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Modelling flow detention through temporary storage in the landscape using Artificial Neural Networks

- A case study of Lake Mälaren

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Preface

This diploma work is the final part of my studies at the masters programme; Environmental Engineering, at Lund University. It was made at the division for Water Recourses Engineering at Lund University, Faculty of Engineering but Klas Cederwall at the Royal Institute of Technology has also been involved and has provided me many of the ideas behind this diploma work.

I would like to give my acknowledgments to the following people whose assistance is highly appreciated. First of all I would like to thank my supervisor Cintia Bertacchi Uvo for her support and guidance throughout the work, especially regarding artificial neural network modelling. I would also like to thank Klas Cederwall, mentioned above, for the valuable comments and ideas he has given me. Last but not the least I would like to thank SMHI for having provided me with all the data used in this diploma work.

Abstract

Several strategies can be used to mitigate flood risks, many of them involves construction of embankments around threatened locations or attempts to spread the flood wave in time and space. In this thesis, the effects of a mitigation strategy called eco-flooding are studied in the catchment of Lake Mälaren. The methodology involves a hypothetical storage in the terrain used as an off-line detention basin for the peak flow. Artificial Neural Networks (ANN) is used as a modelling tool and the potential of using it for flow detention modelling is discussed. Two models were constructed, one describing the entire catchment of Lake Mälaren and one describing the sub-basin of Kolbäcksån. Results show that very large surfaces would have to be submerged in order to achieve a significant flow reduction, even in the relatively small sub catchment of Kolbäcksån. Finding the optimal combination of timing, duration and size of the diversion is also important for the mitigation success. The modelling technique showed to have some drawbacks, for example difficulties with introducing a reservoir into the ANN-model.

Keywords: Flow detention modelling, Flood mitigation, Eco-flooding, Artificial Neural Networks, Lake Mälaren

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1 Introduction

1.1 Floods

Riverine floods are natural phenomena occurring when the capacity of a streambed is too small to handle a high flow. They are caused by an extensive rainfall, a large snowmelt, or a combination of these two factors. The excess water will cause the stream to overtop its banks and extend onto the floodplain (Cuny, 1991).

Because of urbanisation and industrialization, many floodplains are today highly developed. The rise of a river or a Lake above the banks is therefore often associated with large economical costs, and in severe cases also loss of human lives. Several strategies for flood control have been developed to mitigate the flood hazard. One of the most common methods is construction of levees along the rivers or around threatened settlements. Other methods include various ways of enlarging the discharge capacity, either by building relief channels or making channel improvements such as straightening, widening, deepening or removal of obstacles. Although these methods can provide a good local flood protection a large disadvantage is that the increased flow capacity risk aggravates the flood situation downstream of the improved section. Another common strategy is to use storages as detention basins to balance the flow by holding back some of the peak flow and then slowly release the water when the flood wave has passed. The storages can be designed exclusively for flood control, or be multi purpose reservoirs. (Ward, 1978)

Beside the traditional detention methods, a method called eco-flooding has been proposed as a method for flood control. It is based on the principle of flow detention but uses temporary storage on lands that are normally not covered by water. Suitable terrain types are the ones that will not be damaged by being submerged for a short time period, for example wetlands and forests (Cederwall, 2006).

This study investigates the feasibility of using eco-flooding for flood control in the catchment of Lake Mälaren, which is located in eastern Sweden. The size of Lake is 1120 km^2 and its watershed is 22600 km^2 divided into 12 smaller sub basins (see figure 1). The catchment contains several locations that are sensitive to floods. To reduce the flood risk it has been proposed to increase the release capacity from Lake Mälaren (SOU, 2006). Increasing the outflow will however not affect the upstream flood risks, but a diversion and temporary storage of floodwater as was described in the previous paragraph can be a solution for these parts.

1.2 Objectives of the study.

The objectives of this diploma work can be separated into two main distinct phases:

1) The first step is to use artificial neural networks (ANN) to develop a model for describing the hydrology of the basin of Lake Mälaren. The model should not only be able to predict flow with acceptable results, but it should also be possible to introduce hypothetical flow diversion so that eco-flooding scenarios can be simulated.

2) The second step is to use the developed model to perform a consequence analysis in order to evaluate the potential for reducing flood risks by flow detention in an eco-flooding setting, i.e. divert and temporary store water during high flow events. The effects will be studied both on the total system and locally in specially selected sub basins.

Determining exact locations and sizes of the detention basins are considered to be out of the boundaries of this diploma work, instead will the study be made on a theoretical level with focus on the methodology. That is; investigate if artificial neural networks are a good tool for flow detention modelling in a watershed that is built up by several parallel sub basins (like the catchment of Mälaren). It involves the training and learning procedure of the ANN and determining the best combination of inputs for the specific case. Creating the eco-flooding scenarios involves finding a method for diverting storing and returning the water, as well as finding the optimal timing for starting and ending the diversion.

2 Restrictions

The purpose of this diploma work is to use an ANN to create a model for predicting flow in the catchment of Lake Mälaren and use this model to evaluate the effects from temporary storage of peak flow. The methodology used has some limitations that are listed below;

- Almost all major streams within the basin are regulated and no information about this is given as input. An artificial neural network can nevertheless learn the statistical connections between the regulated flows to some extent, but not completely.

- The amount of available data is a major restriction in this work. The length of the available time series are generally sufficient, but the amount of gauges are limited in the study area, and the location of them is not always optimal for the purposes of this study. This is a major problem when predicting flow in smaller sub basins in the catchment of Lake Mälaren.

- Due to the structure of a feedforward ANN, all attempts to change catchment physics in the model has to be made through modifications of the input matrix. Thus, the only locations where flow reductions can be simulated are the sites where measurements were made.

3 Site description

3.1 Geography

The case study of this thesis is the basin of Lake Mälaren, which is located in eastern Sweden. The basin is 22600 km^2 and has a more or less rectangular shape. Distance from east to west are 200 km and from north to south 150 km. Average precipitation is 600-700 mm/year, evaporation about 400 mm/year and the runoff is between < 200 to 250 mm/year (SMHI, 1990). The catchment area and the 12 sub-basins are shown in figure 1.

