3.3 Influence of Simple model on Prediction

The use of a simple model for the prediction is compared under different conditions. The four dimensional input vector contains values for the mass flow rate, the velocity of the air flowing over the heat exchanger, the temperature of the water flowing into the heat exchanger and the temperature of the air. For the first predictions 81 equally spaced data points have been used. This means a corresponding data set containing information on two dimensions would consist of only nine samples. The training samples were positioned at both edges of the range of each sample and the middle of the range of each sample. In (Table 3.3-1) the values of the independent variables of the training samples are shown. The value of the effectiveness for each possible combination of variables make up one training sample.

Mass flow rate	**Velocity air**	**Temperature Water in**	**Temperature air**
0.5 kg/s	12.5 m/s	300 K	300 K
1.7 kg/s	25 m/s	350 K	350 K
2.9 kg/s	37.5 m/s	400 K	400 K

Table 3.3-1 Values for 81 training samples

In the plots (Fig. 3.3-1) and (Fig. 3.3-2) the solid line labeled "real eff" is the true value of the effectiveness that GRNN should predict. These results were calculated with the model that was used to generate the training samples, described in Section 3.1. The training samples are not shown in the following figures. It is always mentioned in the caption how many samples were used and how they were spaced, equally or unequally. The two other lines show the result of the prediction using the two different approaches of using an underlying function or not using an underlying function. These predictions are labeled "eff GRNN+Simple" or "eff GRNN". The results are always shown for two different conditions. It always shows the plots effectiveness versus mass flow rate. The temperatures for which the predictions are performed do not change for the two different conditions, $T_{air}=300K$, $T_{in,water}=360K$. The velocity of the air in all the first plots (Fig. 3.3-1) is at the lower bound of 12.5 m/s, the velocity in the second plots (Fig. 3.3-2) always is 25m/s, which is in the middle of the range of the velocities. The smoothness parameter was chosen using the wiggle-method. The number of allowable inflections was two for the following examples using 81 equally spaced training samples.

The predictions differ from each other in values and shape. The prediction using the simple model for both conditions yields more consistent predictions than the prediction not using the simple model (Fig. 3.3-1, Fig. 3.3-2). GRNN used by itself turns out not to perform as desired. As expected and shown already in Chapter 3, the trend the simple model gives forces the prediction to follow this trend.

The results for the second plot (Fig. 3.3-2) for which the velocity is centered in the middle of the range of the training samples show better predictions. The prediction of the effectiveness for a very small mass flow rate, which should yield a high effectiveness, is too low for the approach using no simple model. This is the influence of the extreme values at edges, as discussed in Chapter two. For a velocity of 25m/s the predictions are generally better than for the position of a low velocity. The reason for this difference can be referred again to the problem of the prediction towards edges, as discussed in Chapter two. Predictions of extreme values, yield bigger values than expected for minimal values and smaller values for maximal values respectively.

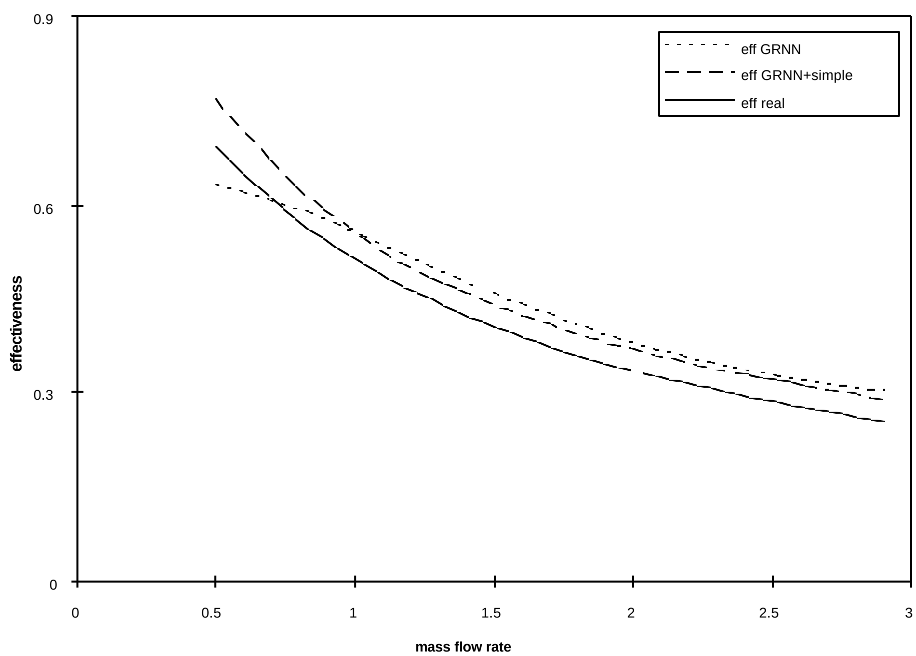

Fig. 3.3-1 Effectiveness versus mass flow rate using 81 samples, equally spaced, plotted for Tin,water=360K, Tair=300K, velocity=12.5m/s

