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Extracting a Set of Robust Pareto-Optimal Parameters for Hydrologic Models using NSGA-II and SCEM

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Abstract—**In this paper, we will present a heuristic method in order to combine the information about the parametric space of a conceptual hydrologic model from two different sources. On one hand, multi-objective evolutionary optimization algorithm NSGA-II is used to find a set of pareto optimal solutions. On the other hand, a Markov Chain Monte Carlo-based algorithm, i.e. Shuffled Complex Evolution Metropolis (SCEM) is used to highlight a set of parameters with higher posterior distribution. By covering the interval between the most crowded locations in the parametric space extracted by both algorithms, we will identify a set of pareto optimal solutions which is more robust than the initial non-dominated set extracted by only NSGA-II.**

I. Introduction

THE strength of multi-objective evolutionary algorithms has been reported by several researchers in recent years. The key feature of these algorithms is being population-based which enable them to find a diverse set of pareto optimal solutions in a single simulation run [1]. Having a vast interval for pareto optimal solutions is a great advantage in order to assess different regions of attraction for a particular model parameter; however, this diversity may reduce the certainty about the model output by producing a wide range of possible model response. This wide bound for possible model answer in many cases, is a disadvantage particularly when we are dealing with prediction or long-term simulation of a process. This issue will be more highlighted when we are dealing with real world modelling problems which contain some other sources of uncertainty that can affect the performance of overall model output. Furthermore, having a fine approximation of multi-objective response surface is time consuming in the case of real world modelling which may limit the number of function evaluations and consequently the number of running generation for multi-objective algorithms. Taking these difficulties in to account, along with the complexity of response surface reported for many real world modelling problems, make us to have a re-evaluation on the pareto-optimal solutions based on the model output robustness, in a way of focusing on a particular set of pareto-optimal solutions that has more certainty in terms of model output.

While considerable attention has been given to the development of powerful multi-objective evolutionary algorithms which aim to efficiently find a diverse number of parameters that simultaneously optimize a set of objective functions, much less attention has been given to a realistic assessment of parameters uncertainty in the multi-objective formulation. The lack of a well-defined method for estimating uncertainty makes it hard to prune the set of initial non-dominated solutions resulted by evolutionary algorithms and extracts a set of still non-dominated but less variant in terms of model output.

In this paper, a simple heuristic method will be set up in order to combine different knowledge about response surface of a hydrologic model coming from two different formulations for model calibration. One is the set of non-dominated parameters set estimated by NSGA-II and the other is the posterior distribution density of the model parameters inferred by single-objective formulation of the likelihood measure in the form of Bayesian statistics in order to maximize the model likelihood. The outline of this paper will be as follows: First, the considered real world modelling problem, i.e. rainfall-runoff modelling will be briefly introduced and the problems around modelling calibration will be addressed. In the next two sections the applied calibration formulations for rainfall-runoff models will be introduced for NSGA-II and SCEM respectively. By analyzing the most crowded parametric regions estimated by both methods, a heuristic rule will be introduced in order to combine the parametric knowledge coming from both algorithms. Then the applied conceptual hydrologic model will be used for simulating the rainfall-runoff process in a US catchment located in Kansas. Comparing simulation results, it will be proved that the applied heuristic method can result to a set of still non-dominated solutions with less variation in error indices. Finally, the paper will be summarized and the conclusions will be derived.

II. Rainfall-runoff modelling

The conversion of rain and snow to runoff has long been studied by engineers to design hydraulic systems and by scientist to develop an understanding of the process involved [2]. Rainfall-runoff process is assumed as the transformation of total amount of rainfall to the reduced amount of runoff [3]. This natural process has two main characteristics. First, the retained amount of water varies with time which is proving the non-stationary origin of the