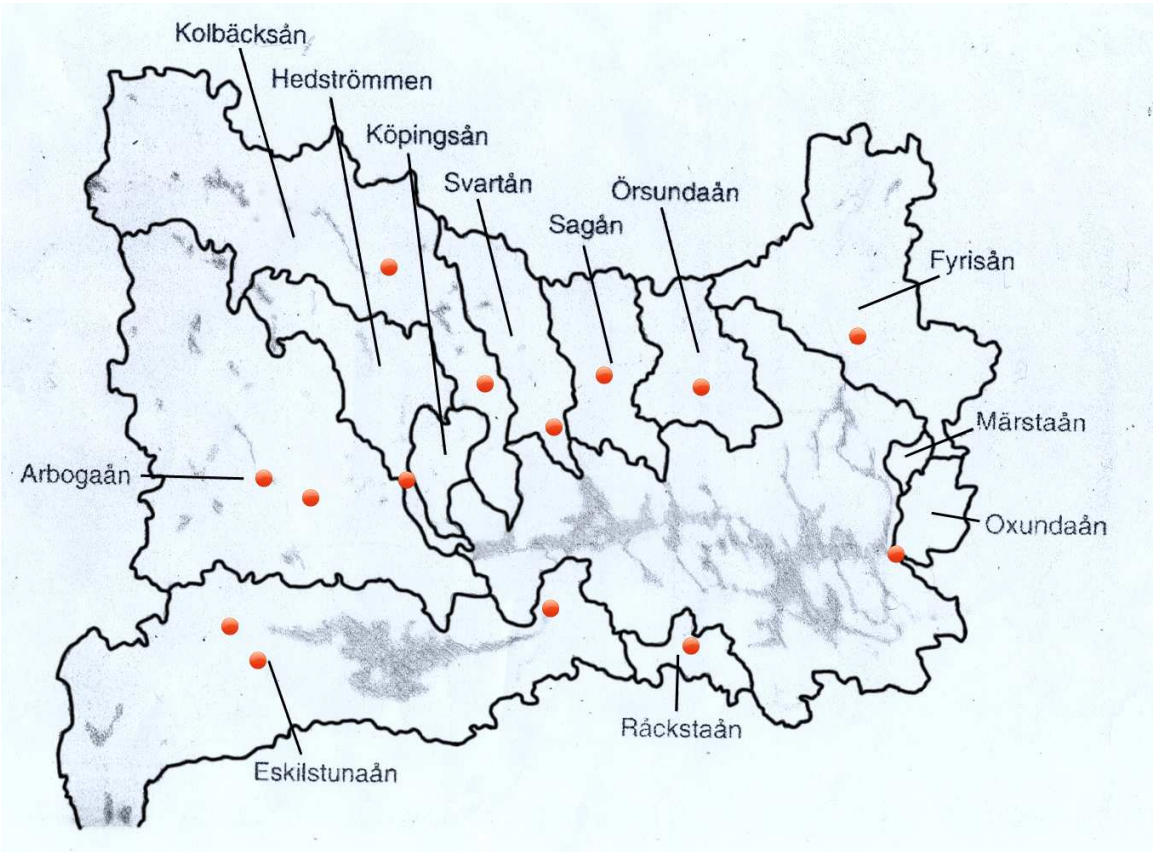

Figure 1. Drainage basin of Lake Mälaren and the 12 sub basins. Stations for flow-measurements are shown by red markers.

The watershed contains two major Lakes. The largest one is Lake Mälaren which has an area of 1120 km^2. The other is Lake Hjälmaren. Its surface area is 480 km^2 and it is located entirely within the sub-basin of Eskilstunaån. However it will not be studied in detail in this work, but is considered as a part of Eskilstunaån sub-basin. The bulk of the inflow to Mälaren discharges into to the western side of the Lake through the 5 large streams Arbogaån, Hedströmmen, Kolbäcksån, Eskilstunaån and Svartån. Other important recharges are Sagån Örsundaån and Fyrisån to the north and east. The main outflow from the Lake is to the Baltic sea through Norrström in the east end of the catchment. There are also a few other outlets, for examples the sluices in Hammarby and

Södertälje, but the flow released through these is very small compared to the total outflow.

3.2 Spatial variations

There are some geographical and climatological differences within the studied area. The North-western part of the basin has a more hilly terrain than the rest of the area whose terrain is relatively flat. This part of the catchment also has slightly longer and colder winters compared to the southern part of the catchment. As a result, streams in this part should have a different hydrology with lower flows during the winter, and a later and more distinct spring peak compared to streams in the southern and eastern parts. Most of these differences are however cancelled by the effects of hydropower regulation. To illustrate this, the hydrographs from the regulated Kolbäcksån in the north-western part and the unregulated Fyrisån in the eastern part is compared in figure 2a. For comparison the outflow at Norrström is also shown (fig. 2b). One difference that remains, despite the regulation, is that the spring peak occurs later in the north-eastern part than in other parts of the basin (fig. 2a).

