A NEURAL NETWORK BASED OPERATIONAL RESERVOIR INFLOW FORECASTING MODEL FOR AN ALPINE HYDROPOWER PLANT

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In the research reported, an artificial neural network based (ANN) reservoir inflow forecast model for a high Alpine catchment in Northern Italy is developed. The model performs a forecast of the Vernagt reservoir inflow on a daily basis for a lead time of 1, 2, and three days. For model training and development, measurements of precipitation, temperature, snow heights and reservoir inflow were used. The model developed is based on multilayer feedforward neural networks (MFNN). All tested ANN in this study were trained with Backpropagation.

Forecasting software uses data from two meteorological stations (precipitation, daily temperature range, snow heights) and data from meteorological forecasts. Besides, the model uses observed inflow from the preceding days and also additional information like date, amount of precipitation fallen at days with mean temperatures below 0°C, or averaged temperatures over a longer time frame.

A total of 74 ANN models with different architectures was tested. The authors distinguish between (i) preliminary tests (M1-M60), (ii) tests on extreme events (M61 - M70), and (iii) a final test for a three step forecast (M71 - M74). The applied performance criterion to evaluate the quality of the simulation is the R^2 (Nash-Sutcliffe coefficient).

At the preliminary tests model M59 behaves best with an $R^2 = 0.971$. A comparison of a predicted and a measured hydrograph can be found in figure 1.

The input and hidden layer configuration of model M59 was taken as basis for further model development. Configuration of input and hidden layer from model M70 was taken as configuration of models M71-M73 and model M74. Model 74 has three output nodes for Q(t), Q(t+1) and Q(t+2) to perform a three-step forecast. Performance of this multi-step forecast model was then compared with the performance of models M71, M72, and M73. These models have one output node and are "specialized" to predict either Q(t), Q(t+1), or Q(t+2).

The R^2 performance criterion shows that the specialized models with one output node (M71, M72, M73) perform better than the multi-step forecast model M74. The authors presume that this is caused by a Herd effect (Fahlman and Lebiere, 1990). Therefore, multi-step models should not be based on the given multilayer-feedforward architecture. Alternatively, cascade-correlation learning architectures (Imrie et al., 2000) or recurrent neural networks (Chang et al., 2004) should be tested.

A software called HYDRO-OPT was developed incorporating the necessary features for reservoir inflow forecasting based on ANN predictions and reservoir operation.

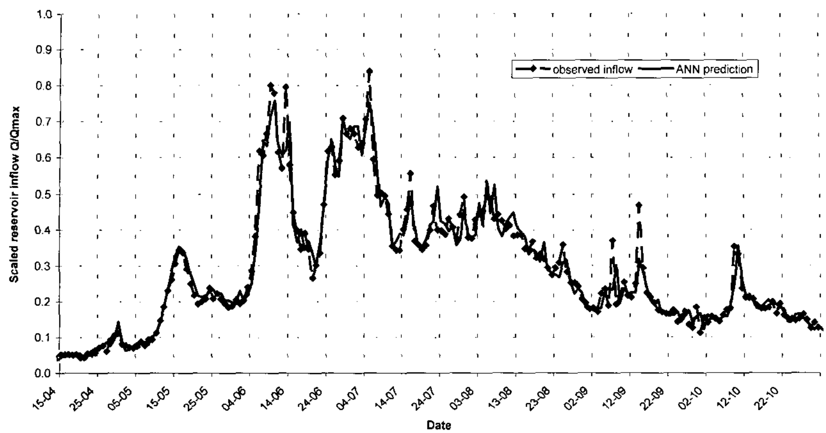

Fig.1 Test of model 59: Predicted reservoir inflow vs. observed inflow, 1 day forecast lead time

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