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process under consideration. The other main feature of rainfall-runoff process is non-linearity which is coming from a large scale process, containing several sub-processes and internal complexities. These two aspects make the rainfall-runoff modelling a difficult modelling task. Regardless to the intensive research attempts, there is still no rainfall-runoff model being able to simulate the process in all circumstances [4]. Several modelling paradigms have been applied in the context of rainfall modelling ranging from crisp physical mechanistic models, based on solving governing partial differential equations [5, 6], to conceptual models, based on a realistic representation of the process with two simple lumped modules for Soil Moisture Accounting (SMA) and routing respectively [7, 8]; and from statistical system theoretic models such as ARMAX [9] to some pure data-driven models such as neural networks [10, 11], fuzzy systems [12], and recently some hybrid soft computing-based models [13]. Because of many practical reasons, conceptual rainfall-runoff models are still the most accepted way to describe this process in time (local modelling) and space (regionalization). The latter task is an important goal in current rainfall-runoff modelling investigations when it is required to extrapolate the model parameters to a similar catchment which does not have enough measurements in order to calibrate the model. As mentioned, all conceptual hydrologic models contain two general parts (modules). The function of the moisture accounting modules is to transform total rainfall into effective rainfall, the rainfall that will occur as the runoff, and includes a number of different indications for evapotranspiration and soil moisture storage. The routing module simulates the lateral flow processes through various pathways, i.e., overland flow, throughflow and groundwater flow which convert the amount of effective rainfall to its corresponding runoff quantity. A variety of soil moisture accounting and routing modules have been introduced in the literature.

From the modelling point of view all the conceptual models confirm two criteria [14]: (1) the structure of these models should be selected before any modelling activity and (2) the structure contains some parameters that do not have any explicit physical interpretation and should be approximated through calibration; therefore the identification process of conceptual models consists of two general steps: first, selecting an appropriate model structure which is mainly subjective and then approximating the best parameter set of this structure regarding to the input/output measurements, which can be formulated as an objective optimization problem. Previous studies in the area of model calibration reveal the model calibration as a complicated task due to different sources of uncertainty around modelling process which can affect the model output [15]. These uncertainties are mainly from following sources [16]:

- Immeasurable randomness which is an inherent part of all natural phenomena.
- Data uncertainty, i.e., error in the measurements or by data pre-processing.
- Model specification uncertainty, i.e., the lack of convergence to a single best parameter set, regarding to the calibration versus available data. This problem is basically known as the identifiability problem and can be represented in calibration as producing a complex response surface with multiple local optima containing both small and large region of attractions and lots of discontinuities.
- Model structure uncertainty, which is resulted from simplifications and/or assumptions in the description of natural process. It can be represented in calibration procedure as observing quite distinct optimal parameter sets for different periods in hydrograph such as low and high flow periods.

There are several calibration procedures applied in the literature, ranging from primitive manual calibration procedures [17] to some complicated population-based approaches [18]. Most of previous attempts are concentrating around single objective formulation of calibration [19], but recent practical experiences with the calibration of hydrological models suggest that single objective function, no matter how carefully chosen, are often inadequate to properly measure all of the characteristics of the observed data and corresponding simulated values [20]. This is mainly because of structure uncertainty of the conceptual models which makes the modeler to consider a trade-off for modeling performance in different periods of hydrograph particularly for long-term daily simulations in which there is no explicit priority can be considered for any period and/or characteristic in the hydrograph. These observations have opened a new direction to the multi-objective calibration of rainfall-runoff models.

III. THE EVOLUTIONARY-BASED MULTI-OBJECTIVE OPTIMIZATION PROCEDURE NSGA-II FOR CALIBRATION OF RAINFALL-RUNOFF MODELS

Non-dominated Sorting Genetic Algorithm II is a state-of-the-art multi-objective evolutionary algorithm introduced in 2002 [21] in order to improve the main drawbacks of previous algorithms, such as computational complexity, lack of elitism and not being parameterless. Analyzing some test problems, it was shown that NSGA-II has a better diversity preservation comparing to other elitist multi-objective evolutionary algorithms and it is able to compete with them regarding to its convergence to the true pareto-optimal front in both constraint and non-constraint problems. From then, NSGA-II has been used successfully in several real world problems such as multi-speed gearbox design [22], designing industrial cracking units [23], long-term groundwater monitoring design [24], traffic signal timing optimization [25], water distribution network design [26] and medicine [27].