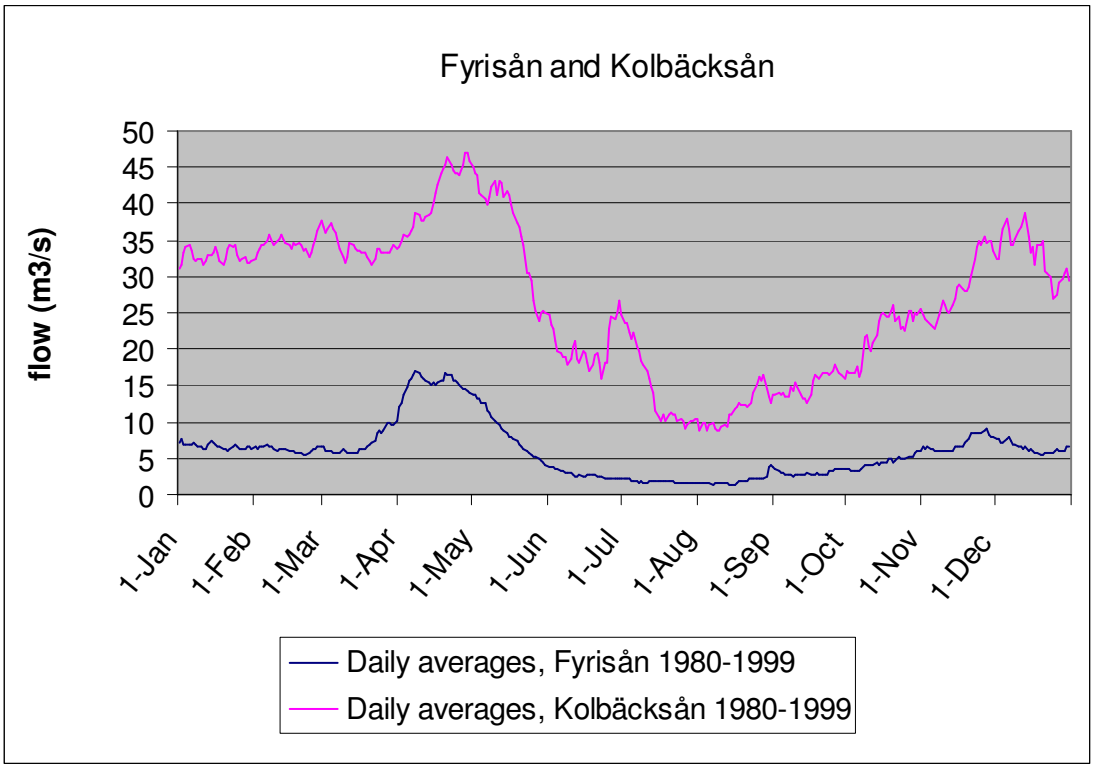

Figure 2a. Seasonal flow variations in Fyrisån and Kolbäcksån, the figure shows daily flow averages from the period 1980 to 1999.

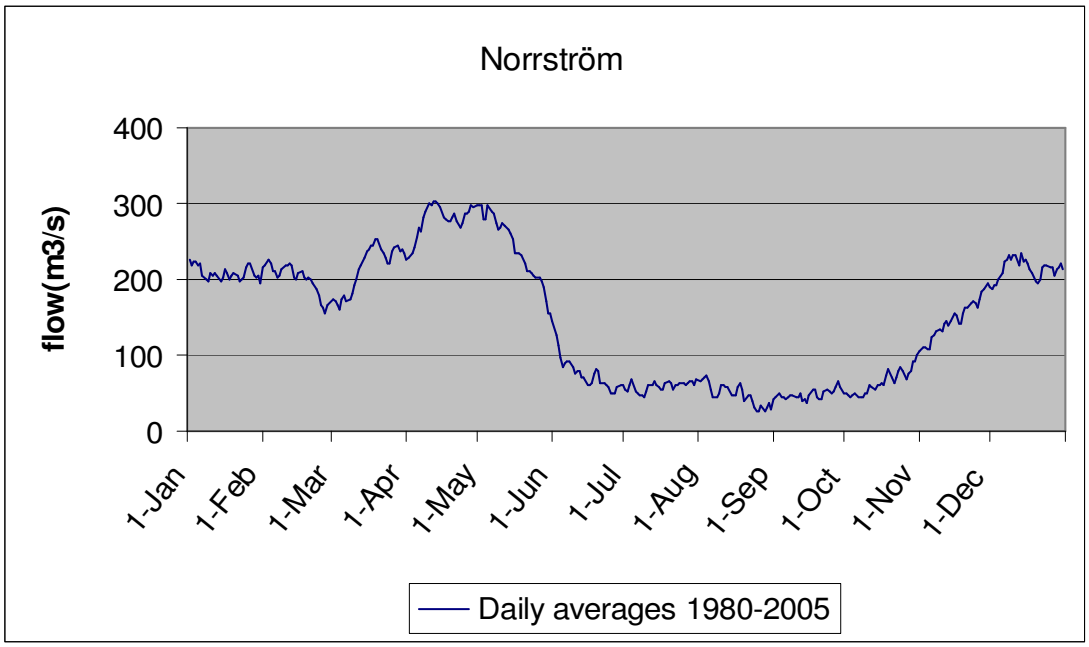

Figure 2b. Seasonal flow variations in the outflow from Mälaren, the figure shows daily flow averages from the period 1980 to 2005.

3.3 Flood situation in Mälaren

Historically the water levels in Lake Mälaren have fluctuated relatively much, but regulations made in the mid 19-hundreds have reduced the magnitude of the variations. The most important effects from the regulation were the raise of lowest levels and reduction of highest levels (SOU, 2006). Despite the improvements, the water level still risk to reach levels that causes problems along the shores of the lake. Even at the predicted 100-year level, considerable structural damages are expected and also interruptions of important infrastructure in Stockholm, e.g. power and water supply and train traffic (SOU, 2006). Climate changes may also increase the problems with high water levels in the future. An official report has therefore been made to evaluate potential approaches to reduce the risks. The suggested solution is to increase the release capacity of Lake Mälaren from the current 805m^3/s to 1500-1800 m^3/s. (SOU, 2006).

Significant flood risks are also present upstream in the catchments of some of the recharging streams. Locations that are sensitive to high flows are for example Örebro (in the sub-basin of Eskilstunaån) and Arboga (in the sub-basin of Arbogaån). The later also contain a number of buildings of high cultural historical values that should be protected (Cederwall, 2006).

3.4 Flow regulations

A majority of the inflow to Mälaren as well as the outflow from the lake is regulated. Most of the lakes and streams in the basin are regulated for hydropower production purposes (Mälarens vattenvårdsförbund, 2007). The effects are visible in figure 2 where the magnitude in the regulated stream is much smaller than in the unregulated stream. The mean water table of Lake Mälaren is just 66 cm above the sea level (SOU, 2006), hence is the lake not suitable for hydropower production. The purpose for regulating Mälaren was instead to reduce the flood risk and provide better conditions for shipping by raising the lowest water levels (SOU, 2006). A further benefit from the raise of the low water-levels is that the cases with saltwater intrusion to Mälaren have been reduced. Since the initial regulation of Lake Mälaren in 1943 the regulation schemes has been updated several times in order to mitigate the problems with high and low water levels more effectively.

4 Eco-flooding

Eco-flooding is an off line flood mitigation strategy that has been proposed to be used as a complement to more traditional flood control methods, in the catchment of Lake Mälaren, by Klas Cederwall at the Royal institute of technology, Sweden.

