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A Simple Automatic Calibration Routine for the HBV Model

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A simple, but efficient, method for automatic calibration of the conceptual HBV rainfall-runoff model was developed. A new criterion, which combines the commonly used efficiency criterion R^2 and the relative volume error was introduced. Optimising this combined criterion resulted in R^2 values nearly as high as those for optimising only R^2, but with much smaller volume errors. An earlier automatic calibration method for the HBV model relied on the use of different criteria for different parameters. With the simplification to one single criterion, the optimum search method could be made more efficient. The optimisation is made for one parameter at a time, while the others are kept constant. This one-dimensional optimisation is repeated in a loop for all parameters. A new loop is performed as long as there is a sufficiently large improvement since the last one. After each loop a search is made in the direction which is defined by the differences in parameter values between the two latest loops. The calibration routine was developed for, and tested with, the HBV model, but it should be general enough to be applicable to other models as well.

Introduction

A comprehensive overview of current hydrological models in the world was recently given by Singh (1995). The models can be divided into two main categories: physically based models and conceptual models. Both need to be adapted to the local conditions of a basin. This usually involves a calibration, with the aim of finding

model parameters which give a good fit between the recorded and computed discharges. Even the SHE model, which is perhaps the most comprehensive physically based model, requires calibration (Refsgaard and Storm 1995). The calibration can be made either manually or automatically. A disadvantage of manual calibration is that the results depend on the experience and opinion of the hydrologist who is doing the calibration. Other disadvantages are that the procedure is time-consuming and thus expensive. Many models have therefore been complemented with automatic calibration schemes (*e.g.*, Sugawara 1979; Harlin 1991 and Kite 1995). A comprehensive overview of methods for automatic calibration was given by Sorooshian and Gupta (1995).

The HBV model is a conceptual rainfall-runoff model originally developed at the Swedish Meteorological and Hydrological Institute, SMHI (Bergström 1976 and 1995). Different automatic calibration methods have been tested with the model. Bergström tested the hill-climbing Rosenbrock scheme, but without satisfactory results. Harlin (1991) developed a process-oriented calibration scheme which tried to mimic the way in which an experienced hydrologist would calibrate the model manually, whereas Vehviläinen (1992) used the Rosenbrock method. However, even the objective methods are subjective in the sense that one has to choose an error function which is to be minimised. The efficiency criterion R^2 (Nash and Sutcliffe 1970) is often used, but Harlin used different criteria for different parameters and different subperiods. A disadvantage of the method is that it is somewhat complicated to understand and apply. The search algorithm is not particularly efficient when the parameters are interdependent, something which is often the case.

During the development of a new HBV model version (Lindström *et al.* 1996) with a higher spatial resolution, the length of optimisation runs using Harlin's scheme became annoyingly long, sometimes up to a week. Instead of using many different criteria and subperiods it would be easier to rely on one single criterion evaluated for the whole calibration period. It would thereafter be a question of finding the parameter set which produces the best fit, *i.e.*, the optimum. Different methods could be used for finding the optimum, *e.g.* Monte Carlo simulations, computations over a grid, or direct search methods. The two first methods would be very time-consuming since a large number of parameter combinations would have to be tested. Therefore, an efficient method for a direct search of the global optimum appeared to be the most promising alternative.

Objective

The objective of this work was to develop an efficient method for automatic calibration of the HBV model, which should be easy to understand, implement and apply.

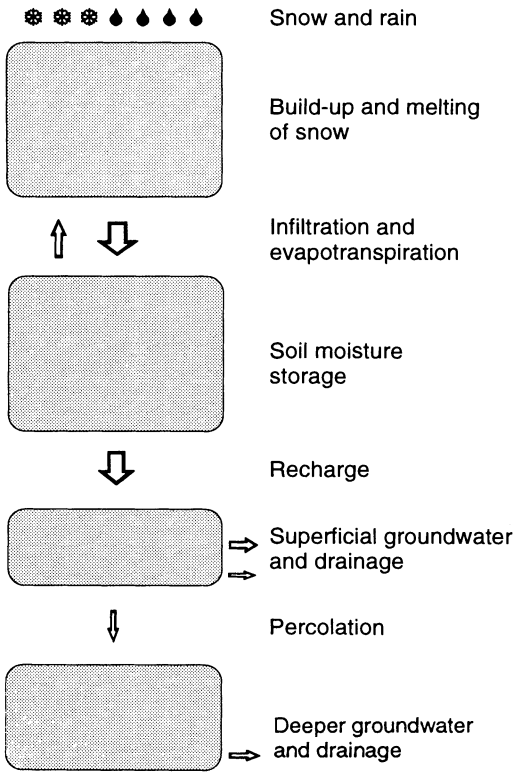

Fig. 1. Schematic structure of the HBV model.