In order to implement NSGA-II for calibrating rainfall-runoff models, it is necessary to introduce an error vector, which should be optimized via the algorithm. Classically, there are several goodness-of-fit measures which have been used for calibrating or checking the performance of rainfall-runoff models [28]. Among these measures, we will stick to six:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{n}} \tag{1}$$

which is well-known RMSE measure, frequently used in different fields. In this equation Q_i is observed runoff at time step i, n is the total number of time steps and $\hat{Q}_i$ is the estimated runoff in time step i produced by model.

$$Cor. = \frac{\sum_{i=1}^{n}(\hat{Q}_i - \overline{\hat{Q}})^2}{\sum_{i=1}^{n}(Q_i - \overline{Q})(\hat{Q}_i - \overline{\hat{Q}})} \tag{2}$$

which is correlation coefficient, showing the degree of linear dependency between model output and observed runoff. Relating to the above formulation, $\overline{Q}$ and $\overline{\hat{Q}}$ are the mean values of observed and simulated runoff respectively.

$$N-S\ Co. = 1 - \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n}(Q_i - \overline{Q})^2} \tag{3}$$

which is derived by Nash and Sutcliffe , which allows comparison of a model's performance over different catchments.

$$EP = (Q_p - \hat{Q}_p)/Q_p \tag{4}$$

which is the error of model in simulating the peak of hydrograph. It is trying to measure the performance of model in confronting with the extreme flood measured in catchment.

$$EV = \frac{\sum_{i=1}^{n}(Q_i - \hat{Q}_i)}{\sum_{i=1}^{n} Q_i} \tag{5}$$

which is error in volume, representing the ability of model in satisfying long-term mass conservation.

There is also another objective, rather important for water resources management, which is simulating the drought periods in a catchment. In order to quantify the ability of model in confronting with low-level flows, we used the logarithmic form of RMSE measure as follows:

$$RMSE_{LOG} = \sqrt{\frac{\sum_{i=1}^{n}(\log(Q_i) - \log(\hat{Q}_i))^2}{n}} \tag{6}$$

Although each error measure tries to capture different characteristics of simulated runoff, all of the above equations use the whole period of simulation for calculating the efficiency index. In other words, it is assumed that a unique parametric set is capable to simulate the entire hydrograph. Recent studies of Boyle et al. [17] showed the existence of different response modes on catchment's hydrograph, during the wetting up and drainage periods. It can be also shown that there are different response modes during high and low flows in both wetting and drainage periods. These observations inspired some researchers to apply some segmentations procedures in order to cut the whole hydrograph into different response modes and trying to find a behavioral error measure relating to each segment. In this study we applied a heuristic segmentation approach introduced by Wagener and Wheater [29] which is using the gradient of the hydrograph and an additional threshold as segmentation criteria to cut the whole hydrograph into different response modes. The flow gradient separates the hydrograph into wetting up and drainage periods in a way that positive gradient shows the rainfall periods, i.e. wetting up times and negative gradient shows the drainage periods. A threshold is used to separate period of high and low flow, which is mean flow for wetting periods and 50% of mean flow for drainage periods. In order to quantify the behavior of the model for each segment, the RMSE in each mode was used. For instance for Driven High flows (FDH), the following error measure can be defined:

$$RMSE_{FDH} = \sqrt{\frac{\sum_{i=1}^{nFDH}(Q_i - \hat{Q}_i)^2}{nFDH}}, i \in FDH \tag{7}$$

The above formulation can be easily extended to other response modes on the total hydrograph, i.e. Driven Low (FDL), Non-driven quick (FNQ), and Non-driven Slow (FNS) flows.

IV. Shuffled Complex Evolution Metropolis (SCEM) Algorithm for Uncertainty Assessment of Rainfall-Runoff Models

While classical calibration procedures treat model parameters as a fix but unknown variables, Bayesian approaches assume them as probabilistic variables; each has a joint posterior probability density function, which represents the probabilistic belief to the parameter's value in the presence of observed data. This posterior probability distribution would be proportional to the product of the likelihood function and the prior density function. The prior density is the information about parameter's value before any data is collected. Beven and Binley [30], showed that regarding to the complexities of response surface of hydrologic models, the prior density should be a uniform (non-informative) distribution over the feasible parameter space.