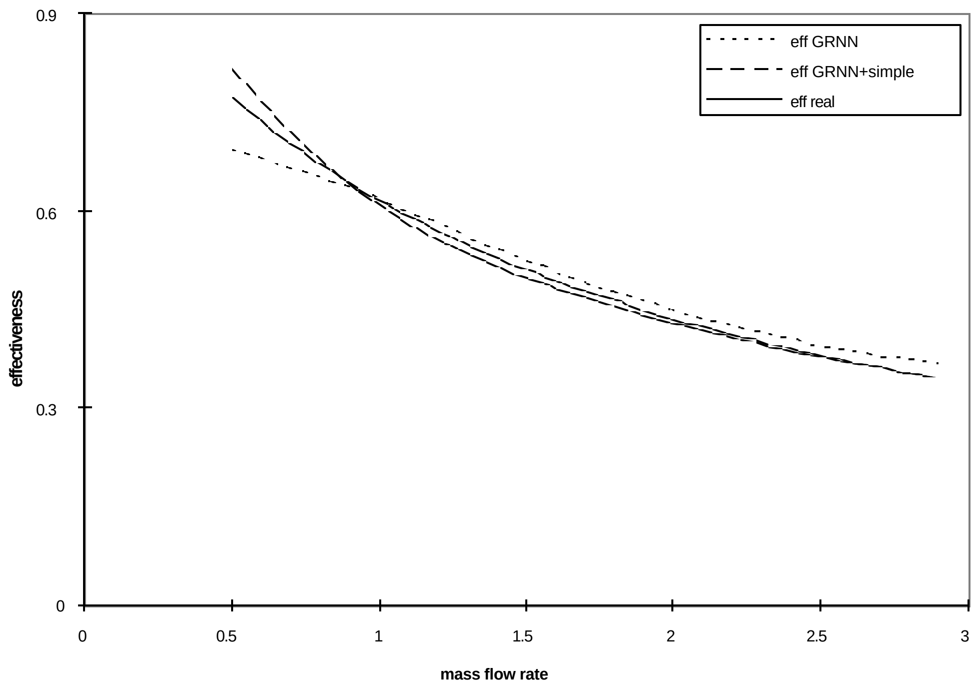

Fig. 3.3-2 Effectiveness versus mass flow rate using 81 samples equally spaced, plotted for $T_{in,water}$=360K, T_{air}=300K, velocity=25m/s

In all the following plots the two different approaches will be compared under different conditions and the results for the same conditions are compared with each other. A prediction should fulfill certain requirements. A prediction should not only be close to the real values but it should as well have the same shape as the shape of the real function.

For the further discussion the precision of a prediction refers **only** to the correctness of the predicted values compared to the function value and not the shape of the prediction.

In the following plots (Fig. 3.3-4, Fig. 3.3-5, Fig. 3.3-6, Fig. 3.3-7) unequally spaced data has been used. Two different sets of data have been used for training. The first one for the prediction shown in (Fig. 3.3-4, Fig. 3.3-5) consisted of 500 unequally spaced samples, the second one for the predication shown in (Fig. 3.3-6, Fig. 3.3-7) consisted of only 150 unequally spaced samples. None of the data included noise. The plots include the correct curve of the effectiveness calculated, using the detailed model, as discussed in Section 3.1.

Unequally spaced data influences the prediction as discussed in Chapter two. In order to yield a smooth curve as needed for several applications the smoothness parameter had to be chosen such that it accommodates for the desired number of inflection points. The smoothness parameter was chosen using the wiggle method. The number of allowable infelctions for the following examples using unequally spaced data was three.

The predictions in (Fig. 3.3-3, Fig. 3.3-4), using 500 unequally spaced training samples, do not include wiggles but the precision of the prediction especially for the method without the simple model is not very high for the shown examples. The slope for extreme values of the effectiveness, at low mass flow rates, declines very much (Fig. 3.3-3, Fig. 3.3-4). The difficulty for the fit is to predict a curve that has only the allowable number of wiggles, this means that the smoothness parameter has to be chosen to be a larger value. A larger value of the smoothness parameter has as well the result that the predicted curve will be a lot flatter, closer to the average value of the training samples as well. The tradeoff between smoothness and precision that was discussed in Chapter two has to be made here too.

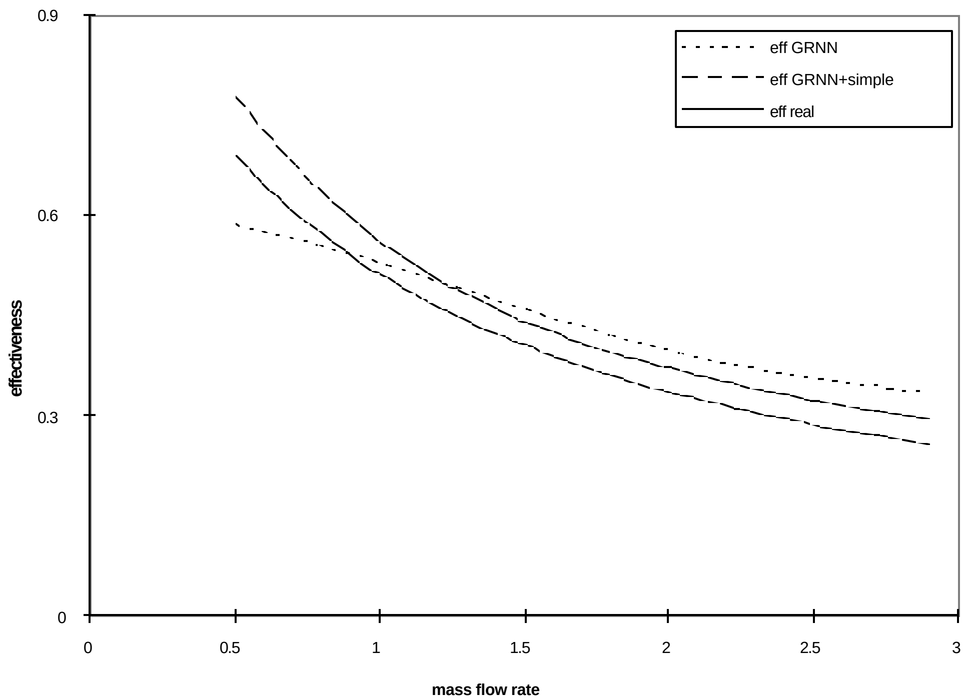

Fig. 3.3-3 Effectiveness versus mass flow rate using 500 samples unequally spaced, plotted for $T_{in,water}$=360K, T_{air}=300K, velocity=12.5m/s