The principle behind the eco-flooding concept is to retain a part of the flood wave during critical flow situations by diverting it into temporary storage in the landscape (Cederwall and Svensson, 2005). Suitable locations for these storages are terrains that are not damaged if submerged for a limited time period, for example wetlands and forests. Farmland may be used, although it should be considered less suitable due to potential crop damages.

Characteristics of the eco-flooding storages are that they are shallow and flat and therefore require a large surface area. Depending on the situation, certain structural improvements of the natural storage would be necessary, like the construction of embankments to confine the water. A realistic water depth in these types of storages would be up to about 1 metre (Cederwall, 2006), but water depth may be even higher if larger storage is required. A problem that follows from higher water depths is that more extensive investments would be needed, e.g. expensive embankments, but also safety precautions such as fencing the storage area may be necessary (Cederwall, 2006).

A requirement for this type of regulation is that a large suitable area to be flooded is available. Therefore is eco-flooding not a suitable solution for developed areas. Adequate inflow and outflow capacity from the storage is also required. A proper flood mitigation scheme is also necessary in order to achieve the optimal beneficial effects from the diversion. Sanders et al., (2006) showed in a study that active control of an off-line reservoir gave a 2-4% flow decrease at a specific runoff event, whereas a passive control at the same situation lowered the maximum peak flow by less than 1%.

4.1 Use of the eco-flooding strategy in other catchments

The idea of reducing floods by allowing water to inundate certain areas outside the streambed is not new and the strategy has been given many different names by various authors. The methodology has received criticism in the past for not having worked efficiently (Silva et al., 2001). According to the same authors the bad performance was mainly caused by poor management when filling up the storage, using passive control only.

The interest for the methodology has increased lately because of new flood risks due to global warming and an increased awareness of the ecological values in rivers and wetlands. In the Netherlands actions that resemble eco-flooding has been decided to be incorporated into the general flood mitigation strategy at several places. Emergency retention areas have for example been proposed in the lower areas of the Rhine river

basin (Jonkman et al., 2004) and (Silva et al., 2001). Another project is the Green river where excess water is thought to inundate a corridor alongside the normal channel. The main purpose of the inundation is to retain water, but it will also help by increasing the discharge capacity at a bottleneck point in the river delta (van der Werff, 2004).

A similar approach with a temporary storage of floodwater has also been used with success by the Miami conservancy district in Ohio (Miami conservancy district, 2007). The main difference with their solution is that it is a completely passive control method and it widely relies on constructed dams that are designed for much deeper storage depth. But the basic principle and philosophy is the same; that is: the storage is only designed for use during limited time periods with high flow and can be used for other activities during the rest of the time. The system has been very successful and has prevented flooding several times since the completion in 1922 (Miami conservancy district, 2007).

5 Methods

In this thesis an artificial neural network was used to create the hydrological model of the basin of Lake Mälaren. Input to the model was flow, precipitation and temperature from several locations within the catchment. To model the diversion of water a new input file was created. Flow data from upstream measurements was altered in a way that would correspond to the diversion of water in an eco-flooding setting. The neural network toolbox release 2006a for MATLAB was used for all simulations.

5.1 Artificial Neural Networks

5.1.1 Brief description.

Artificial Neural Networks (ANN) is a mathematical and statistical system used for processing information. It is inspired by biological neural networks both by its structure and by the way they work and like the human brain an ANN learns by example. If the network has been properly trained and the input data is of acceptable amount and quality, the network is capable of solving problem by using data it hasn't previously seen. Although ANN originally was inspired by biological neural networks, the goal today is not to imitate the biological NN but mere to find a solution to a practical problem by using a more mathematical approach.

5.1.2 Basic structure of an artificial neural network

The basic element of an ANN is the neuron, also referred to as a node in this thesis. A schematic diagram of a typical neuron displayed in figure 3 below.

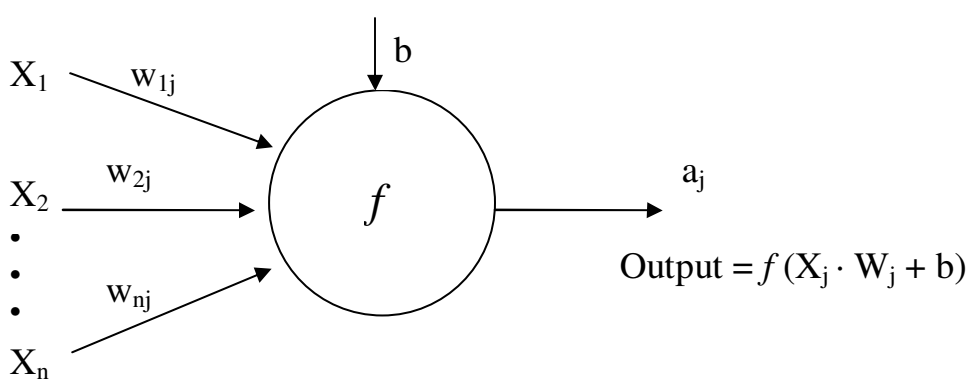

Figure 3. Schematic structure and output from the node j

Each node receives a number of inputs (X_1, X_2,…, X_n) who may come either from another neuron or from a source outside the ANN. Each input is given a weight (w_{1j}, w_{2j},..., w_{nj}) that is multiplied to it. The weighted inputs are then summed (provided there is more than one) and fed through a transfer function (f) which produces the output from the node j (a_j). Sometimes a threshold value, called bias (b), is added to the weighted

inputs. The idea behind the weights and bias is that that these parameters can be adjusted so that the desired output is produced from the given input (Demuth et al., 2007).

A number of interconnected neurons then make up a Neural Network. The links between the nodes are very important since the characteristics and function of an ANN to the most part is not decided by the neurons themselves, but rather how information is transferred between them, and the method for adjusting weights and bias (ASCE, 2000a).

Neurons in a network are usually divided into layers. In general an ANN consists of: an input layer containing the same amount of neurons as there are inputs. One or more "hidden layers" containing an arbitory number of neurons, depending on the situation. The optimal amount of neurons in the hidden layer is highly problem specific and is usually decided by a trial and error procedure (Dawson and Wilby, 2001). According to Han et al. (2007) is: 2/3 · (number of input neurons + number of output neurons) a good guideline for the number of hidden neurons. Too few nodes in the hidden layer will result in a bad approximation, and with to many nodes the network risk to be overtrained (ASCE, 2000a). Finally there is an output layer containing one neuron. An example of a three layer feedforward network is shown in figure 4.