Model and Data Base

The development of the new calibration method was made using a simplified version of the HBV model (Fig. 1), without any division into subbasins or elevation zones. The standard HBV model has been described by Bergström (1976 and 1995), Bergström *et al.* (1992), Zhang and Lindström (1996) among others, and only the main characteristics are given here. Snowmelt is calculated by the degree-day method. The recharge as a fraction of infiltration increases with increasing soil wetness, as does the actual evapotranspiration as a fraction of its potential value. The two groundwater tanks are emptied by use of recession coefficients, and by a constant rate percolation from the upper to the lower tank. Finally, a linear triangular filter delays the runoff over a time of concentration. Altogether 13 model parameters were calibrated.

Ten years of data from seven basins in different parts of Sweden was used. Most important physiographic conditions in Sweden are covered, from almost alpine basins in the north (Suorva) to forested low-land basins in the south (Torsebro). The seven basins – Suorva, Kultsjön, Ströms Vattudal, Torpshammar, Höljes, Blankaström and Torsebro – range from about 1,000 to 6,000 km^2 in size, 7 to 14% in lake fraction and 3 to 74% in forested area.

Criteria for Optimisation

The optimisation attempts to minimise the error E, *i.e.* the difference between the computed, q_{com}, and recorded, q_{rec}, discharges. This can, however, be measured in many different ways, for example

$$E(p) = \frac{1}{n} \sum_{i=1}^{n} |q_{com}(i) - q_{rec}(i)|^p \quad (1)$$

If the exponent p is set to 2 this will be the ordinary mean square of errors, *mse*. A commonly used criterion for evaluation of hydrological models is the efficiency criterion R^2, introduced by Nash and Sutcliffe (1970)

$$R^2 = 1 - \frac{mse}{Var(q_{rec})} \quad (2)$$

where $Var(q_{rec})$ is the variance of the recorded discharge series. The R^2 criterion is thus based on the exponent p=2. Another important measure is the volume error *ACCDIFF*, or the accumulated difference between the computed and recorded discharges in mm

$$ACCDIFF(t) = \sum_{i=1}^{t} (q_{com}(i) - q_{rec}(i)) \quad (3)$$

This criterion measures the systematic volume errors over longer periods. Manual calibration of the HBV model at SMHI mainly relies on R^2 and visual inspection of graphs of the model output, together with the *ACCDIFF* curve. A more practical number for the whole period is the bias, or relative volume error, D_V

$$D_V = \frac{ACCDIFF(n)}{\sum_{i=1}^{n} q_{rec}(i)} \quad (4)$$

Both R^2 and D_V were used in the WMO (1986) intercomparison of snowmelt runoff models. In Harlin's method for automatic calibration different criteria are used for different parameters, but the criteria are variations of the ones described here. One of the reasons behind the use of many criteria is that a maximisation of R^2 alone can lead to a significant, often negative, volume error. Fig. 2 shows that this problem is not only restricted to the exponent p=2 in the error function E, Eq. (1), but that it occurs for other exponent values as well.

Combination of R^2 and Volume Error

The difficulty in finding a parameter set which does not give systematic volume errors can partly be due to a flat response surface around the optimum for R^2. This means that a large change can be made in a parameter without much change in R^2,