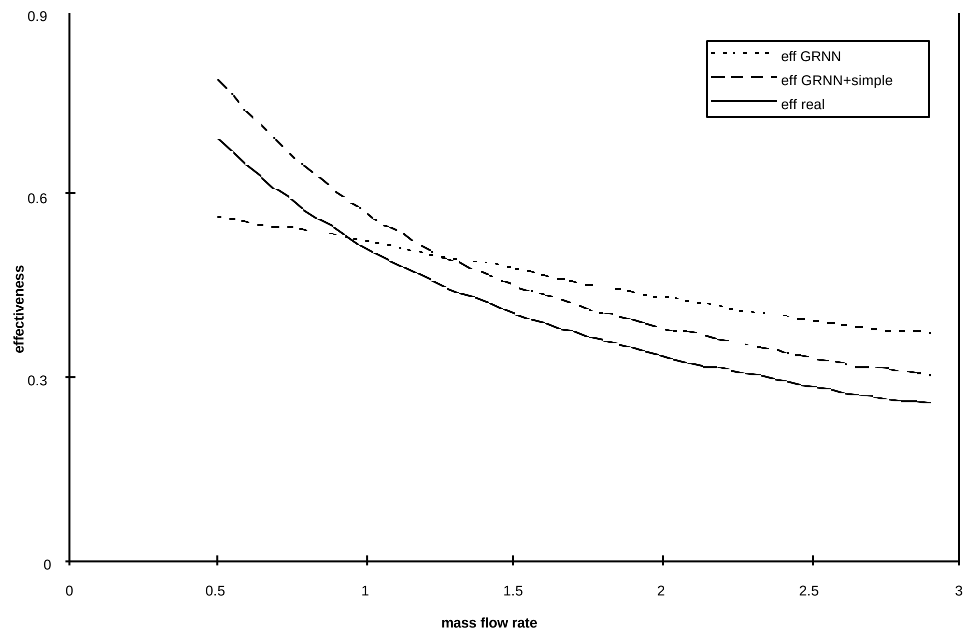

Fig. 3.3-4 Effectiveness versus mass flow rate using 500 samples unequally spaced, plotted for $T_{in,water=}$360K, T_{air}=300K, velocity=25m/s

The following two examples (Fig. 3.3-5, Fig. 3.3-6) used only 150 training samples that were unequally spaced. The correct curve for the effectiveness under these conditions is shown again as a solid line. The first example seems to fit better than the second even though the prediction for the first example was performed for an extreme value of the velocity and the second for a velocity that is right in the middle of the range. The influence of the unequally spaced data is such that it dominates the influence of the prediction under extreme conditions. In this case the unequally spaced data has a positive influence but in (Fig. 3.3-6) the positive influence does not hold for each position of prediction. The prediction for a more central position is worse than for an extreme position.

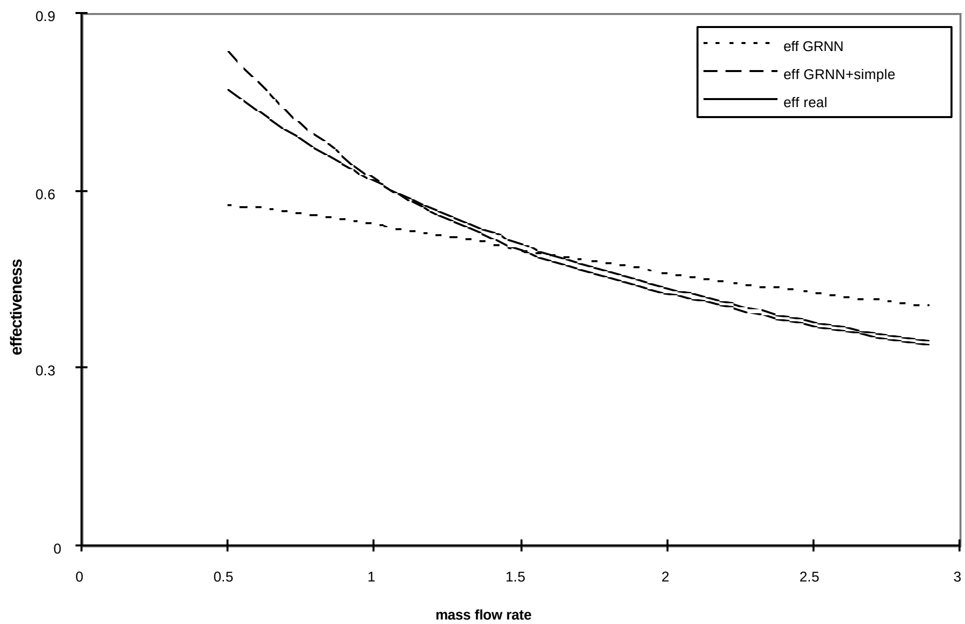

Fig. 3.3-5 Effectiveness versus mass flow rate using 150 samples unequally spaced, plotted for $T_{in,water}$=360K, T_{air}=300K, velocity=12.5m/s

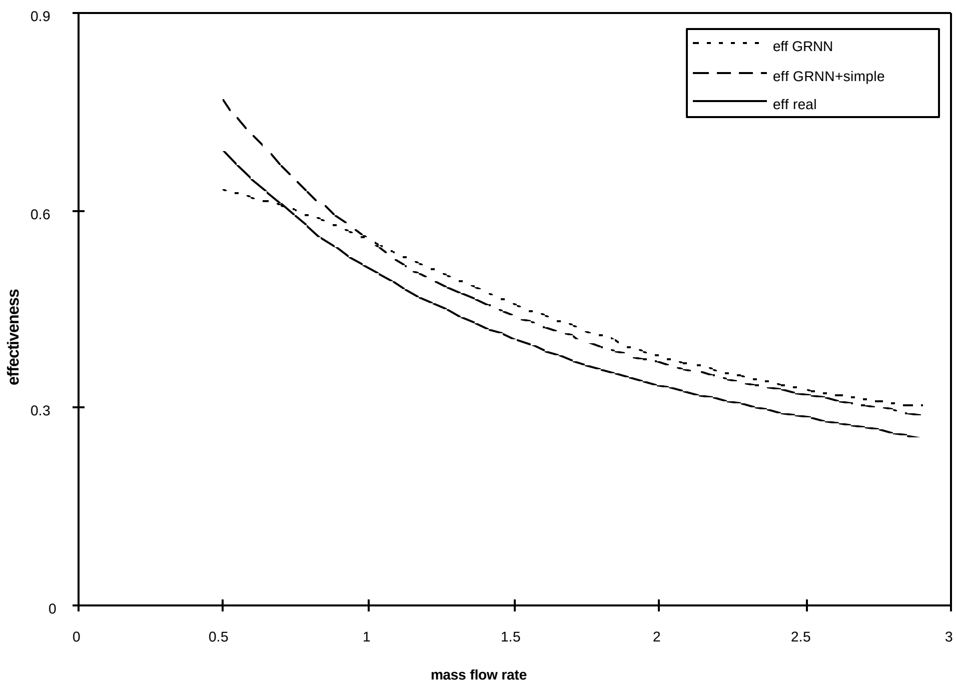

Fig. 3.3-6 Effectiveness versus mass flow rate using 150 samples unequally spaced, plotted for $T_{in,water}$=360K, T_{air}=300K, velocity=25m/s

It can be stated already from these few examples that using the approach including a simple model yields better results than performing a prediction ignoring this knowledge. In the plots above it is possible to compare the shape of the curves. The prediction using the simple model yields curves for which the shapes of the curve is close to the shape of the curve of real effectiveness. The precision can be compared as well in previous figures but only for certain values of variables.

