	PEST 95% confidence interval
Interflow scaling factor	K_i	–	0-10	1.48	1.80	1.67	1.65–1.70
Groundwater recession coefficient	K_g	d^{-1}	0–0.05	0.0063	0.0085	0.0084	0.0079–0.0090
Initial soil moisture factor	K_s	–	0-2	1.00	1.06	0.99	0.98–1.00
Correction factor for PET	K_e	–	0–2	1.13	1.28	1.14	1.13–1.14
Initial groundwater storage	K_{gi}	mm	0–500	41.0	46.0	51.0	42.5–59.4
Groundwater storage scaling factor	K_{gm}	mm	0–2000	133	427	113	97–129
Base temperature for snowmelt	K_t	°C	−1–1	0.230	0.963	0.53	0.53–0.54
Temperature degree-day coefficient	K_{td}	mm °C^{-1} d^{-1}	0–10	0.891	1.100	1.012	1.004–1.019
Rainfall degree-day coefficient	K_{rd}	°C^{-1} d^{-1}	0–0.05	0.0204	0.0297	0.0500	0.0211–0.0789
Surface runoff coefficient	K_m	–	0–5	2.62	3.02	2.86	2.84-2.89
Rainfall scaling factor	K_p	mm	0–500	266	451	500	192–808

HESSD

6, 243–271, 2009

Multiobjective rainfall-runoff calibration using GA

M. Shafii and F. De Smedt

Table 2. Evaluation criteria values of the Pareto optimal solutions (no. 1–27) obtained with NSGA-II (top), and the best solutions obtained with PEST (bottom) using the same initial starting parameter values as for NSGA-II (no. 1) or starting from the 27 NSGA-II solutions (no. 2).

		Calibration period			Validation period		
	no.	CR_1	CR_2	CR_3	CR_1	CR_2	CR_3
NSGA-II Pareto front solutions	1	0.003	0.737	0.701	0.043	0.638	0.735
	2	0.006	0.748	0.697	0.028	0.663	0.733
	3	0.002	0.740	0.691	0.038	0.677	0.753
	4	0.008	0.753	0.667	0.010	0.678	0.754
	5	0.005	0.748	0.687	0.015	0.675	0.747
	6	0.014	0.726	0.715	0.045	0.664	0.748
	7	0.014	0.739	0.705	0.018	0.668	0.743
	8	0.001	0.734	0.713	0.031	0.656	0.741
	9	0.003	0.722	0.714	0.031	0.654	0.738
	10	0.001	0.749	0.649	0.028	0.660	0.743
	11	0.001	0.745	0.659	0.033	0.650	0.742
	12	0.012	0.753	0.678	0.005	0.673	0.751
	13	0.017	0.749	0.687	0.003	0.680	0.748
	14	0.034	0.715	0.718	0.072	0.652	0.742
	15	0.005	0.755	0.574	0.033	0.683	0.748
	16	0.001	0.728	0.688	0.039	0.692	0.746
	17	0.043	0.757	0.635	0.006	0.662	0.729
	18	0.008	0.758	0.624	0.012	0.687	0.756
	19	0.033	0.741	0.700	0.002	0.675	0.729
	20	0.020	0.755	0.640	0.032	0.683	0.763
	21	0.003	0.754	0.614	0.020	0.673	0.746
	22	0.051	0.755	0.642	0.014	0.648	0.722
	23	0.002	0.745	0.671	0.028	0.654	0.750
	24	0.025	0.708	0.716	0.060	0.637	0.731
	25	0.008	0.753	0.637	0.015	0.663	0.746
	26	0.042	0.754	0.656	0.007	0.658	0.726
	27	0.007	0.758	0.592	0.022	0.686	0.752
PEST	1	0.005	0.746	0.568	0.024	0.703	0.747
	2	0.000	0.758	0.556	0.022	0.686	0.752

HESSD

6, 243–271, 2009

Multiobjective rainfall-runoff calibration using GA

M. Shafii and F. De Smedt

HESSD

6, 243–271, 2009

Multiobjective rainfall-runoff calibration using GA

M. Shafii and F. De Smedt

Table 3. Correlation between the WetSpa model parameters derived from the Pareto front solutions of all NSGA-II iterations.