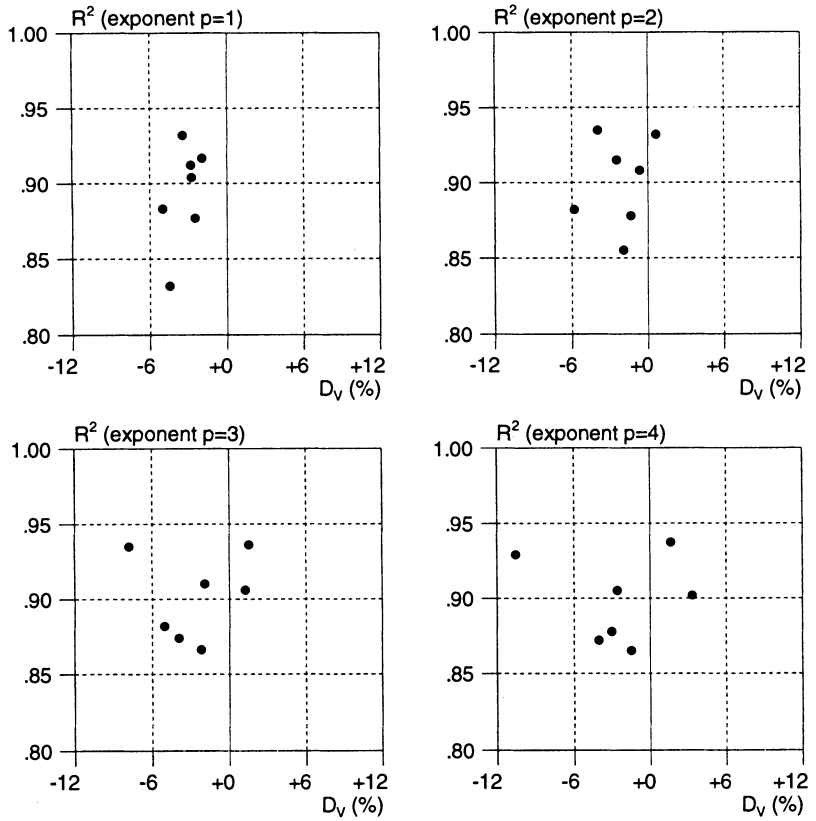

Fig. 2. R^2 versus the volume error D_V for the 7 test basins optimised using different exponents p in the criterion E.

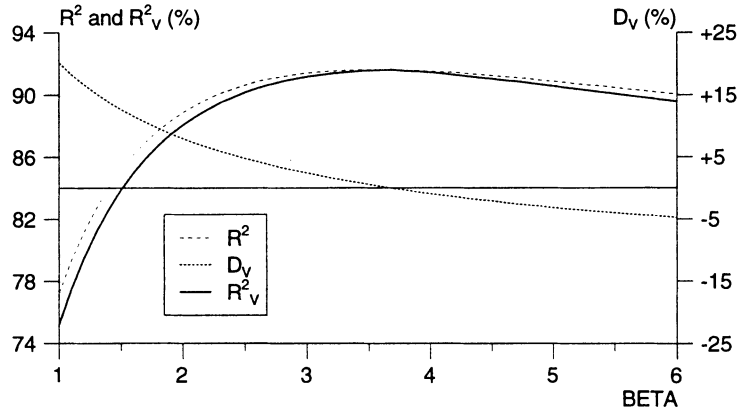

Fig. 3. Efficiency criterion R^2, volume error D_V and the combined criterion R^2_V (with the weight $w = 0.1$) *versus* the model parameter *BETA* (a curve parameter in the soil routine). Example from Torpshammar, 1979-1989.

but in some cases with a large impact on volume (Fig. 3). What is really sought is a set of parameters which gives both a good agreement between the computed and recorded discharges, and a small volume error. A very simple way of doing this is to combine the two dimensionless criteria, R^2 and D_V

$$R^2_V = R^2 - w|D_V| \quad (5)$$

where w is a weight. R^2_V is thus essentially the same as the ordinary R^2 value, but with a small penalty for any remaining volume error. The optimum became slightly better defined for R^2_V than for R^2 alone (Fig. 3).

When R^2_V was maximised, instead of R^2, almost the same R^2 values were reached but this time with smaller volume errors (Table 1 and Fig. 4). It was found that setting $w = 0.1$ normally gave a good compromise between R^2 and volume error. Since R^2 in itself focuses on peak flow rather than low flow, the combined criterion will do the same. The principle of combining a measure of the daily errors as in R^2 with an overall volume error, could of course be used with other exponents p than 2, or even with R^2 for logarithmic flow data if low flow was of great concern. In practice, however, R^2 is often used. Bergström (1976) noted that "the best fit according to visual inspection and the R^2-value mostly coincide".

Table 1 – Mean R^2 and D_V for 10 years of calibration and varying weights w in the criterion R^2_V as an average over 7 test basins.

w =	0.00	0.01	0.05	0.10	1.00
Mean R^2 (%)	90.4	90.2	90.2	90.0	87.0
Mean D_V (%)	-1.7	-1.7	-0.8	-0.1	0.0

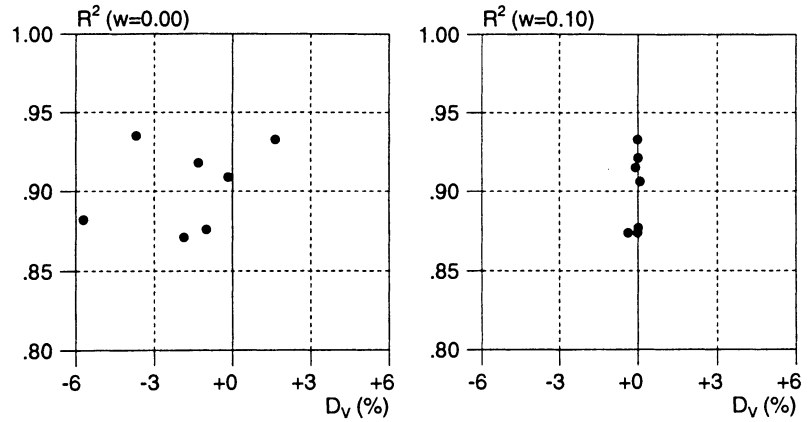

Fig. 4. Efficiency criterion R^2 and volume error D_V after optimisation of the combined criterion R^2_V with two different weights w (w=0 corresponds to the ordinary R^2).