A better way to compare precision is to plot the predicted effectiveness against the real effectiveness for many different conditions. 999 predictions for random values of variables were performed and compared to the true values for these input vectors. The true values were obtained by calculating them again with the detailed model. This is a procedure that is fortunately possible since we are operating in an artificial environment. Usually the only data available is the data that was already used for training.

The effectiveness calculated with the simple model was plotted (Fig. 3.3-7) versus the real effectiveness. The results are widely spread but they show a good trend to start off with.

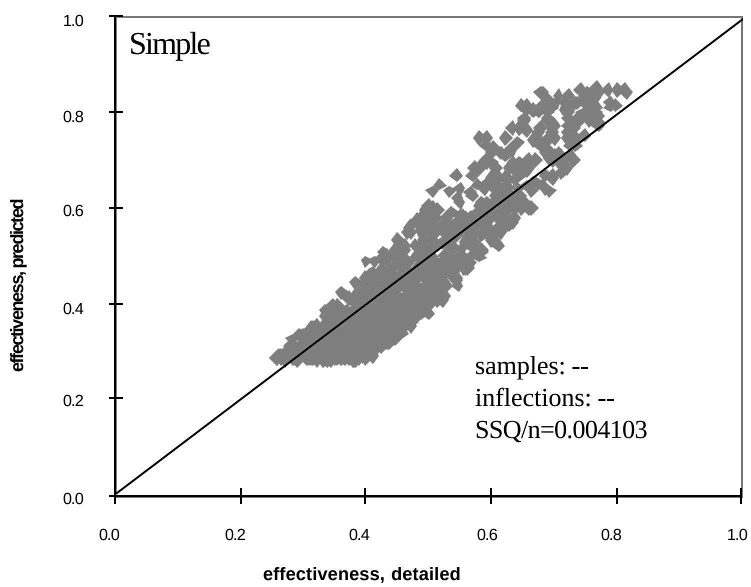

Fig. 3.3-7 Predicted effectiveness using the simple modelversus effectiveness from detailed model for 999 randomly picked points

In (Fig. 3.3-8) 81 equally spaced training samples have been used for the training of GRNN for the approach without a simple model. The predicted effectiveness was plotted against the real effectiveness. The prediction of extreme values is worse than for the middle area of the effectiveness. This result is the result of the influence of edges as it was discussed in Chapter two.

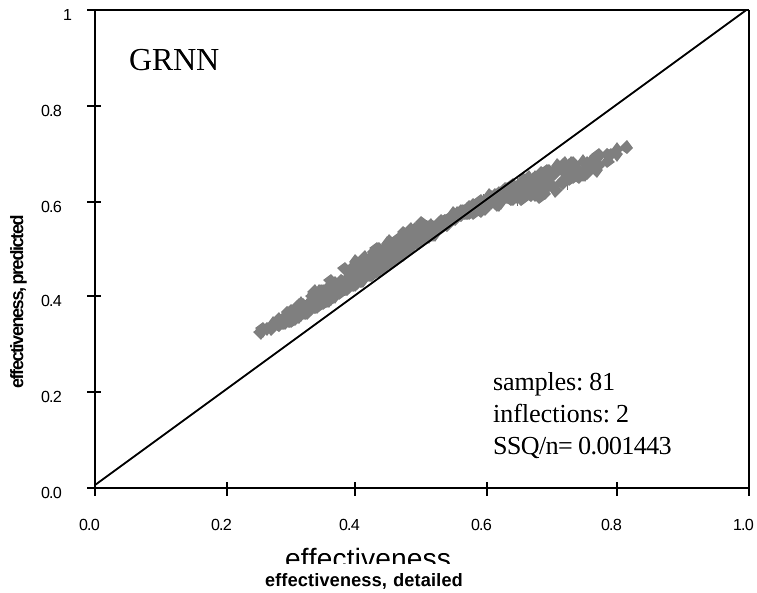

Fig. 3.3-8 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 81 equally spaced training samples, using the approach using no additional knowledge

In the following plot (Fig. 3.3-9) the simple model was used as an underlying function and the difference to the real effectiveness was corrected. The precision is better than for the approach not using the simple model and better than the use of the simple model alone as well. The trend of the prediction is good. The predictions at the edges are a little off. Comparing (Fig. 3.3-1) with (Fig. 3.3-9) the effectiveness at high effectiveness was too big for the simple model alone and the correction from the prediction was not big enough for the combined approach.

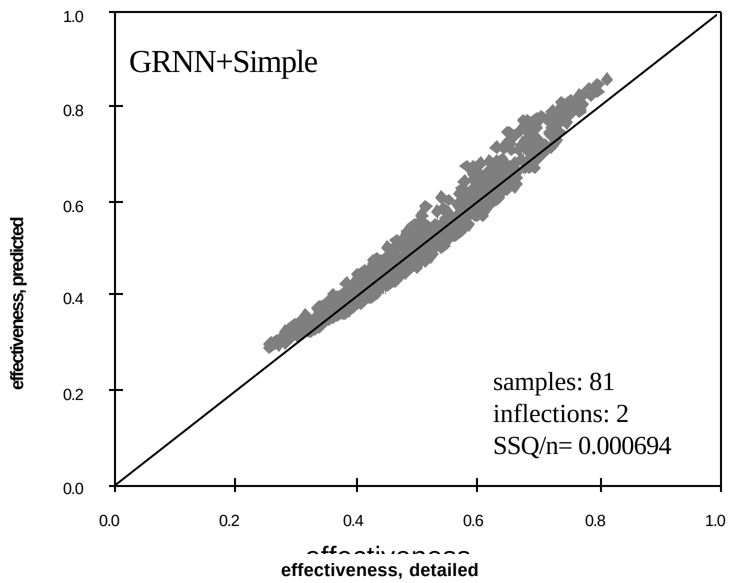

Fig. 3.3-9 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 81 equally spaced training samples, using the approach to correct simple model

For the prediction of the effectiveness in (Fig. 3.3-10) and (Fig. 3.3-11) 500 unequally spaced training samples were used. The predictions show the same characteristics for small and big values of the effectiveness as the prediction for 81 equally spaced training samples. The characteristics for 81 equally spaced training samples are about just as distinct as for the use of 500 unequally spaced training samples. The results using 500 unequally spaced training samples makes the results for 81 training samples in (Fig. 3.3-8) even more surprising.