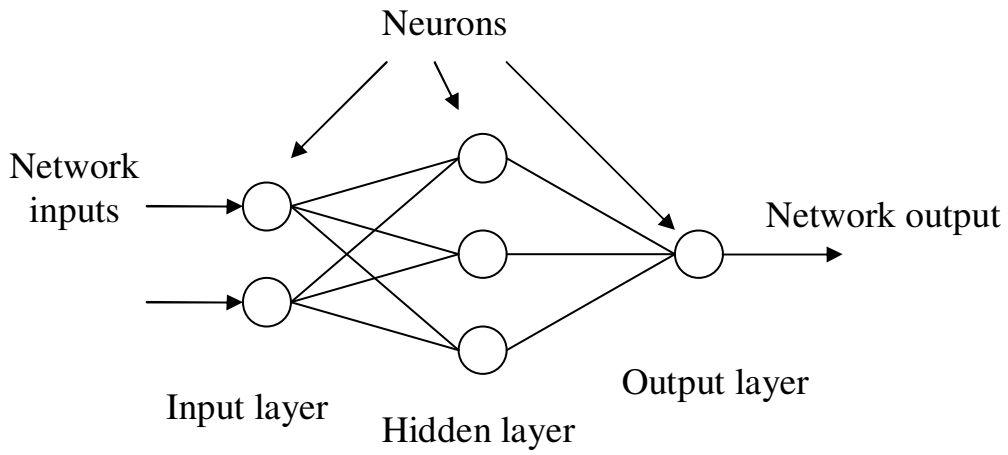

Figure 4. Structure of a three layer feedforward ANN with two inputs

5.1.3 Different types of networks

Artificial neural networks can be either feedforward or recurrent. In a feedforward ANN the information only runs in one direction, from the input layer to the output layer. Neurons in a feedforward network only receive information from neurons in a previous layer and pass on its output to the following layer. No information is transferred between neurons within the same layer. In a recurrent ANN on the other hand information runs in both directions, and output from one layer may be returned and used as input to a previous layer.

5.1.4 Transfer functions

A large number of transfer functions have been developed, some of the most commonly used transfer functions in a feedforward ANN are: a logistic sigmoid transfer function or a hyperbolic tangent transfer function in the hidden layer. In the output layer a linear transfer function is almost always used. This combination is in theory capable of reproducing any finite function (Demuth et al., 2007).

5.1.5 Network training

In order for an ANN to be able to generalize and produce accurate outputs, it has to be properly trained. Training is carried out by various training algorithms; these will however not be described in detail in this thesis. For more information about training algorithms the reader is referred to the Neural Networks Toolbox user's guide (Demuth et al., 2007). The back-propagation algorithm which is one of the most common training algorithms is used in this diploma work. In this algorithm the error from the neural network (i.e. the difference between the desired and the actual output) is propagated backwards through the network and the weights and biases are updated according to an error correction rule (Haykin, 1994).

The purpose of the training process is to adjust the bias and weights so that the output from the network is as close as possible to the desired output. During the training process the network is presented to a calibration set, sometimes also called a training set. The output from the network is then compared to a target-vector which represents the desired result. If the result is not satisfactory, weights and biases will be adjusted and the training set is run again. This procedure is repeated until the error function reaches a predetermined value. To determine whether the output from the network is acceptable or not most training algorithms uses an error function that the primary goal is to minimize. Mean square error is by far the most common error function used. The properties that make it popular are that it is easily calculated and is sensitive to large errors (Maier and Dandy, 2000). Each pass through the calibration set is called an epoch and the training procedure may be repeated over a pre-set number of epochs, or until the error function reaches a desired value.

The error function that is used to train the network often has several local minima surrounding the global minima (Cheng and Titterington, 1994 in Maier and Dandy, 2000). Because the initial values of the weights and bias are set randomly when the network is initialized, the training can be stopped at different local minima depending on the start values. The output from the ANN can therefore vary slightly between different simulations, even when the inputs and neural networks are identical. To reduce instabilities in this diploma work, the average output from 10 runs was used as a final output, as have been suggested by (Hsieh and Tang, 1998) and (Nilsson et al., 2006).

Artificial neural networks are generally good at interpolating, but bad at extrapolating outside of the range of the data given as inputs (ASCE, 2000b). For that reason data should be divided in such way so that the training set will contain both extremes of the data range.

5.1.6 Validation

When evaluating the performance of the model, the ANN should be tested by running the network with an independent validation set that have been separated from the training set. If the available data is limited it may not be wise to extract a part of the data set for validation, because a proper training requires a minimal amount of data. In these cases a method called cross-training can be used (ASCE, 2000a).

5.1.7 Overfitting

One problem associated with training is overfitting. Overfitting occurs when the network becomes over-familiarized with the training set and learns to reproduce it (including errors and noise), rather than the underlying physics (ASCE, 2000a). It also fails to learn trends and thereby loses its ability to generalize (Maier and Dandy, 2000). As a consequence it produces good results from the training set, but performs poorly when facing input data it hasn't previously been presented to. Overfitting usually occurs when there are too many neurons in the hidden layer or if too many epochs are used (ASCE, 2000a).

Various methods have been developed in order to eliminate the problem with overfitting; one of them is early stopping. When using this method the data is divided into three sub-sets: a training, a validation and a test-set. The function of the two first sets have already been described, the test set is used to know when to stop training. During the training process, the test set is monitored. At first the error function is usually decreasing, but when the network starts to overfit the data, the error of the test set starts to rise, and when the error has increased for a pre-determined number of epochs, the training is stopped. (Demuth et al., 2007)

5.1.8 ANN:s in hydrological models

Artificial neural networks have become a highly popular computing tool for use in hydrological applications during the last decades. Models that use ANN can be described as mathematical black box models that approximate the output variable, based on statistical relationships between the inputs and outputs used. This is in contrast to physical models which are based on mass and energy balances, and conceptual models that uses interconnected boxes to represent simplified key processes of the hydrological system (Dawson and Wilby, 2001).