Search Method

The existing search method in the operational HBV modelling system at SMHI, is based on Harlin's (1991) method. Since different criteria are used for different parameters, a one-dimensional optimisation is made for each parameter, one at a time. The Brent parabolic interpolation method as described by Press *et al.* (1992) is used for this purpose. Since the aim of developing a new calibration scheme was to implement it into the same operational system, the existing scheme was used as a starting point. This scheme is briefly described below.

Parabolic Interpolation

For each parameter one must specify a starting point, upper and lower boundaries and a tolerance. The criterion is first computed for the starting point. A step is thereafter taken into the largest of the two intervals between the starting point and the boundaries. The length of this step is based on the golden section and is about 38% of the interval length. Similar steps according to the golden section are taken until the parabolic interpolation can start.

In the parabolic interpolation a parabola through the three best values of the parameter is estimated (Fig. 5). The optimum point according to the curve is computed, assuming that this point is near the true optimum. The formula for the optimum point x_{opt} through the three points $(a, f(a))$, $(b, f(b))$ and $(c, f(c))$, where $a<b<c$, is given by (Press *et al.* 1992)

$$x_{opt} = b - \frac{1}{2} \frac{(b-a)^2\{f(b)-f(c)\} - (b-c)^2\{f(b)-f(a)\}}{(b-a)\{f(b)-f(c)\} - (b-c)\{f(b)-f(a)\}} \qquad (6)$$

The objective function f is computed for the new point x_{opt}, and this point replaces the worst of the three earlier points a, b or c. A new parabola is estimated and the

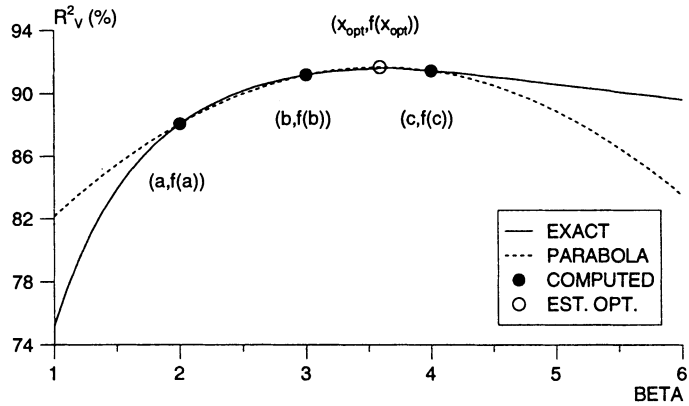

Fig. 5. The criterion R^2_V as a function of the curve parameter *BETA* in the soil routine, and the approximating parabola through three computed points a, b and c. Example from Torpshammar, 1979-1989.

procedure goes on until the chosen tolerance in the parameter value is reached. The tolerance is measured as a fraction of the parameter value. This can lead to a large number of unnecessary, and time consuming, evaluations of the objective function, when the parameter value is near zero. This can often be the case with for example the parameter *TT* in the HBV model, as this parameter is the threshold temperature for distinguishing between snowmelt and snow accumulation.

Parameter Loop

The above described one-dimensional optimisation is made for all parameters according to an order of parameters which has been chosen beforehand. The dependence between the parameters is taken into account by making a new loop over all parameters after the last one has been finished. These loops continue as long as the improvement in R^2 exceeds a chosen tolerance. No use is made of the fact that the parameter values get more and more stable. After a few loops, most parameters hardly change. Nevertheless, the full Brent optimisation is repeated for each parameter in each loop. This will usually lead to a too large number of runs to be on the safe side.

When one single criterion is used for all parameters, as proposed in this paper, the application of the Brent method becomes equivalent to the multi-dimensional Powell method (Press *et al.* 1992), since all parameters are optimised along the axes, one at a time. This method, in the special case of using the same criterion for all parameters is referred to as the "old method" in the following text. It is thus not equivalent to the calibration scheme developed by Harlin (1991).

Modified Parabolic Interpolation

Many different methods were tested for making the search method more efficient for this particular application. Both the conjugate gradient method and the BFGS method, a quasi-Newton method, were tested, both as described by Press *et al.* (1992). In these methods the gradient must be computed. In addition, a large number of variations of the one-dimensional parabolic method described above were tested. A new method was developed which was found to be simple but yet perform satisfactorily. The method is still based on the Brent parabolic method but with some minor, although significant, modifications.