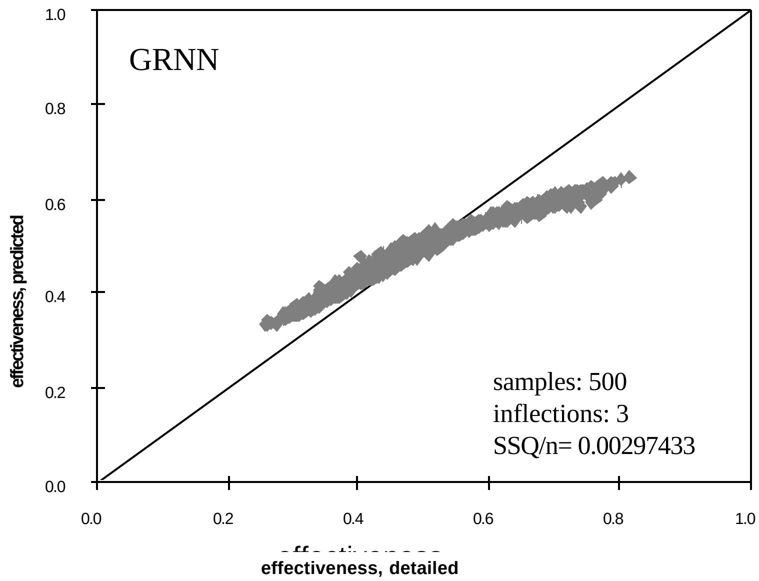

Fig. 3.3-10 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 500 unequally spaced training samples, using the approach using no additional knowledge

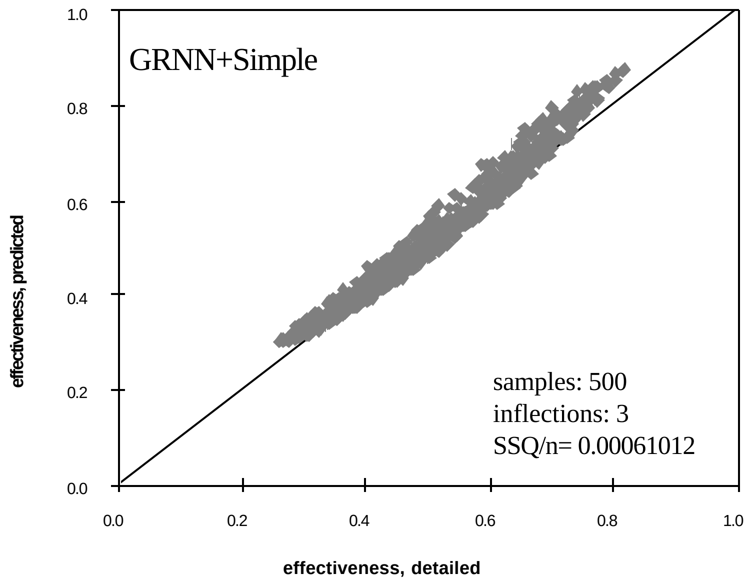

Fig. 3.3-11 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 500 unequally spaced training samples, using the approach to correct simple model

For the following two examples 150 unequally spaced training samples have been used (Fig. 3.3-12, Fig. 3.3-13). The previously discussed characteristics for 81 equally spaced training samples or 500 unequally spaced training samples are more distinct for the examples using 150 unequally spaced training samples. The use of twice as many unequally spaced training samples as equally spaced training samples shows a large effect on the prediction. If still the same smoothness for unequally spaced training samples shall be achieved then the precision of the prediction will significantly decline, especially for the approach using no underlying function. With the underlying function the influence of the unequally spaced training samples is not as big.

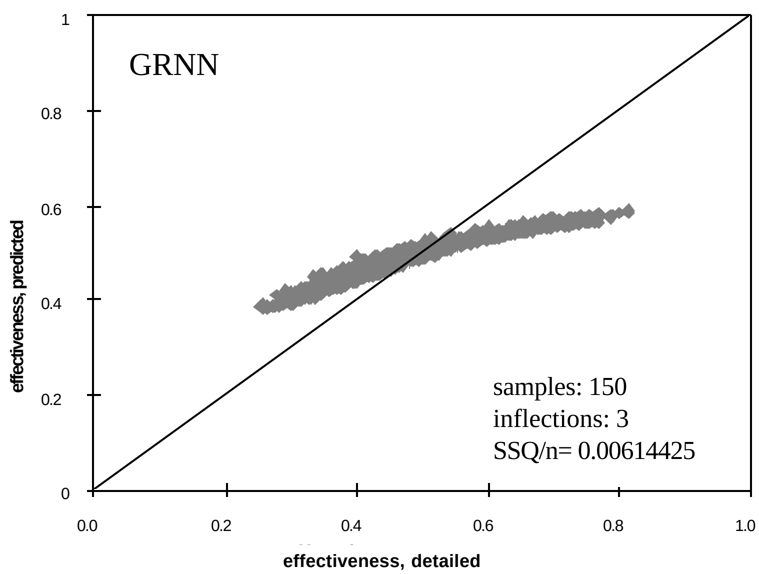

Fig. 3.3-12 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 150 unequally spaced training samples, using the approach using no additional knowledge

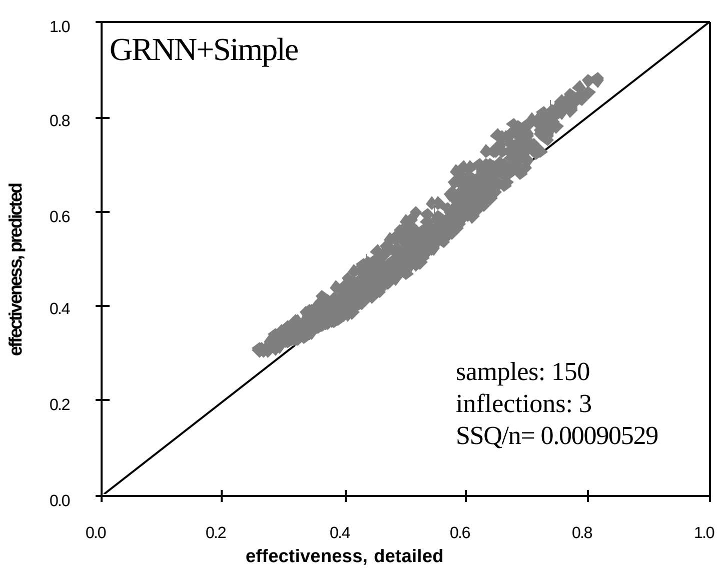

Fig. 3.3-13 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 150 unequally spaced training samples, using the approach to correct simple model