If the model residuals are independent random variables, with constant variance and Gaussian distribution, Box and Tiao [31] proved that the likelihood of a parameter set $\theta^{(t)}$ for representing data y can be calculated using:

$$L(\theta^{(t)} \mid y) = \exp\left[-\frac{1}{2}\sum_{i=1}^{N}\left(\frac{e(\theta^{(t)})_i}{\sigma}\right)^2\right] \tag{8}$$

In the above equation $e(\theta^{(t)})_i$ is the model residual at time step i using parameter set $\theta^{(t)}$. Considering a uniform prior in the form of $p(\theta) \propto \sigma^{-1}$, it can be shown that the influence of σ can be integrated out which is giving the following form of the posterior density [32]

$$p\left(\theta^{(t)} \mid y\right) \propto \left[M\left(\theta^{(t)}\right)\right]^{-\frac{1}{2}N} \quad (9)$$

where

$$M\left(\theta^{(t)}\right) = \sum_{i=1}^{N} e\left(\theta^{(t)}\right)^2_i \quad (10)$$

SCEM is a Markov chain Monte Carlo sampler introduced in 2003 for optimization and uncertainty assessments of hydrologic models [33]. This algorithm is a modified version of original Shuffled Complex Evolution algorithm developed by Duan et al. [34]. SCEM algorithm tries to combine the strengths of the Metropolis algorithm, controlled random search, competitive evolution and complex shuffling, in order to continuously update the proposal distribution and evolve the sampler to the posterior target distribution. The algorithm can be briefly explained as follows: First an initial population is generated from the priory distribution and the posterior density of the individuals is computed using Equation (9). Based on the calculated posterior density, the population is ranked in order of decreasing posterior density, i.e., the sample with the highest posterior density gets the first position. Then a number of parallel sequences are initialized by choosing the first q points of the ranked population in which q is the number of considered sequences. Then for each parallel sequence a complex is composed from the ranked population. If the initial population has p samples and q parallel sequences are considered then each complex will have p/q samples. By applying these configurative steps, the algorithm is ready to evolve the population. The population is evolved by applying Metropolis algorithm in each parallel sequence and its corresponding complex. After all parallel sequences and their corresponding complexes evolved, the complexes are shuffled together and make the new population which substitutes the initial population. The new population is ranked again and the algorithm is repeated again up to the time that the termination criterion is satisfied. The detailed explanation of SCEM can be found in the original paper by Vrgut et al. [33]. They also extend this algorithm to multi-objective optimization [20]. In the original paper, the algorithm was successfully tested on three test problems including a conceptual hydrologic model. The MATLAB implementation of the algorithm is downloadable via [35], which was used for uncertainty assessment of applied model in the considered case study.

V. Heuristic combination procedure

NSGA-II and SCEM extract different information from the response surface of the model. NSGA-II is a multi-objective optimization procedure which tries to highlight a set of non-dominated parametric values without considering uncertainty; whereas SCEM is a single objective Monte Carlo sampler for inferring the most likely parametric values in the light of observed data and considers uncertainty about the exact parametric values. Obviously, the posterior distribution of the parameters found by SCEM is not an uncertainty description for the results of NSGA-II, but combining both pieces of information in a proper way may integrate the strengths of both algorithms and reduce their drawbacks. On one hand, NSGA-II is producing a diverse set of non-dominated parametric values which may be located in the whole feasible parametric region. Consequently the variation of model prediction resulted by using the set of non-dominated parametric values can be quite high. On the other hand, SCEM converges to narrower parametric region which is more robust (less variant) in terms of model output. However, SCEM results are only based on a single objective function. The motivation for combining the results of NSGA-II and SCEM is checking the possibility for extracting a parametric region which is still non-dominated but it is more robust in terms of model output. Here, we developed a simple heuristic procedure in order to combine the information about the response surface extracted from both algorithms.

i) For each parameter identify the most crowded region in non-dominated parametric values computed by NSGA-II. Also identify the most likely region for the parameter value inferred by SCEM.
ii) Identify the upper bound and lower bound of these regions.
iii) Select the region between the minimum of lower bounds and maximum of upper bound as the extracted region.
iv) Uniformly sample number of parametric values in the extracted region. Store the non-dominated parametric values.