As in the old method, the optimisation is made for one parameter at a time, while keeping the others constant. The criterion $f(x)$ is a function of the current parameter, here called x. The normal step length in the Brent method was often found to be too pessimistic in this application. In the proposed method only small steps are taken around the starting point. It was usually appropriate to take steps of 10% to the left and to the right as the second and third steps in the computation of $f(x)$. Thereafter the parabola is estimated as described above. An important difference is, however, that a tolerance in the criterion is set, rather than a relative tolerance in the parameter value as in the original method. The problem of too many computations when the

parameter value is near zero is hereby avoided. Instead, most computational effort is spent on the parameters which have the strongest influence on the results. It is thus no longer necessary to select different tolerance levels for different parameters, as was done in Harlin's method.

The optimisation of the current parameter is continued until the difference in criterion between the centre point b and the point x_{opt}, estimated according to the parabola, is less than a pre-set level, $tol1$

$$|f(b) - f(x_{opt})| \leq tol1 \tag{7}$$

The best value so far of the current parameter is saved for the analysis of the next parameter. Since the parameters are dependent on each other, quite a few loops over all parameters are normally required. It is therefore not necessary to use a very small tolerance here. An appropriate value for the criterion R^2_V was found to be $tol1$ = 0.001.

Modified Parameter Loop

When a parameter has been optimised the procedure is repeated for the next one. The method is explained below for the simple case of two parameters, here called x and y (Fig. 6), but it is easily extended to a larger number of parameters. The criterion becomes a function of two parameters, here called $g(x,y)$. The optimisation starts in the point (x_0,y_0). The parameter x is first optimised as described above. The best x value, x_1, replaces x_0 and the optimisation of the parameter y continues from the point (x_1,y_0). After a loop over the two parameters, the point (x_1,y_1) has been reached. The step which has been taken is given by

$$(\Delta x, \Delta y) = (x_1 - x_0, y_1 - y_0) \tag{8}$$

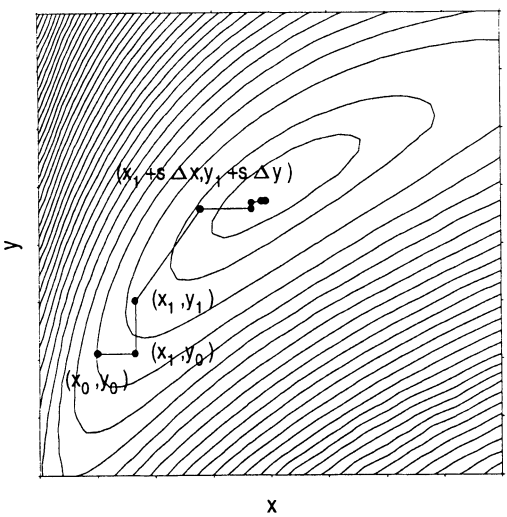

Fig. 6.
Illustration of the search method in two dimensions. Only the points after each one-dimensional optimisation are shown.

Since an improvement was obtained in the direction from (x_0,y_0) to (x_1,y_1) it is probable that further improvements can be found along the line through these two points. The following optimisation is therefore made along this line. A step s from the new point is defined by

$$(x,y) = (x_1,y_1) + s(\Delta x,\Delta y) \quad (9)$$

The criteria $g(x_0,y_0)$ and $g(x_1,y_1)$ correspond to $s = -1$ and $s = 0$ respectively, and are already known. The criterion is then evaluated for $s = +1$, and from these three points the one-dimensional parabolic Brent optimisation of a function $h(s)$ is performed as described above. The new optimum point after this is then given by $(x_1+s_{opt}\,\Delta x, y_1+s_{opt}\,\Delta y)$.

The model parameters x and y are thus complemented by a new one, the step s, which accounts for the interdependence between the parameters. By this procedure the number of evaluations of the criterion, *i.e.*, model runs, can be reduced significantly. The difference compared to a gradient method is that no time is used for computing the gradient. The fact that the parameters are of different magnitude is taken into account by the method in a simple way. Another advantage is that the order in which the parameters are adjusted can be controlled. It is for example not of much use to start adjusting rather insignificant model parameters, such as the base flow parameters *K2* and *PERC* in the HBV model, as long as the total volume is far from correct.

After a few loops, many of the parameters hardly change at all. It was found that the optimisation of these parameters could be turned off, and they were put into the calibration scheme only every second loop as long as they remain unchanged. After each loop over all parameters the improvement in criterion is checked. The calibration is stopped when the improvement is less than a tolerance, *tol*2. Appropriate values of *tol*2 for the criterion R^2_V are in the order of 0.001 or 0.0001.

Computational Details

In the search process all parameter changes must be made with the restriction that no parameter value may cross a chosen boundary. Parabolic steps which reached outside of the allowed range of a parameter were replaced by a step half way to the limit. By restricting the parameters within reasonable limits, a limiting value itself can often become the optimum value. In the coding of the method great care was taken not to repeat any model runs for which the criterion was already known. Some parameters, typically the threshold temperature *TT*, can have both negative and positive values. It is therefore not suitable to use the initial steps of 10% around the starting value for these parameters. Instead a fraction of the distances to the limits were used as the steps around the initial point for such parameters.