In Chapter two it was shown how the precision increases at the values of the training samples for smaller smoothness parameters. This was possible on the cost of smoothness. On the technical system the effect of the allowable number of inflection points on the precision and smoothness of the prediction was tested. It is known that for an increased number of inflection points in the wiggle-method, the wiggle-method will select a smaller smoothness parameter. A smaller smoothenss parameter will yield more precise values of the training samples but the prediction will also include more wiggles. The plots shown in (Fig. 3.3-14) and (Fig. 3.3-15) represent again 999 randomly picked points for which the prediction was performed. The predicted effectiveness was plotted again versus the calculated effectiveness with the detailed model. For the calculated effectiveness the same detailed model was used, that was used to calculate the training samples.

The results in (Fig. 3.3-14) are very scattered. The results for allowing more inflections are worse than the results in (Fig. 3.3-8). At least for equally spaced data the right number of allowable inflections in the wiggle method is very important.

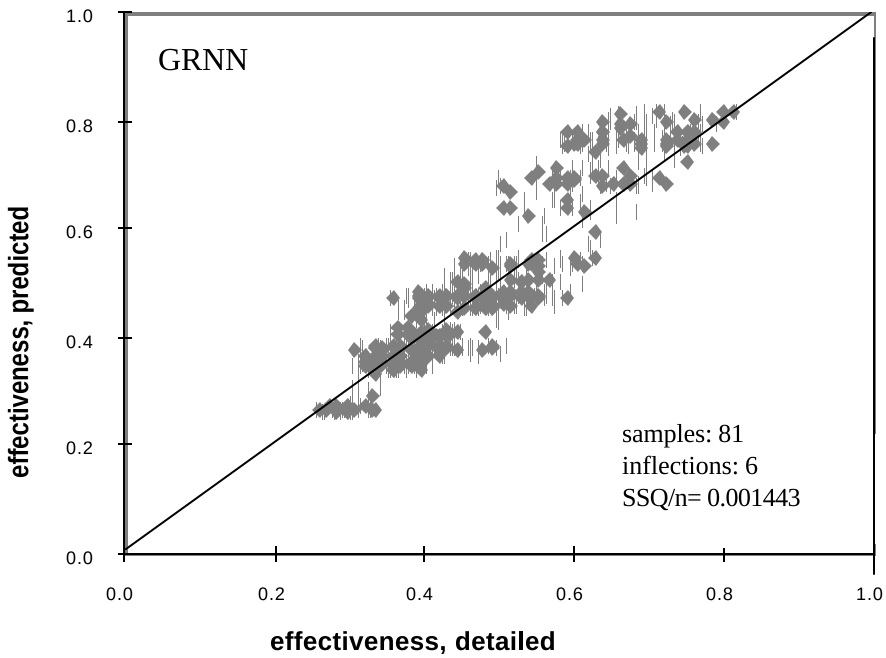

Fig. 3.3-14 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 81 equally spaced training samples, using the approach using no additional knowledge, allowing 6 wiggles in the wiggle method

In (Fig. 3.3-15) the simple model was used as an underlying function. Again 999 points were predicted and compared to the calculated values of the effectiveness. The results of this approach are better than the previous result of not using the simple model. The distribution is a lot narrower and more evenly distributed than for the use of no simple model. Compared to the prediction in (Fig. 3.3-9), the prediction in (Fig. 3.3-15) is just a little worse. The simple model by itself is not bad and the correction of the small mistake does have a good impact on the prediction. The scatter of the prediction of the correction does not appear in these plots, since the correction is on a smaller scale than the effectiveness itself. The use of the underlying function has a good influence as well on the use of a very high number of inflections in the wiggle method. The use of the simple model disguises again the possible problems GRNN can have.

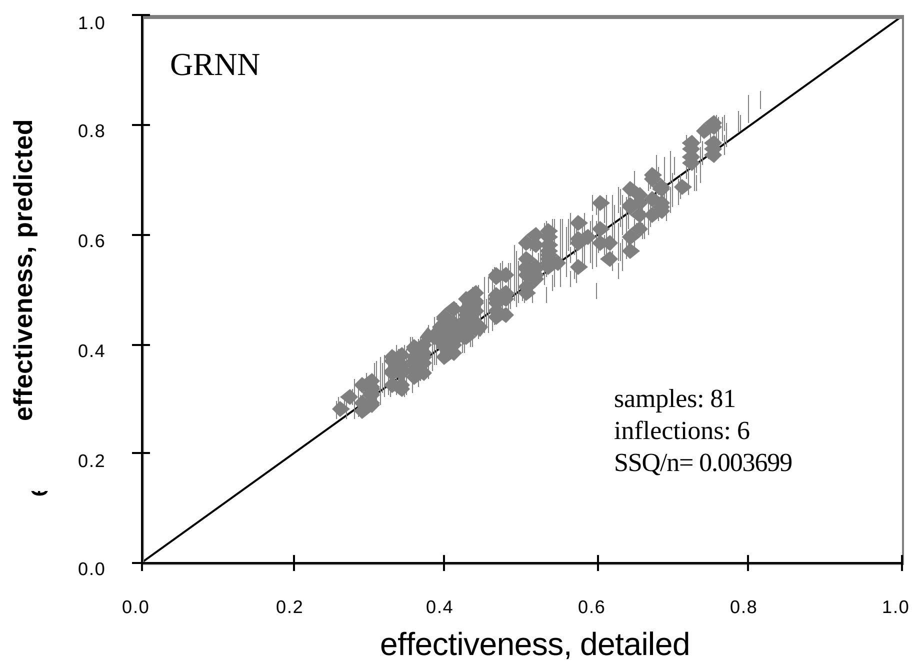

Fig. 3.3-15 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 81 equally spaced training samples, using the approach using the approach to correct the simples model, allowing 6 wiggles in the wiggle method

More inflection points mean a smaller smoothness parameter and a small smoothness parameter means as well that the predicted curve includes wiggles. The following plots (Fig. 3.3-16) and (Fig. 3.3-17) show the curves of the predicted effectiveness for the same smoothness parameter that was used for the plots of predicted effectiveness versus the calculated effectiveness (Fig. 3.3-14, Fig. 3.3-15). The curves are shown again for two different velocities of the air; *12.5m/s* and *25m/s*. The temperatures for both predictions were *360K* of the water and *300K* of the air The predicted effectiveness in both examples for the use of no simple model includes severe sudden changes in the value of the effectiveness. The predicted effectiveness jumps back and forth from overestimation to underestimation of the real effectiveness. The shape of the curve is therefore not useful for many applications. The prediction for using a simple model is a lot better than the prediction for not using the simple model. There are still sudden changes in the prediction but the magnitude of the changes is a lot smaller than the magnitude of the changes for not using the simple model. The sudden changes of the prediction happen on a smaller scale than the changes of the prediction without the simple model.