Figure (2) shows schematically how this heuristic combination works in a simple two dimensional parametric space X1-X2. Consider that the results of NSGA-II are highlighted by circular dots while the results of SCEM are shown by square dots. The rectangular region which contains the most crowded regions results from both algorithms is the new extracted region identified by applying introduced heuristic combination procedure.

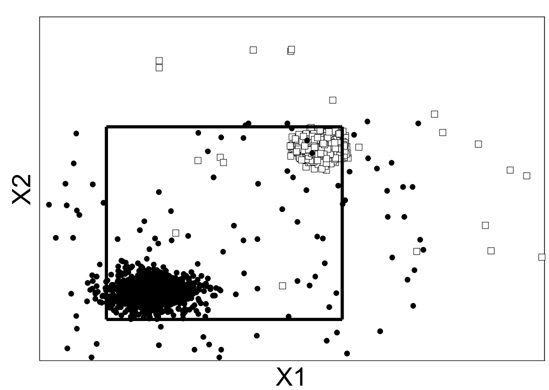

Fig 2. Schematic application of the introduced heuristic combination procedure

VI. Applied Conceptual Model and Considered Case Study

Different researches have reported that there is no need to consider too many parameters to describe key behavior of natural hydrologic process. In other words, increasing the number of free parameters does not significantly increase the model performance [36]. On the other hand, some other studies have suggested that usually up to six model parameters can be approximated using daily measurements with single objective calibration [37]. Therefore some researchers concluded that only conceptual models that have less than six free parameters should be used for describing the daily hydrologic response of natural catchments. These findings support the application of simpler (parsimonious) conceptual structures that only try to describe the key response modes of natural hydrologic systems.

One of the frequently used parsimonious soil moisture accounting modules is Catchment Wetness Index (CWI) which is used in PC-IHACRES model and recently implemented in RRMT. This loss function is related to the well-known Antecedent Precipitation Index, used in several conceptual models. The detailed description of this module can be found in [38], [39], [40], and [41]. In brief, in this interpretation, the portion of effective rainfall at each time step is the average value of modulated system moistures at the considered time step and one step before. Modulated system moisture at each time step equals to the sum of the rainfall input at this time step and the modulated system state at one step before minus the depletion due to losses to stream and evapotranspiration. The depletion itself is an exponential function of temperature. In total, this loss model contains five parameters. Among them, two parameters are needed to be calibrated: time constant of catchment losses, and modulation factor. The other two, i.e. initial moisture of the catchment and reference parameter can be fixed and the fifth parameter, volumetric constant, is explicitly calculated from data. However, in this work it is assumed that initial catchment state is also variable and will be estimated via calibration.

The simplest routing module that has been used in the context of conceptual modelling is a single parametric reservoir that can be linear or nonlinear. The behavior of this reservoir can be described by combining two equations: a storage function describes the relationship between outflow and the amount of reservoir storage, which can be linear or nonlinear and a mass balance equation describing the rate of change in storage as the difference between inflow and the outflow. This module has two free parameters which should be calibrated: time constant and nonlinearity parameter. Details can be found in [42].

In this study, the conceptual model resulted from combination of these two modules is used. MATLAB implementation of this model is available in RRMT package and can be called by functions SMA_CWI and R_CRES in MATLAB platform. The RRMT model is available in internet and can be downloaded from the Imperial college portal website [43]. The acceptable range of parameters applied in this study is reported in Table I based on recommendations on [44].