Because of its structure ANN based models do not require any knowledge about the on-going hydrological processes, but if they are only used as an output approximators they don't provide any increased scientific understanding of the processes either. Drawing conclusions from ANN-model would require more than a simple black box approach; physical components should also be incorporated into the modelling technique (ASCE, 2000b).

5.1.9 Selection of neural network

A multilayer feedforward ANN was selected for the model. This is the most popular network type in hydrological applications. The number of layers and the optimal amount of neurons in each layer was determined by a trial and error approach, resulting in a three layer network with 25 neurons in the input layer and 14 in the hidden layer. The output layer contained 1 neuron. The transfer functions associated with the neurons where, a logarithmic sigmoid transfer function (eq. 1) in the input and hidden layers and a linear transfer function (eq. 2) in the output layer.

Logarithmic sigmoid transfer function: $$o = \frac{1}{1+e^{-i}} \quad (1)$$

Linear transfer function: $$o = i \quad (2)$$

Where i is the input and o the output from the transfer function.

The network was trained with the; gradient decent with adaptive learning rule backpropagation algorithm (Demuth et al., 2007) and the early stopping method was used to prevent it from overfitting. Mean square error was used as error function.

The accuracy of the model was verificated by running it against an independent validation data-set. 20% of the data set was separated for validation and testing respectively. The remaining 60% was used for training the ANN.

5.1.10 Selection of network inputs

Selecting the optimal input vector to the ANN is a very important part of the network designing. First it has to be determined which antecedent data that has an influence on the runoff and which parameters should be included (flow, precipitation, temperature, etc.) In this diploma work most of the selection process was made by using a trial and error approach.

The time lag between the upstream flow measurements and the Lake outflow at Norrström was created in the model by feeding the ANN with inputs containing measurements from 15 previous days. I.e. when simulating the outflow from Mälaren at day t, inputs to the ANN are flow and precipitation from day t-2 to day t-15. The optimal numbers of days to be used was determined by starting with only day t-1 as an input and then stepwise add more inputs (Q_{t-2}, Q_{t-3},…) until the performance of the model no longer improved.

5.2 Flood control scenarios

The aim of the diversion-scenarios is to try and imitate a “real life” scenario where flow will be regulated in a configuration that follows the eco-flooding philosophy that is described in chapter 4. This will be done by introducing a hypothetical off-line reservoir

within one or several sub basins, depending on the regulation scenario. Diversion is assumed to be carried out in step-wise configuration with a gate that is opened if streamflow exceeds a critical level.

Technically this is executed in the model by creating a new input file where the flow is altered in the stream/streams that will be subjected to the diversion and storage of floodwater. Threshold values and a diversion rate are also selected. For every time step (day) where the unregulated flow is above the threshold value, flow in the input file will be reduced by the diversion rate, provided the storage is not already filled. The same principle is used when the stored water is returned but the flow is instead increased when the flow falls below another threshold. A vector is used to monitor the stored volume to ensure that more water than the storage can hold is not diverted and that water is not returned if the storage is empty. Potential losses due to increased evaporation infiltration rate, etc. are assumed to be negligible because of the short storage times (Cederwall, 2006). The new hypothetical input file that contains the modified flow is then entered as input to the ANN and the output is then compared to the output from the case with the unregulated flow.

The parameters used in the diversion scenarios were set in the following way:

- The eco-flooding strategy is only thought to be used during the largest peaks, so the threshold for beginning diversion was set to 75 percent of Q_{max}, and a safe level for returning the water was assumed to be $0.3 \cdot Q_{max}$,
  where Q_{max} = the highest daily flow within the simulation period

- The positive effects from an actively controlled off-line reservoir are best when the storage captures less than 20% of the flood volume (Sanders et al., 2006). Two diversion rates were used; $0.10 \cdot Q(t)$ and $0.20 \cdot Q(t)$,
  where $Q(t)$ = the flow at day t

5.2.1 Diversion scenarios

Two different versions of the ANN-model were created. The first was used to model the outflow from the entire Mälaren basin, the second was used to model flow in Kolbäcksån, which is one of the sub basins. The reason for using two different areas is to model the eco-flooding diversion at different scales. Lake Mälaren is actually to large for being effectively controlled by upstream methods and the level is to most part controlled by the outlet (SOU, 2006). It is therefore more interesting to look at the effects in the sub basins but due to lack of data it was not possible to use ANN:s in the way described above to model the smaller sub basins, except for Kolbäcksån.

Several diversion scenarios where made in the basin of Lake Mälaren. Three simulations were run when diversion only was carried out in one of the recharging streams to Mälaren. For this part, some sub catchments with different characteristics were selected to see if the effects of eco-flooding are affected by the terrain type. The catchments chosen for this study where, Kolbäcksån which is thought to represent a hilly runoff area,

and Arbogaån to represent a flat catchment. As an intermediate area the catchment of Fyrisån was selected. The next scenario included an attempt to evaluate the full potential for using eco-flooding as a complement to other flood control strategies in the catchment. In this scenario the hypothetical diversion and storage adopted in all the major inflows to Mälaren.

The model describing Kolbäcksån was used to model the peak reduction for six diversion scenarios. The diversion-schedule was identical to the one described in the paragraph 5.2 but different storage sizes and diversion rates where used. A last a simulation was also made to see what diversion settings is required to achieve a peak reduction of 10%.

5.3 Model verification

There is not a single test that can be used to evaluate the performance of a hydrological model that takes all aspects associated with flow prediction into consideration. Instead a multi-criteria assessment of the following statistical verification methods was used.

Coefficient of efficiency (CE): is a global measure that tells the overall performance of the model. It ranges from -∞ to +1 and a satisfactory model is usually considered to have a CE between 0.8 and 0.9 (Shamseldin, 1997 in Wang et al., 2006).

$$CE = 1 - \frac{\sum_{i=1}^{n} \left(Q_{obs}(i) - Q_{\mathrm{mod}}(i)\right)^2}{\sum_{i=1}^{n} \left(Q_{obs}(i) - \overline{Q_{obs}}\right)^2}$$

Root mean square error (rmse): is sensitive even to small errors and is usually good at evaluating the model at high flows (Dawson and Wilby, 2001).

$$rmse = \sqrt{\frac{\sum_{i=1}^{n} \left(Q_{obs}(i) - Q_{\mathrm{mod}}(i)\right)^2}{n}}$$

Q_{mod} is the modelled flow Q_{obs} is the observed flow and $\overline{Q_{obs}}$ is the mean of the observed flow

Correlation coefficient:
The correlation coefficient is a measure of how well the predicted hydrograph follows the observed flow. It ranges from -1 to +1 and a correlation coefficient of +1 represents a perfect model, -1 is an inverse correlation and 0 is no linear correlation at all.