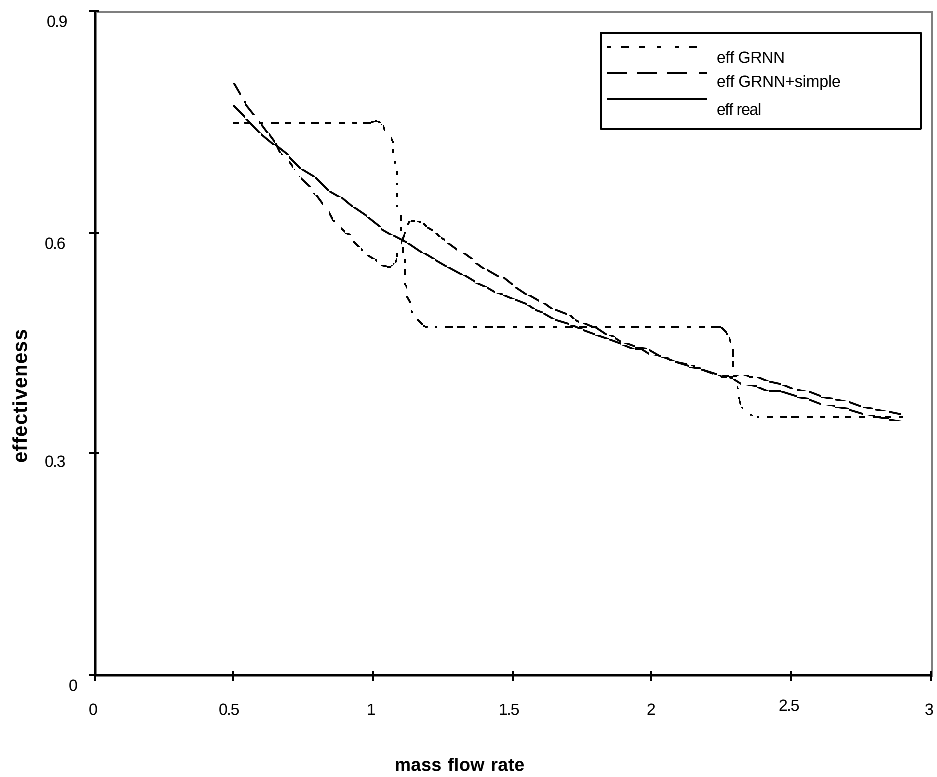

Fig. 3.3-16 Effectiveness versus mass flow rate using 81 samples equally spaced, plotted for $T_{in,water}$=360K, T_{air}=300K, velocity=12.5m/s, allowing 6 inflection points in the wiggle method.

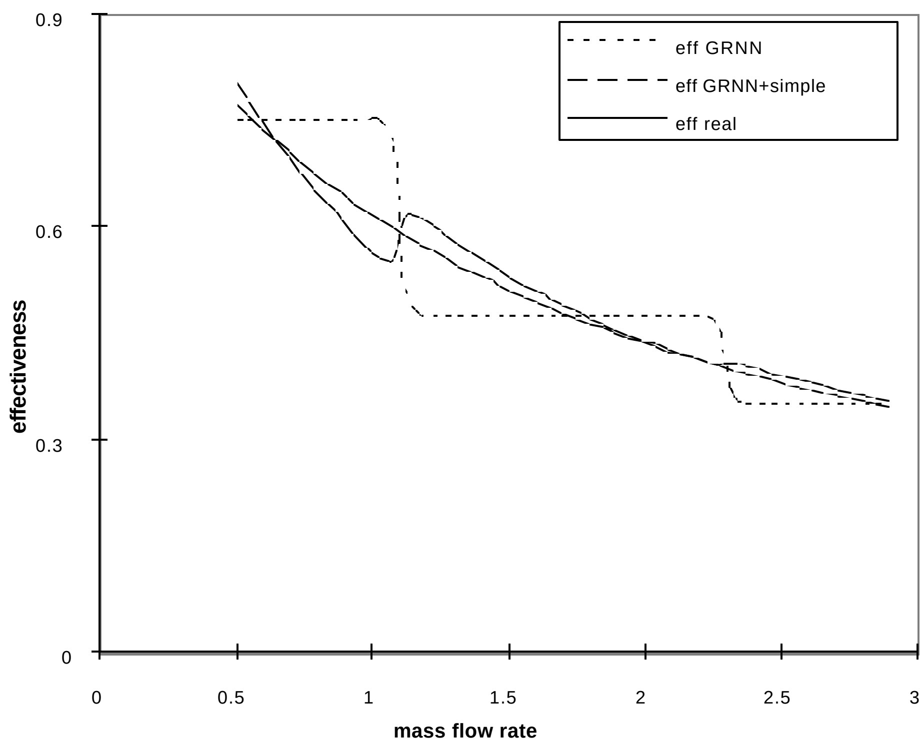

Fig. 3.3-17 Effectiveness versus mass flow rate using 81 samples equally spaced, plotted for $T_{in,water=}$360K, T_{air}=300K, velocity=25m/s, allowing 6 inflection points in the wiggle method

Allowing more inflection points in the wiggle method for unequally spaced data can have a better impact on the prediction than it had for equally spaced data. In Chapter two it was shown how the prediction changes for unequally spaced data and that unequally spaced data by it's own nature introduces more inflection points into the prediction. The different densities of training samples caused inflections in the prediction. An example for 150 unequally spaced training samples with eight instead of three inflections in the wiggle method is shown in (Fig. 3.3-18). Only the approach of the direct prediction was tested. The results for the use of the simple model in the prediction will be not as distinct as they are here. The results of the effectiveness are a lot more scattered for allowing more inflections in the wiggle method. The general trend though is better. Again the tradeoff between smoothness and precision has to be made. The precision of the prediction for the use of unequally spaced training samples and allowing more inflection points yields about just as good results as in (Fig. 3.3-14) for using equally spaced training samples and allowing more inflections.