The initial state variables, for example *SM*, depend on the chosen parameter values. Therefore the first period, typically the first year, should be excluded from the computation of the criterion.

The order in which the parameters were optimised influenced the final result, and many different alternatives were tested. The best results were obtained when the model was calibrated from top to bottom, *i.e.*, starting with the snow routine, followed by the soil routine, the groundwater routine and the transformation function. This order is almost the same as the one proposed by Harlin (1991) with the exception of the transformation function. One alternative was tested in which the parameters were adjusted in order of sensitivity. This did not, however, work better than the simpler top to bottom order.

Summary of the Calibration Method

The calibration method is summarised below:

1) R^2 is maximised but with a small penalty for any remaining volume error.
2) The criterion is not evaluated during the first year in order to avoid the influence of the initial state.
3) A loop is performed over all the parameters, from top to bottom, in the model.
4) The parameters are calibrated one at a time, while the others are kept constant. Each parameter is optimised using a parabolic interpolation method until a chosen tolerance in the criterion is reached.
5) When a loop over all the parameters has been finished, a parabolic search is made in the direction defined by the differences in parameter values between the two latest loops.
6) Parameters which do not change between loops are temporarily taken out from the optimisation.
7) A new loop over all parameters is performed as long as there is a sufficiently large improvement since the last one.

Results

After the modifications in the search method significantly fewer model runs were needed. Examples of search paths according to the old and new method are shown in Fig. 7.

The performance of the new method is compared to the old method in Fig. 8. The main advantage of the new search method is the increased speed. In addition, slightly higher values in the objective function R^2_V were found (+0.001 as an average for the 7 basins).

Unfortunately the final parameter values were found to depend on their respective initial values to some degree. The calibration results for some parameters were scattered over a large range, whereas other parameters were more well-defined, and var-

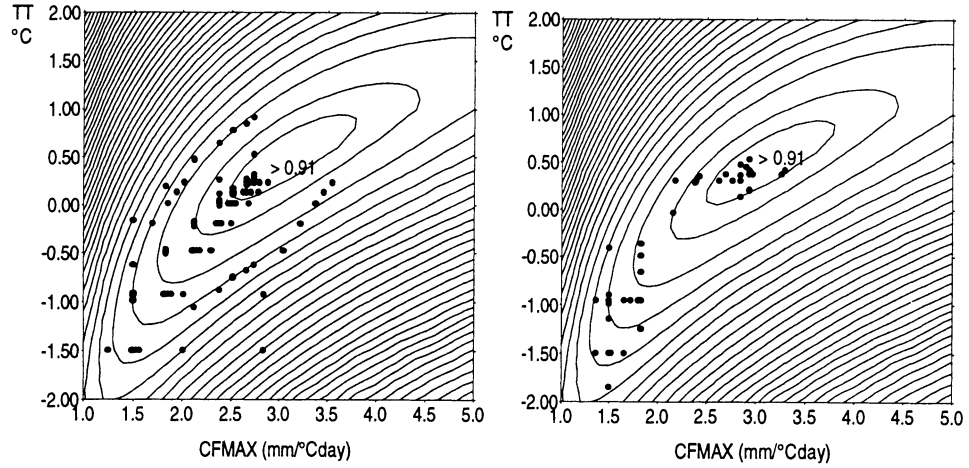

Fig. 7. Example of search paths according to the old (left) and new (right) search method. Isolines for the criterion R^2_V are shown. Each point represents a model run.