Parameter	K_i	K_g	K_s	K_e	K_{gi}	K_{gm}	K_t	K_{td}	K_{rd}	K_m	K_p
K_i	1	0.25	0.20	0.23	0.44	0.12	0.00	0.42	0.12	0.21	0.01
K_g		1	0.34	0.09	0.43	0.05	0.13	0.70	0.05	0.21	0.03
K_s			1	0.02	0.29	0.14	0.01	0.47	0.12	0.08	0.00
K_e				1	0.32	0.57	0.05	0.36	0.08	0.08	0.07
K_{gi}					1	0.17	0.00	0.65	0.09	0.16	0.01
K_{gm}						1	0.04	0.33	0.14	0.00	0.09
K_t							1	0.02	0.00	0.01	0.03
K_{td}								1	0.13	0.14	0.01
K_{rd}									1	0.04	0.00
K_m										1	0.22
K_p											1

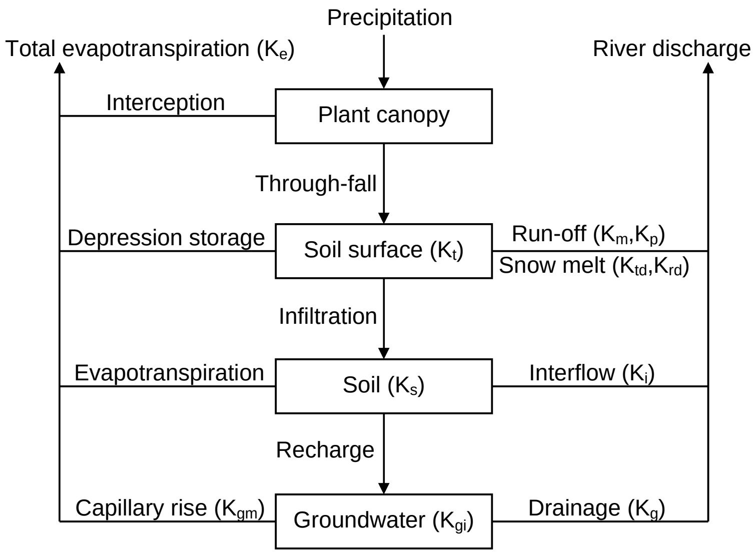

Fig. 1. Schematic representation of the general model structure of WetSpa: arrows represent hydrological processes, boxes represent storage zones, symbols between brackets refer to WetSpa global model parameters to be calibrated as explained in Table 1.

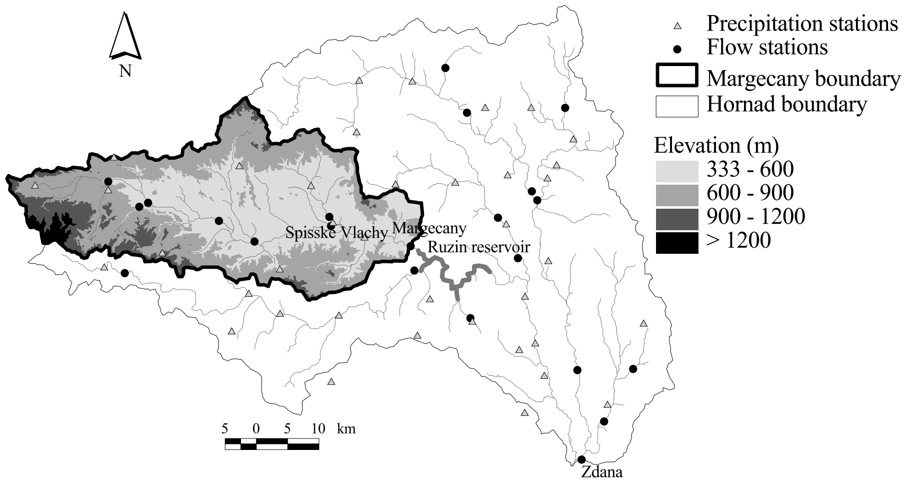

Fig. 2. Hydrologic network of the Hornad catchment with topography of Margecany subcatchment and location of gauging and meteorological stations.