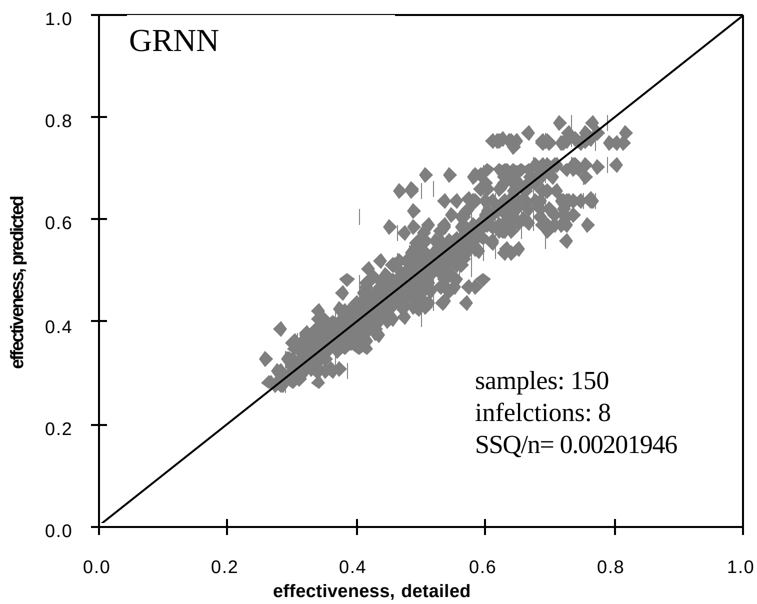

Fig. 3.3-18 Predicted effectiveness versus effectiveness from detailed model for 999 randomly picked points for 150 unequally spaced training samples, allowing more inflections, using the approach using no additional knowledge

Unequally spaced training samples have the characteristic that the influence of the unequally spaced data on the shape of the curve cannot be extrapolated from looking at one position of the prediction. The prediction at this position can be a lot different than the prediction at another position.

The same conditions that were used in the examples at the beginning of the section were used for the following prediction. The precision and the shape of the prediction (Fig. 3.3-19, Fig. 3.3-20) is very good for these conditions. In some other range the shape will look very different and not as good as here. There is some position in this prediction for which the curve has three times as many inflections as the plots at the beginning of the section. The plot of the predicted effectiveness versus the calculated effectiveness indicates by its scatteredness that the prediction includes certain inaccuracy under certain conditions. These conditions were obviously not the conditions that were used for the prediction in (Fig. 3.3-19) and (Fig. 3.3-20)

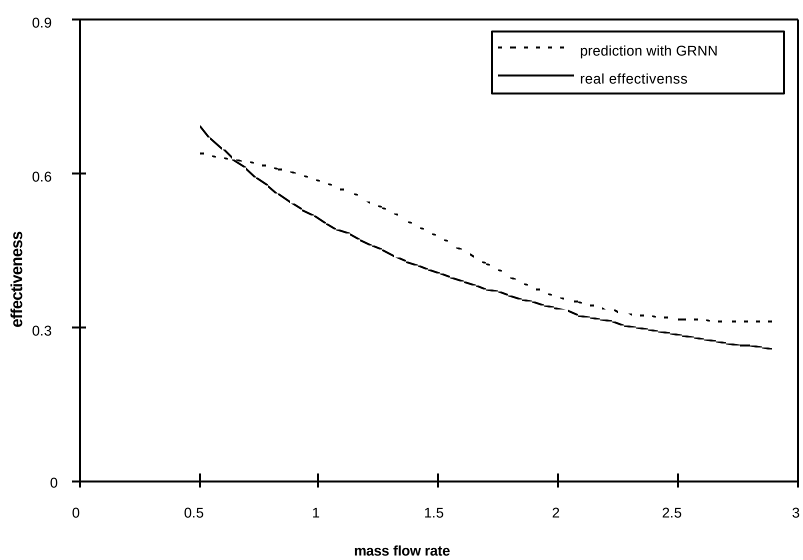

Fig. 3.3-19 Effectiveness versus mass flow rate using 150 samples unequally spaced, allowing more wiggles, plotted for $T_{i,water}$ =360K, T_{air}=300K, velocity=12.5m/s

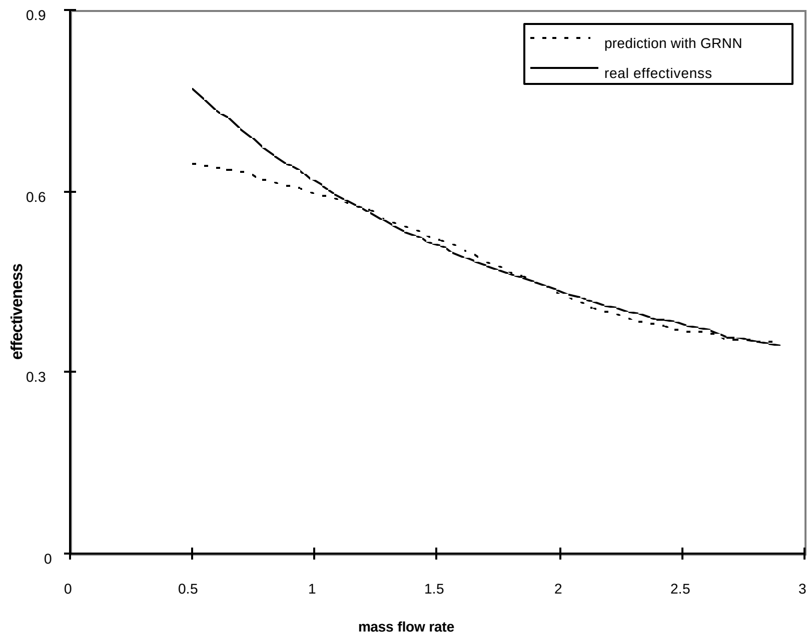

Fig. 3.3-20 Effectiveness versus mass flow rate using 150 samples unequally spaced, allowing more wiggles plotted for $T_{in,water}$ =360K, T_{air}=300K, velocity=25m/s