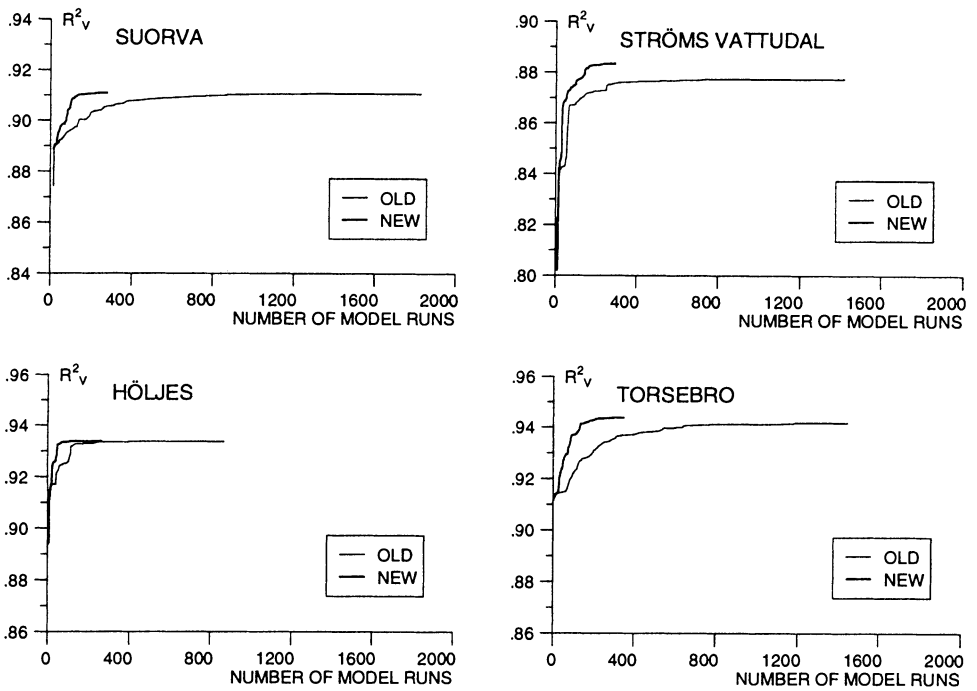

Fig. 8. The objective function, R^2_V, *versus* number of model runs by the new search method and the old search method in the case of optimisation of one single criterion.

ied within a smaller range. Test runs with synthetic data showed that an average R^2 of 0.998 was reached after a few hundred model runs with random initial parameter values. The efficiency of the search algorithm should thus be sufficient for most practical applications.

Discussion

The proposed method for automatic calibration gave good results despite its simplicity. The simplicity is in line with the philosophy behind the HBV model (Bergström 1991). The method is, however, not model dependent, and should be applicable to different types of models. Good results were obtained after a few hundred model runs. During the development of a new HBV model version with a higher spatial resolution it became important to shorten the calibration time. In the evaluation of different model structures an automatic method for calibration is preferable to manual calibration as one is not tempted to calibrate a preferred model more carefully than another. It would furthermore have taken too much time to make all calibrations manually.

One of the disadvantages with automatic calibration is that the final parameter values usually depend on the initial parameter values. This is caused by local optima and interaction between model parameters. It is known that the existence of local optima is one the major obstacles for automatic calibration (see *e.g.* Sorooshian and Gupta 1995). The difficulty of finding the optimal parameter set has also been discussed by Sugawara (1995) and Beven *et al.* (1995) among others. The possibility for a search method to find the optimum of course depends on the existence of such an optimum, *i.e.* that there really is only one set of correct parameters values. Many, very different, parameter sets can produce almost equally high values of the chosen criterion. For the HBV model this was shown by Harlin and Kung (1992). As long as a model is calibrated using recorded data, the best parameter set will furthermore depend on the chosen time period, the chosen criterion and the chosen input data stations. For many operational purposes, it is less important to find the global optimum. It is usually sufficient to find a good set of parameters, but with the requirement that they give no systematic errors. It is particularly important to keep down the systematic volume error if the model is meant for forecasting of available water resources.

Experience showed that it was a good idea to first make a few manual calibration runs to get the process on the right track, and then let the automatic calibration method do the more detailed polishing of model parameters. This is also in line with the recommendations by Kite (1995). A particularly important parameter proved to be the peak flow parameter, *K0*, in the HBV model. The initial volume error should furthermore not be too high. It was also found that the reduction of parameter interdependence by some changes in the model structure and in the definition of parameters could improve the possibilities for a successful calibration. This agrees with the re-

sults by Gupta and Sorooshian (1983). The success of an automatic calibration thus depends both on the efficiency of the calibration method and on the model formulation. In addition, reducing parameter interdependence will make the calibration run faster. It is, however, outside of the scope of this paper to describe these model changes here.

The performance of the calibration scheme was here evaluated over the calibration period only, as the instructions to the scheme is to minimise the errors over that period. The degree to which a calibration results in overfitting is likely to be a function of the model structure and the number of calibrated parameters rather than of the calibration scheme. An evaluation over an independent period could therefore introduce additional uncertainty and make it more difficult to judge the merits of the calibration method itself.

The results from the calibration were found to depend on the order in which the parameters are placed in the optimisation. The best results were obtained when the model was calibrated from top to bottom. However, the importance of the individual parameters differs between basins, and another order could be better for some basins. The results also depended on the initial parameter values. In practice, it may therefore sometimes be appropriate to apply the calibration method several times using different orders and initial values of the parameters.

There is still considerable scepticism about automatic calibration of hydrological models, and many modellers prefer manual calibration for their models, *e.g.* Burnash (1995) and Speers (1995). Others report satisfactory results, *e.g.* Sugawara (1979 and 1995) and Kite (1995). One argument against automatic calibration is that it may produce what is called unrealistic parameter values. This should not, however, be a problem since boundaries for the parameter values are put into the optimisation method, thereby avoiding unrealistic results.