TABLE I
FEASIBLE PARAMERTIC VALUES FOR CWI_CRES CONCEPTUAL MODEL, USED IN THIS STUDY

Model parameter	Definition	Feasible range used for the considered case study
A)SMA_CWI		
Tau	Time constant of the catchment losses	[0 40]
Refp	Reference temperature	[20 20]
Mf	Modulation factor	[0 5]
s(1)	Initial moisture state of the catchment	[0 1]
Volc	Volumic constant	[0 0]
B) R_CRES		
K	Time constant	[0 15]
N	Nonlinearity parameter	[0.2 1]

The 2038 km^2 catchment, NINNESCAH River basin at CHENEY (USGS ID, 07144780), located in Kansas is one of the US catchments used in Model Parameter Estimation Experiment (MOPEX) of NOAA's National Weather Service. Daily gauge measurements including rainfall, runoff and evapotranspiration along with physical characteristics of the catchment is available via [45]. 10 years period (1966/10/1-1976/9/30) is selected for calibrating the introduced conceptual model. In order to have estimation about the shape of the model's response surface, 5000 models was randomly chosen from feasible parametric space. Figure 2 shows the response surface for routing module parameters, i.e. time constant and non-linearity parameter regarding to RMSE, which shows the complexity of response surface and existence of several local optima in the feasible parametric space. Analyzing the shape of response surfaces resulting from other error function introduced in Section III, shows that this complexity can be observed in all response surfaces. In addition the shape of resulting response surface will dramatically change when different error measures are applied, proving the multi-objective orientation of model calibration with high number of objectives. Further investigations showed that except correlation coefficient and Nash-Sutcliffe response surfaces, which can be described by RMSE, the other response surfaces are completely independent from each other.

Khare, *et al* [46] pointed out that most of multi-objective evolutionary algorithms, including NSGA-II, have been mainly tested in the problems with two or three objectives. This observation motivated them to test these algorithms in some test problems with higher number of objectives with concentration on their ability to converge to the global pareto-optimal front, preserving diversity and running time.

The results showed that NSGA-II performed well on convergence and diversity maintenance and it was found faster in comparison with other considered algorithms.

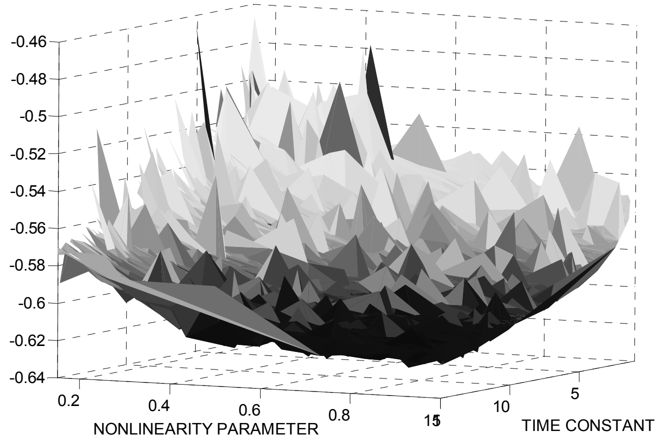

Fig. 2. RMSE response surface of the applied routing module in considered case study. Instead of plotting actual RMSE, -RMSE was plotted.

MATLAB implementation of NSGA-II was used to calibrate the model on the applied case study. Objective functions are considered as all of ten error measures introduced in Section III. Real coding was used and the algorithm started with 50 randomly distributed individuals as initial population. Binary tournament selection and scatter crossover with probability 0.8 were used for selection and crossover operators respectively. For mutation, we used uniform mutation with probability 0.01. The algorithm was run for 100 generations producing a set of non-dominated parametric values.

In order to find the most probable parametric values, SCEM algorithm was used. The algorithm started with 200 random samples covering the feasible parametric space. This set was then divided to 10 parallel sequences each containing 20 samples. Each parallel sequence was evolved 20 times before reshuffling. The maximum number of function evaluation was set at 5000.The last 1000 draws were used to infer the most probable parametric values.

Figure 3 shows this combination procedure for the applied model parameters. Each row represents a model parameter. The first three rows are free parameters of SMA module, which are the time constant for catchment losses, modulation factor and initial storage of the catchment respectively. The last two rows are the parameters relating to routing module which are time constant and nonlinearity parameter. The left column shows the crowding distribution of the non-dominated set assigned by NSGA-II. The most crowded region is within the parametric interval with the highest bar. The middle column shows the posterior parameter distribution. The most likely parameter region is assigned by the highest bar. The right column shows the interval extracted by the introduced heuristic procedure. By applying the combination procedure, it is also possible to define a representative parametric region for each model parameter regarding to the considered catchment.

