Improved Rainfall-Runoff Modeling Combining a Semi-Distributed Model with Artificial Neural Networks

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1. Objective

- Integrated approach to model rainfall-runoff using AVSWAT and Artificial Neural Networks (ANNs).

- **Step 1:** Identify model calibration parameters (LHS-OAT method);

- **Step 2:** Optimized model parameters using automatic calibration (SCE-UA) by matching observed and simulated quick and slow flow;

- **Step 3:** Fit the black box model to the output of the deterministic rainfall-runoff model to create hybrid and cooperative applications.
2. Study area
3. Model set up and data

- Daily maximum and minimum air temperature, relative humidity and daily precipitation were gathered from the Royal Meteorological Institute (Belgium);

- Daily stream data flow data made available by the Flemish Water Administration for Land and Water;

- The Penman-Monteith FAO-56 method was used for the calculation of the potential evapotranspiration (Allen et al., 1998);

- The soil map was available at a scale of 1:25,000, and the soil physical data derived from the Aardewerk-SIBIS Soil Information System (Van Orshoven et al., 1993).

- Landuse was derived using the multitemporal LANDSAT 5 TM 1997.
3. Model set up and data

- Four weather stations.

- The annual rainfall for the period 1994-2002 varied from a minimum of 684.1 mm to a maximum of 1089.1 mm.

- The annual rainfall during the calibration period (1999-2002) was 957.6 mm 21% higher than the regional average annual rainfall.

- Validation period (1994-1998), the annual rainfall was 828.1 mm.
4. Neural network

- Multi-Layer feed-forward neural network

- Focused time-delay neural network
  - Nonlinear time-dependent signals
  - It is simply a static multi layer perceptron with a tap delay line between the input and the first layer
  - This network is well suited to time-series prediction (MATLAB user guide)
5. Multi-objective functions

- The optimal parameter set for one signal might not be the best parameter set for another signal.

- Two general approaches to multi-objective calibration
  - aggregated to form a single objective function
    - the solution is strongly dependent on the way the objectives have been aggregated.
  - concept of Pareto optimality
5.1. Pareto optimal

- A Pareto-optimal solution cannot be improved upon without hurting at least one of the criteria.
- All solutions on the Pareto front equally important and all are the global optimal solutions.
- The user must decide what compromise to make
  - Algorithms: Normal Constraint method, Pattern search, Genetic algorithm, etc...

Fig 1. Mating the Preto performance space
5.1. Pareto optimality

The aggregated objective function:

\[ F_{agg} = \omega g_1(F_1) + (1 - \omega) g_2(F_2) \]  \hspace{1cm} (1)

- Compensate for difference in magnitude between MSE terms

\[ g_i(F_i) = \frac{F_i}{\sigma_i} + \varepsilon_i, \quad i = 1, 2 \]  \hspace{1cm} (2)

- Transformation constant

\[ \varepsilon_i = \max \left\{ \min \left\{ \frac{F_j}{\sigma_j}, \quad j = 1, 2 \right\}, \quad i = 1, 2 \right\} - \min \left\{ \frac{F_i}{\sigma_i} \right\} \]  \hspace{1cm} (3)

6. Result

Fig 2. Objective function values of evaluated parameter sets.

<table>
<thead>
<tr>
<th>Layer 1</th>
<th>Layer 2</th>
<th>Delay time</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>200</td>
<td>4.00</td>
</tr>
<tr>
<td>2</td>
<td>600</td>
<td>3.00</td>
</tr>
<tr>
<td>2</td>
<td>800</td>
<td>3.00</td>
</tr>
<tr>
<td>9</td>
<td>1600</td>
<td>4.00</td>
</tr>
</tbody>
</table>
6. Result

Table 1. Summary of the statistics for the daily total water and slow flows in the calibration and validation periods

<table>
<thead>
<tr>
<th>Statistical criteria</th>
<th>Average daily total water flow</th>
<th>Average daily slow flow</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Calibration</td>
<td>Validation</td>
</tr>
<tr>
<td>RMSE (m$^3$ s$^{-1}$)</td>
<td>SCE</td>
<td>Hybrid</td>
</tr>
<tr>
<td></td>
<td>1.45</td>
<td>0.57</td>
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<tr>
<td>EF</td>
<td>0.72</td>
<td>0.83</td>
</tr>
<tr>
<td>R$^2$</td>
<td>0.80</td>
<td>0.89</td>
</tr>
</tbody>
</table>
6. Result

Figure 3: Comparison of observed and simulated daily total flows outlet during the model calibration (1998-2002), for observed, hybrid and SCE methods.
6. Result

Figure 4: Comparison of observed and simulated daily total flows during the model calibration (1994-1997), for observed, hybrid and SCE methods.
7. Conclusion & recommendation

- Recent developments in stochastic analysis, are opening up new horizons in hydrology modelling.

- Significant progress is being made in hybrid method.

- This survey is on-going.

- Keep working team work.
Thank you for your attention

Question?