Conclusions

It was possible to calibrate a simplified HBV model automatically with satisfactory results. The proposed method is simple but yet efficient. Test runs with optimisation of 13 parameters showed that a few hundred model runs were sufficient, which is much fewer than for the old method. The proposed method uses a simple combination of the efficiency criterion R^2 and the relative volume error for all parameters. The use of this criterion gave parameter sets with high R^2 values and almost no volume error. Since one single criterion was used for all parameters the search method earlier used with the HBV model could be made more efficient. The calibration method is, however, not dependent on the HBV model, and it should be applicable to other models as well.

The final parameter values depended on their respective initial values. Thus, the

proposed method was not capable of always finding the global optimum. This is, however, usually not necessary since the optimum itself depends on a number of factors, such as choice of criterion, time period, input stations *etc.* For most practical applications it should be sufficient to find a parameter set which gives an almost optimum fit and no volume errors.

Acknowledgements

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References

Bergström, S. (1976) Development and application of a conceptual runoff model for Scandinavian catchments, SMHI RHO 7, Norrköping, Sweden.

Bergström, S. (1991) Principles and confidence in hydrological modelling, *Nordic Hydrology, Vol. 22*, pp. 123-136.

Bergström, S., Harlin, J., and Lindström, G. (1992) Spillway design floods in Sweden. I: New guidelines, *Hydrological Sciences Journal, Vol. 37*, pp. 505-519.

Bergström, S. (1995) The HBV Model. In V.P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 443-476, Water Resources Publications, Highland Ranch, Colorado, USA.

Beven, K. J., Lamb, R., Quinn, P., Romanowicz, R., and Freer, J. (1995) TOPMODEL. In V.P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 627-668, Water Resources Publications, Highland Ranch, Colorado, USA.

Burnash, R. J. C. (1995) The NWS River Forecast System – Catchment Modeling. In V. P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 311-366, Water Resources Publications, Highland Ranch, Colorado, USA.

Gupta, V. K., and Sorooshian, S. (1983) Uniqueness and Observability of Conceptual Rainfall-Runoff Model Parameters: The Percolation Process Examined, *Water Resources Research, Vol. 19*, pp. 269-276.

Harlin, J. (1991) Development of a Process Oriented Calibration Scheme for the HBV Hydrological Model, *Nordic Hydrology, Vol. 22*, pp. 15-36.

Harlin, J., and Kung, C. S. (1992) Parameter uncertainty and simulation of design floods in Sweden, *Journal of Hydrology, Vol. 137*, pp. 209-230.

Kite, G.W. (1995) The SLURP Model. In V.P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 521-562, Water Resources Publications, Highland Ranch, Colorado, USA.

Lindström, G., Gardelin, M., Johansson, B., Persson, M., and Bergström, S. (1996) HBV-96 – En areellt fördelad modell för vattenkrafthydrologin, (HBV-96 – A distributed model for hydropower hydrology, in Swedish) SMHI, RH No. 12, Norrköping, Sweden.

Nash, J. E., and Sutcliffe, J. V. (1970) River flow forecasting through conceptual models. Part I: A discussion of principles, *Journal of Hydrology, Vol. 10*, pp. 282-290.

Press, W. H., Teukolsky, S. A., Vetterling, W. T., and Flannery. B. P. (1992) *Numerical Recipes in FORTRAN. The Art of Scientific Computing*, Second Edition, Cambridge University Press.

Refsgaard, J. C., and Storm, B. (1995) MIKE SHE. In V. P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 809-846, Water Resources Publications, Highland Ranch, Colorado, USA.

Singh, V. P. (Ed.) (1995) *Computer models of watershed hydrology*, Water Resources Publications, Highland Ranch, Colorado, USA.

Sorooshian, S., and Gupta, V.K. (1995) Model Calibration. In V.P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 23-68, Water Resources Publications, Highland Ranch, Colorado, USA.

Speers, D. D. (1995) SSAAR Model. In V.P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 367-394, Water Resources Publications, Highland Ranch, Colorado, USA.

Sugawara, M. (1979) Automatic calibration of the tank model, *Hydrological Sciences, Bulletin, Vol.* 24, pp. 375-388.

Sugawara, M. (1995) Tank Model. In V. P. Singh (Ed.) *Computer models of watershed hydrology*, pp. 165-214, Water Resources Publications, Highland Ranch, Colorado, USA.

Vehviläinen, B. (1992) Snow cover models in operational watershed forecasting. Publications of Water and Environment Research Institute 11, National Board of Waters and the Environment, Helsinki, Finland.

WMO (1986) Intercomparison of models of snowmelt runoff, Operational Hydrology Report No. 23, Geneva, Switzerland.

Zhang, X., and Lindström, G. (1996) A comparative study of a Swedish and a Chinese hydrological model, *Water Resources Bulletin, Vol. 32*, pp. 985-994.

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