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An improvement to the ANN-enhanced flow rating method

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The work reported here builds upon a previous pilot study by the author on ANN-enhanced flow rating (Schmid, 2020), which explored the use of electrical conductivity (EC) in addition to stage to obtain 'better', i.e. more accurate and robust, estimates of streamflow. The inclusion of EC has an advantage, when the relationship of EC versus flow rate is not chemostatic in character. In the majority of cases, EC is, indeed, not chemostatic, but tends to decrease with increasing discharge (so-called dilution behaviour), as reported by e.g. Moatar et al. (2017), Weijs et al. (2013) and Tunqui Neira et al.(2020). This is also in line with this author's experience.

The research presented here takes the neural network based approach one major step further and incorporates the temporal rate of change in stage and the direction of change in EC among the input variables (which, thus, comprise stage, EC, change in stage and direction of change in EC). Consequently, there are now 4 input variables in total employed as predictors of flow rate. Information on the temporal changes in both flow rate and EC helps the Artificial Neural Network (ANN) characterize hysteretic behaviour, with EC assuming different values for falling and rising flow rate, respectively, as described, for instance, by Singley et al. (2017).

The ANN employed is of the Multilayer Perceptron (MLP) type, with stage, EC, change in stage and direction of change in EC of the Mödling data set (Schmid, 2020) as input variables. Summarising the stream characteristics, the Mödling brook can be described as a small Austrian stream with a catchment of fairly mixed composition (forests, agricultural and urbanized areas). The relationship of EC versus flow reflects dilution behaviour. Neural network configuration 4-5-1 (the 4 input variables mentioned above, 5 hidden nodes and discharge as the single output) with learning rate 0.05 and momentum 0.15 was found to perform best, with testing average RMSE (root mean square error) of the scaled output after 100,000 epochs amounting to 0.0138 as compared to 0.0216 for the (best performing) 2-5-1 MLP with stage and EC as inputs only.

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