Volume error:
The volume error is calculated as the percentage difference between the total simulated and observed flow.

$$Volume\ error = \frac{\sum_{i=1}^{n} Q_{\mathrm{mod}}(i) - \sum_{i=1}^{n} Q_{obs}(i)}{\sum_{i=1}^{n} Q_{obs}(i)}$$

Beside the statistical methods, two graphical evaluation methods were also used. These include a plot of the hydrographs of the modelled and observed flow and a scatter plot of the observed versus the modelled values.

Since the purpose of the model is to simulate diversion of water at high flow events, most attention was given to the peak error and the graphical methods.

6 Data

All data was provided by the Swedish Meteorological and Hydrological Institute (SMHI) and included flow measurements from 15 stations within the basin, precipitation data from 12, and temperature from three, gauges spatially spread throughout the catchment (See appendix 1 for a list of all stations and their location). All data is in the form of daily measurements from 1980-01-01 to 2000-12-31. Time series where however not completely continuous, the measurements from a few precipitation gauges contained gaps of up to 30 consecutive days. In those situations data from the closest available gauge was used to fill the gap.

6.1 Data pre-processing

The efficiency of the training process can often be improved by pre-processing the data sets, especially if the network inputs contain vectors measured on different scales. Networks that uses a gradient decent backpropagation algorithm to train the network is particularly sensitive to different scales of the inputs used (Dawson and Wilby, 2001). Without pre-processing input variables of high magnitude will have a larger influence on the training process than inputs of a lower magnitude because the initial weights and bias are randomized within the same finite range (Dawson and Wilby, 2001). To avoid this problem, and ensure that all input variables receive equal attention during the training process data are often rescaled into a suitable interval, for example [-1, 1], [0, 1] or [0.1, 0.9]. An alternative method, called standardization, is to express the data in terms of standard deviations around the mean value (eq. 3).

Standardization: $$P_i = \frac{(P_i - \overline{P})}{\sigma} \qquad (3)$$

Where P_i is the n inputs, $\overline{P}$ is the mean of the n inputs and σ is the standard deviation of P

W.Wang et al. (2006) found that rescaling the inputs and targets into a small range have very little effect if sigmoid transfer functions are used because the output will be less sensitive to changes of the weights and bias. Besides, the rescaling of the inputs may also be offset by the changes of weights and bias. They suggest that data should be standardized instead, especially if the available data set is large enough to include the expected extreme values of the data range. With this in mind, the only pre-processing technique used in this diploma work was standardization.

7 Results and discussion

7.1 Performance of the ANN models

The neural network was run several times with different inputs in order to determine the best combinations of input data. Flow was used in all cases, but temperature and/or precipitation was either included or excluded. Differences are not always clearly seen, especially since the output from the ANN may vary slightly between different simulations, using exactly the same network and inputs. These variations are caused by the initial values of the weights and bias that are set randomly when the network is initialized which may result in the learning process to be stopped at different local minima of the error function. When selecting the appropriate inputs to the network, main focus was to get a correct simulation of the peaks because it is only during these flow events that the simulation-scenarios with flood diversion will be implemented.

To the model of Mälaren only antecedent flows was selected as inputs whereas both antecedent flow, temperature and precipitation was used in the model of Kolbäcksån.

7.1.1 Model of Mälaren

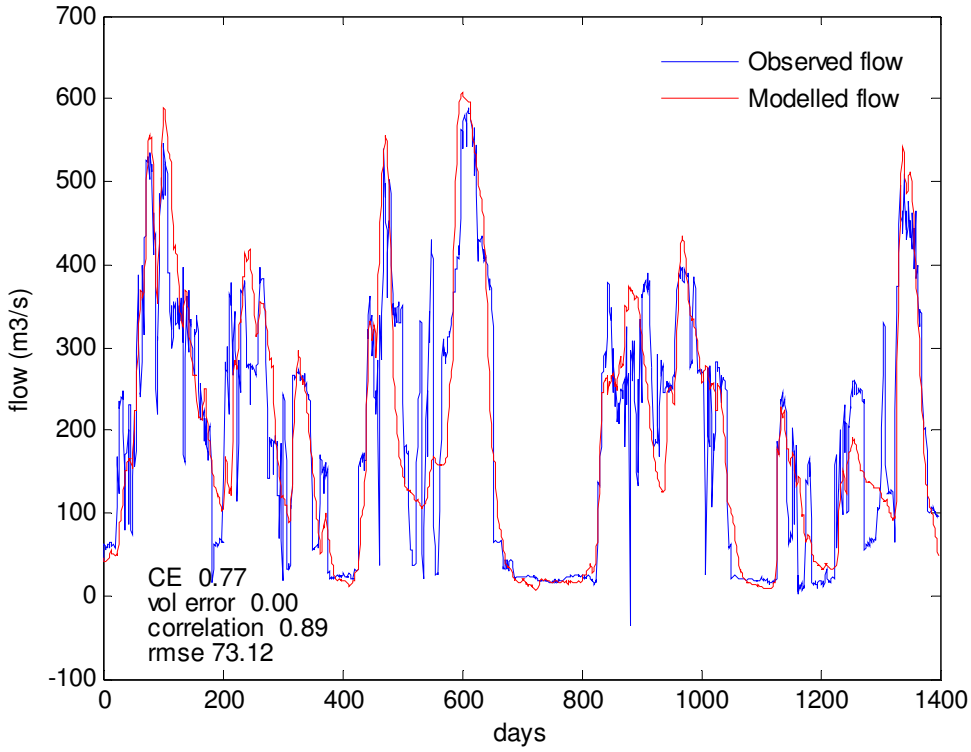

Figure 5. Observed and Modelled outflow from Lake Mälaren, results from the validation period.