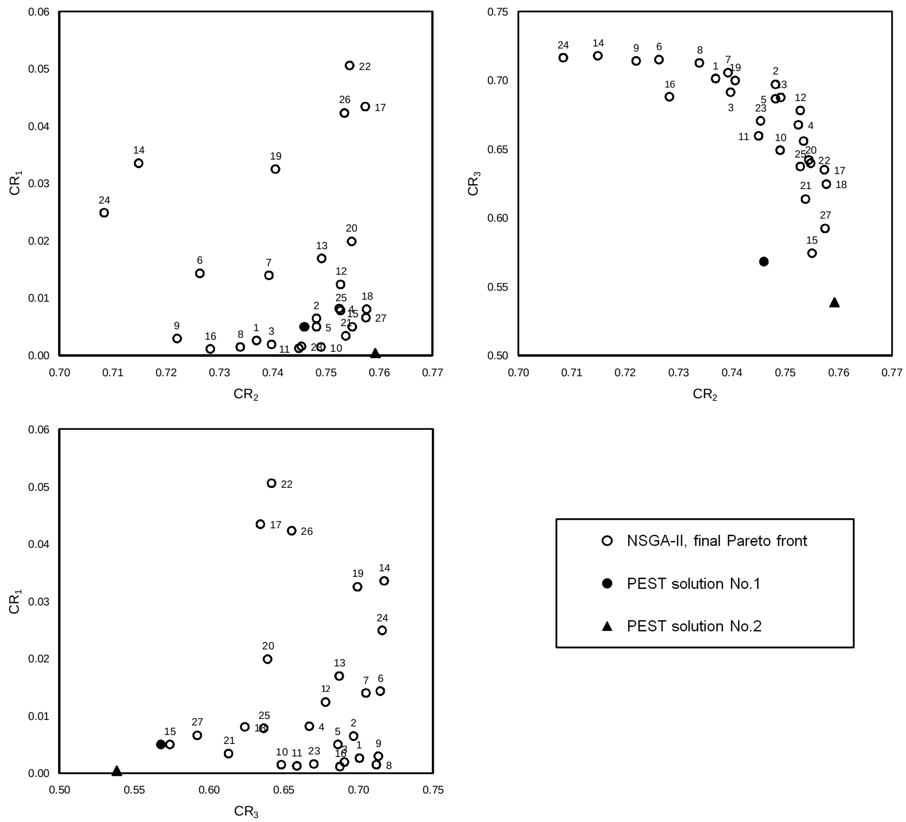

Fig. 3. Bi-criterion figures, for the calibration period, of the final Pareto optimal solutions obtained by NSGA-II, and the solutions obtained by PEST, as given in Table 2.