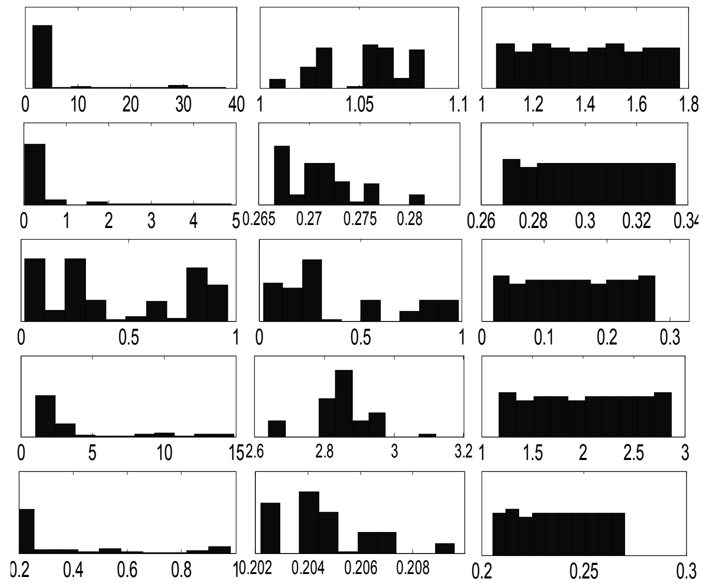

Fig 3. Extracted parametric region resulted by applying the heuristic combination procedure for the applied model in considering case study.

VII. RESULTS AND DISCUSSIONS

Simulation results of this study are summarized in Table II. The results of NSGA-II are the lower and upper bounds of error indices resulted from using non-dominated parametric set extracted by the algorithm. For SCEM, these lower and upper bounds are related to simulation with most likely parameters assigned by SCEM. First of all, it would be interesting to compare the best error indices resulted by these algorithms. As it can be investigated, Equation (9) which is the objective function of SCEM is proportional to sum of squared error. Thus, comparing the result of NSGA-II with SCEM for RMSE can show the ability of NSGA-II in converging to the model index when calibrated in a single objective form. Comparing 0.4466, the best RMSE of NSGA-II, with 0.4359 resulted from SCEM; it is shown that NSGA-II can nearly converge to this value. Comparing the upper bounds of correlation coefficient and Nash-Sutcliffe indices is also supporting this fact, since the shape of their response surfaces are very similar to RMSE. Comparing other error indices, it can be observed that for all remaining measures, NSGA-II can find better error index proving its success in extracting a set of non-dominated parameters regarding to all objectives. However, there is an outstanding difference between the lower and upper bounds for all error measures in NSGA-II, which is duo to great diversity in pareto-optimal parameters. Having such a wide bound for model performance is not approved when the use of model is required for prediction or long-term simulation of the rainfall-runoff process. In addition, as it can be found from Figure 3, it is difficult to assign a reliable representative region for model parameters using just NSGA-II, in case the purpose of modeling is regionalization.

By applying the simple heuristic method, introduced in the last section, it will be possible to merge the advantages of both algorithms, which is extracting a set of non-dominated parameters set with less amount of uncertainty, i.e., narrower possible model output range. As it can be investigated from Table II, combination approach, in all error measures can result to nearly the same optimal value identified by NSGA-II (upper bounds for correlation coefficient and Nash-Sutcliffe measures, lower bounds in the case of other objectives). The new set of non-dominated parameter set can also preserve the multi-objective optimality of the original NSGA-II results by providing less amount of lower bound compared with SCEM for last seven objectives.

It should be noted that, by applying the introduced combination approach, we are not only prune the original set of pareto-optimal solutions extracted by NSGA-II; but it is also possible to find some new pareto-optimal solutions which could not be extracted previously by NSGA-II, since the minimum of lower bounds and maximum of upper bounds were used as the borders of extracted region.

