

4 Conclusion and Recommendations

The later use of the results of any kind of curve fitting determines the need for certain characteristics of the prediction. Consistency in the slope can be much more important than precision of the predicted values. The later use may require a very smooth signal or the smoothness of the signal does not matter at all. Control purposes usually require results that do not only represent the system values in a precise way but also that the derivative of the results represents the system behavior too.

The holdout method as proposed by Specht in [Specht 91] proved to not leave room to adjust the method to the individual needs of the prediction. Most often the holdout method yields a small smoothness parameter. The prediction yields the values of the training samples very well. The small smoothness parameter causes the prediction to include many sudden changes in the slope of the curve. The wiggle method is also an empirical method. It allows the smoothness parameter to be selected such that the smoothness parameter accommodates for the needs of the further use of the prediction.

With the use of the wiggle method GRNN's emphasis on smoothness or on precision can be changed. GRNN can be modified very easily such that more emphasis is put on precision or more emphasis is put on the smoothness of the prediction. Only one parameter, the smoothness parameter, has to be changed to change the sensitivity of GRNN. The change of the smoothness parameter can be performed very easily by changing the allowable

inflections in the wiggle method. For other curve fitting tools more work is necessary in order change the emphasis on either precision or smoothness.

The performance of GRNN for equally spaced data is good. Unequally spaced data though causes GRNN to perform not as desired. GRNN works approximately as good for 81 equally spaced training samples with for four independent variables, $y=f(x_1, x_2, x_3, x_4)$, than for 500 randomly distributed unequally spaced training samples imposing the same requirements for smoothness.

Because of the structure of GRNN, GRNN will deviate from the expected more towards extreme values, especially when they are located at the borders of the available data. This behavior cannot be influenced by the selection of the smoothness parameter. This behavior is intrinsic to GRNN. The use of an underlying function supports the prediction. The magnitude of the problems that GRNN has with predicting extreme values at the borders of the available data, gets decreased and the prediction performs better than without the underlying function. The use of an underlying function does not solve problems but is a cure for a symptom.

A simplified model for a complicated problem is often known. This model can be used to support the prediction such that the prediction will only correct the error made by the simplifications of the problem. This approach is very promising in general. It does not matter what kind of curve fitting tool is used, Splines, Curve Fit or Neural Networks, the use of a simple model in combination with a correction has very big potential.

A good extrapolation can only be performed by a fit of the properties of a mechanistic model to data. GRNN by itself cannot perform extrapolation. In the combination of a simple mechanistic model with GRNN extrapolation is possible.

GRNN has potential in replacing or adding to known curve fitting tools. More understanding of the influence of the smoothness parameter is necessary such that GRNN can finally be an equivalent to the known curve fits. Its simplicity is extraordinary, and its available flexibility is unmatched. The problem that remains is that GRNN has especially problems with unequally spaced data, a problem that is unknown to most other curve fitting tools.

To improve Grnn such that it performs as desired, it would be necessary to have a smoothness parameter that is a function of the position of the training samples and the point of prediction. This way unequally spaced training samples, and predictions of extreme values at the edges of the available training data would make less of a problem. More research is necessary to come up with a method using an adaptable smoothness parameter.

All shown curve fitting methods, Splines, Curve Fit and GRNN cannot work without judgment on certain decisions from the outside. GRNN with B-Splines need the least information from the outside. Other methods need a lot more information. Depending on the problems it seems therefore necessary to choose the method individually.