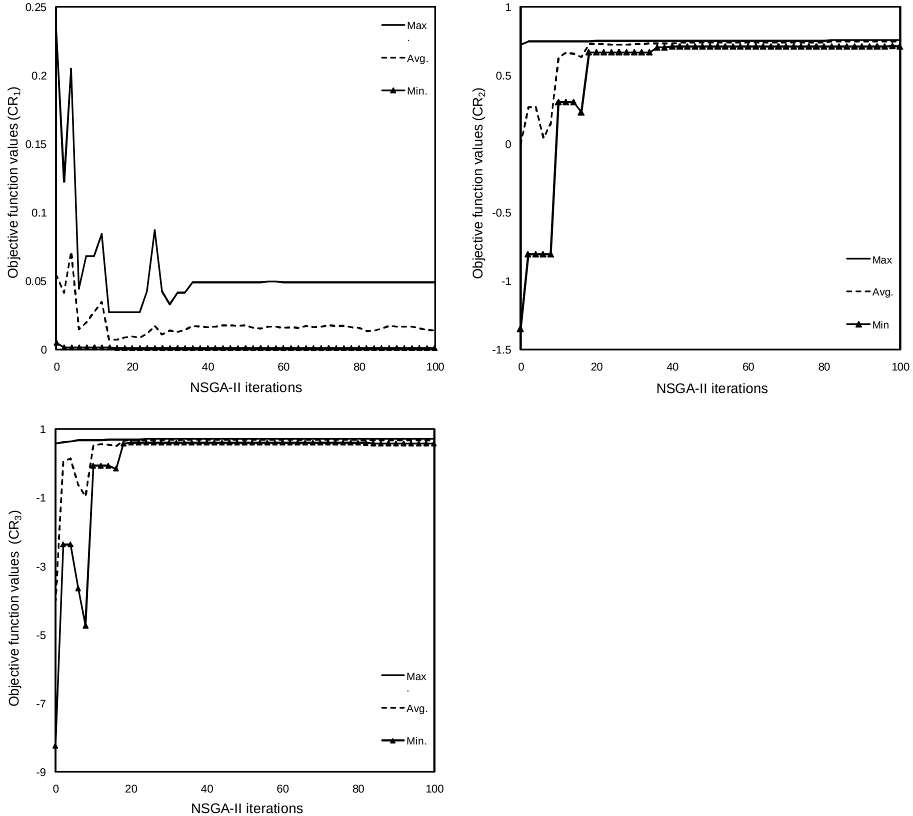

Fig. 4. Plot of minimum, average, and maximum of criteria values of Pareto optimal solutions versus number of NSGA-II iterations.

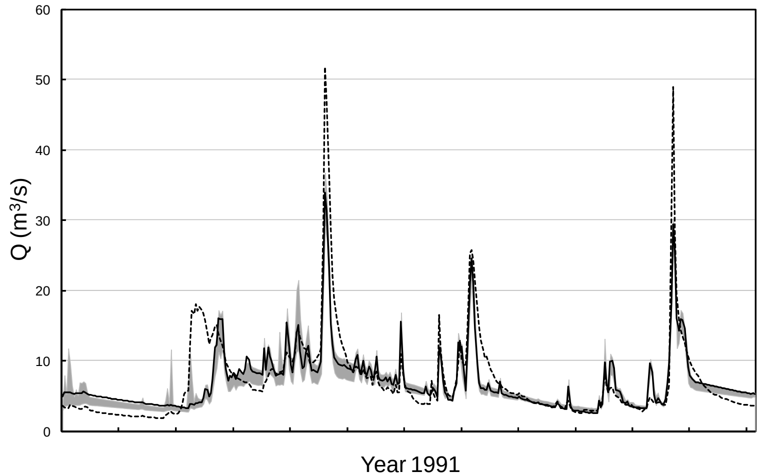

Fig. 5. Observed hydrograph (dashed line), calculated hydrograph with optimal PEST derived model parameters (solid line) and with optimal NSGA-II Pareto solutions (shaded area as the range of all solutions produced by NSGA-II) at Margecany for the year 1991 of the calibration period.

HESSD
6, 243–271, 2009

Multiobjective rainfall-runoff calibration using GA

M. Shafii and F. De Smedt

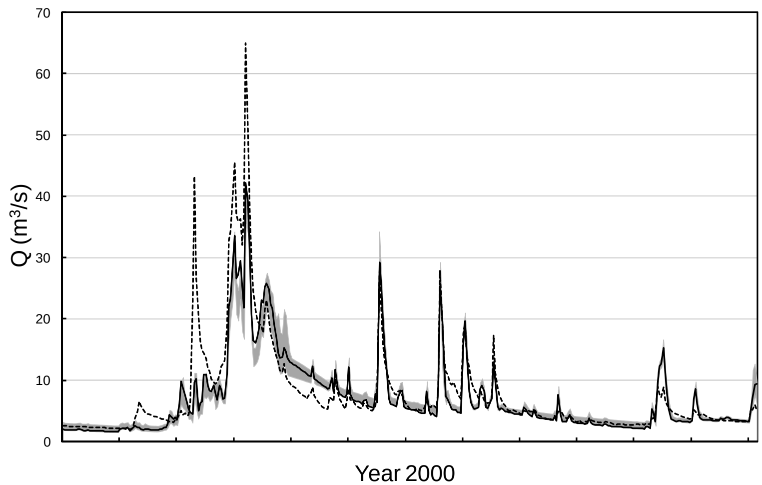

Fig. 6. Observed hydrograph (dashed line), calculated hydrograph with optimal PEST derived model parameters (solid line) and with optimal NSGA-II Pareto solutions (shaded area as the range of all solutions produced by NSGA-II) at Margecany for the year 2000 of the validation period.