TABLE II
POSSIBLE ERROR RANGES FOR NSGA-II, SCEM AND EXTRACTED REGION FOR APPLIED CONCEPTUAL MODEL CONSIDERING THE CASE STUDY

Error function	NSGA-II	SCEM	Combined
RMSE	0.4466 - 0.7569	0.4359 – 0.4417	0.4486 – 0.5024
Correlation coefficient	0.3654 – 0.7310	0.7368 – 0.7474	0.6368 – 0.7299
Nash-Sutcliffe Coefficient	-0.3644 – 0.5251	0.5354 – 0.5476	0.3989 – 0.5208
Error in volume	1.25×10^{-6} - 0.0995	0.0014 – 0.1187	1.17×10^{-4} - 0.0641
Error in peak	0.5506 – 0.9926	0.7366 – 0.7492	0.6515 – 0.7348
Logarithmic RMSE	1.4846 – 7.2309	2.9490 – 6.9366	2.0263 – 5.7682
RMSE of FDH	1.3855 – 2.1546	1.3931 – 1.4445	1.3641 – 1.5430
RMSE of FDL	0.0828 – 0.8534	0.1705 – 0.2023	0.1270 – 0.3605
RMSE of FNQ	0.4154 – 0.7659	0.5522 – 0.5791	0.4413 – 0.6605
RMSE of FNS	0.0964 – 0.1522	0.1194 – 0.1329	0.0992 – 0.1178

VIII. CONCLUSION

Multi-objective evolutionary algorithms provide a set of non-dominated pareto-optimal solutions with a considerable amount of diversity. In the context of real world modelling, this diversity may result to a wide bound of possible model output which limits the applicability of model. In this study we proposed a simple heuristic procedure in order to combine the information from non-dominated parameters set resulted from NSGA-II with the posterior parameter density inferred by SCEM in order to extract a set of still non-dominated but less variant in the terms of model possible output. The simulation results for a simple conceptual rainfall-runoff model show that the combination procedure can result a set of non-dominated parameters, which is more robust than the original results obtained by NSGA-II in considered case study.

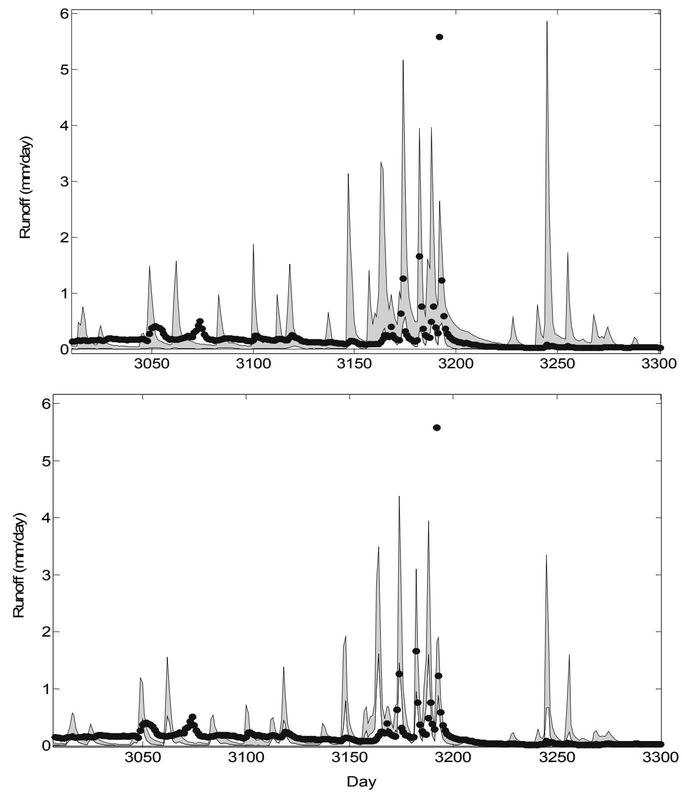

Fig.3. Comparison between the possible model output ranges for a period of 300 days of the hydrograph. The upper figure shows the possible model output using NSGA-II pareto-optimal parametric set. The lower one is produced by using the new pareto-optimal set extracted by the introduced procedure. In both figures, dots are representing observed runoff.

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