HESSD

6, 243–271, 2009

Multiobjective rainfall-runoff calibration using GA

M. Shafii and F. De Smedt

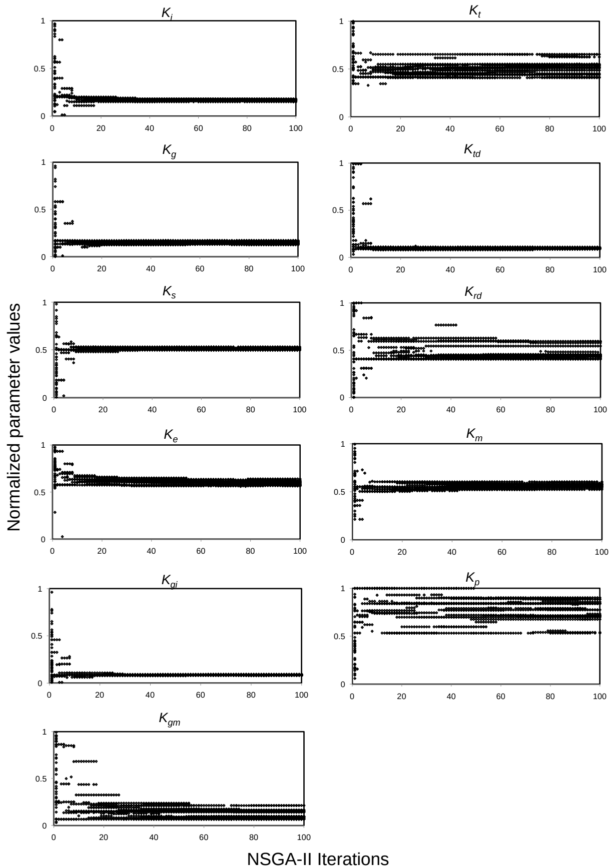

Fig. 7. Plot of normalized values of the WetSpa model parameters versus number of iterations of the NSGA-II search algorithm; shown are all parameter values of all Pareto front solutions through 100 iteration.

HESSD

6, 243–271, 2009

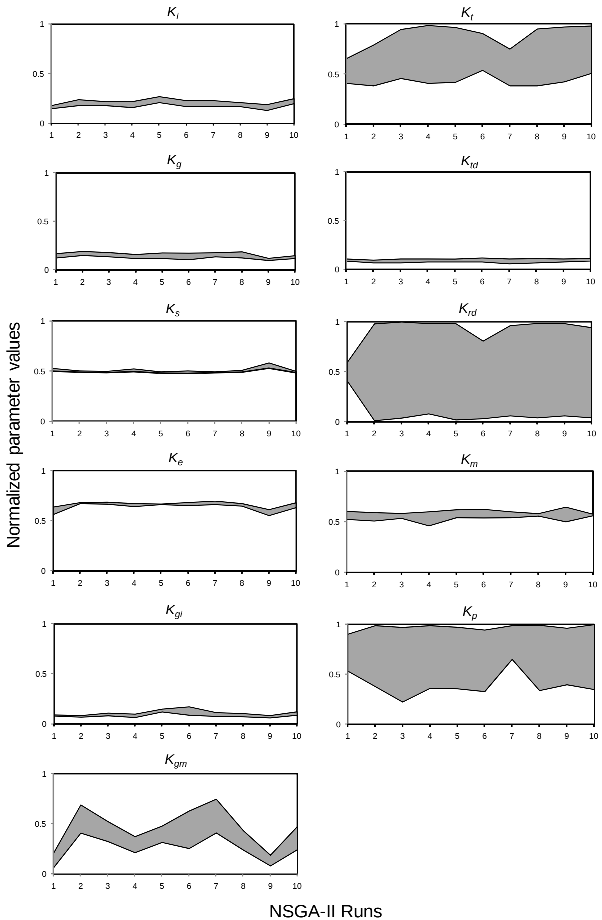

Fig. 8. WetSpa parameter ranges obtained with 10 NSGA-II runs starting from different initial parameter values (the first run corresponds the results contained in Fig. 6).