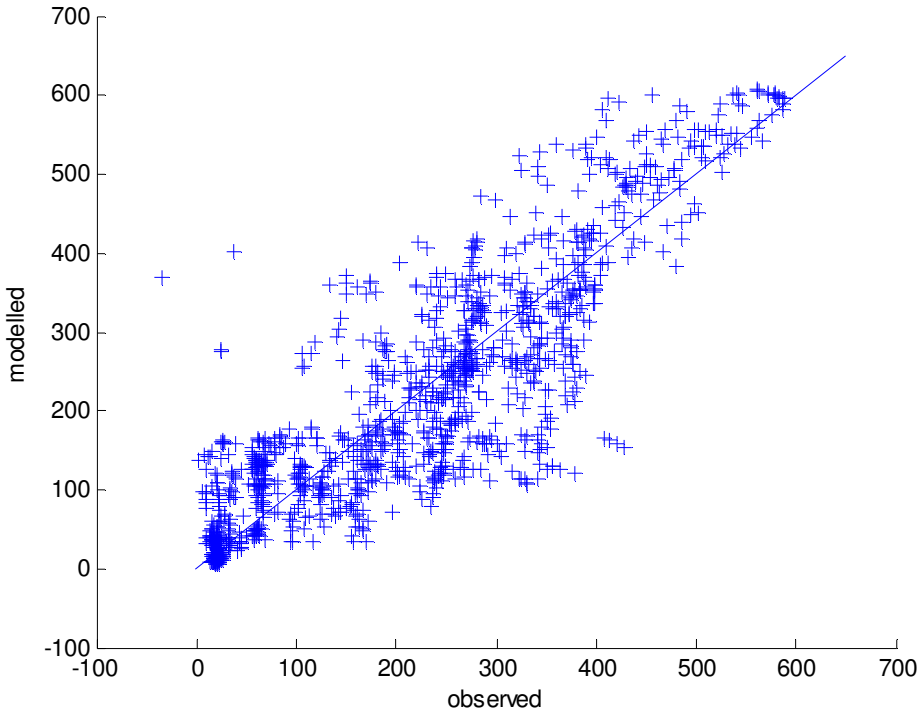

Figure 6. Scatter plot of the observed versus the simulated flow during the validation period.

The results from the validation period from the model predicting the outflow from Mälaren are shown in figure 5 and 6. The predicted flows are particularly bad for three periods. At day 880 the flow is negative, i.e. seawater is entering Mälaren. A drawback in the model is that it does not take sea level in consideration and is therefore not capable of predicting these events. This is a fault in the model, but the events where flow is running in the wrong direction are quite rare and has only occurred a few times since the regulation-system was updated in 1968. In a previous diploma work (Larsson, 2005) the long time effects of the seawater-level on the water levels in Lake Mälaren was evaluated and no correlation was found between sea level and the water level in Mälaren for the periods with regulated flow. Seawater intrusion does therefore probably not have a large effect on the results of this thesis but is perhaps something that should be included in other hydrological applications of Lake Mälaren.

Two of the intermediate peaks are also completely missed by the model (approximately at day 550 and day 1300 in fig. 5). It is very hard to tell exactly what causes the model to fail to predict these peaks, but a likely explanation is that the outflow from Mälaren, as well as many of the Lakes inflows are regulated, and the ANN might have difficulties with learning that. It is therefore possible that the inclusion of regulation schemes, etc. could improve the model performance. Better quality of the input data could also help to improve the model.

7.1.2 Model of Kolbäcksån

The Performance of the model from Kolbäcksån is very similar to the model of Mälaren described in the previous paragraph. Predicted and observed flows generally show a good correlation and most peaks are predicted correctly, except from a few intermediate peaks that are underestimated (see figure 7 and 8). The weaker peaks are probably caused by the ANN:s difficulties to learn the regulation and lack of inputs.

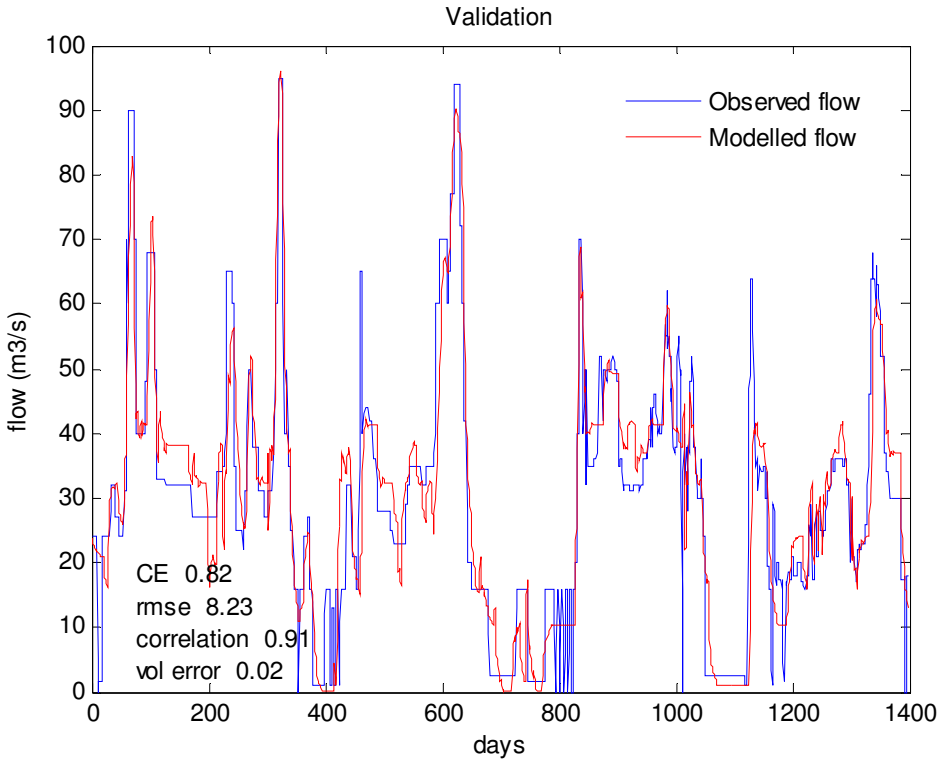

Figure 7. Observed and predicted flow in river Kolbäcksån, results from the validation period.

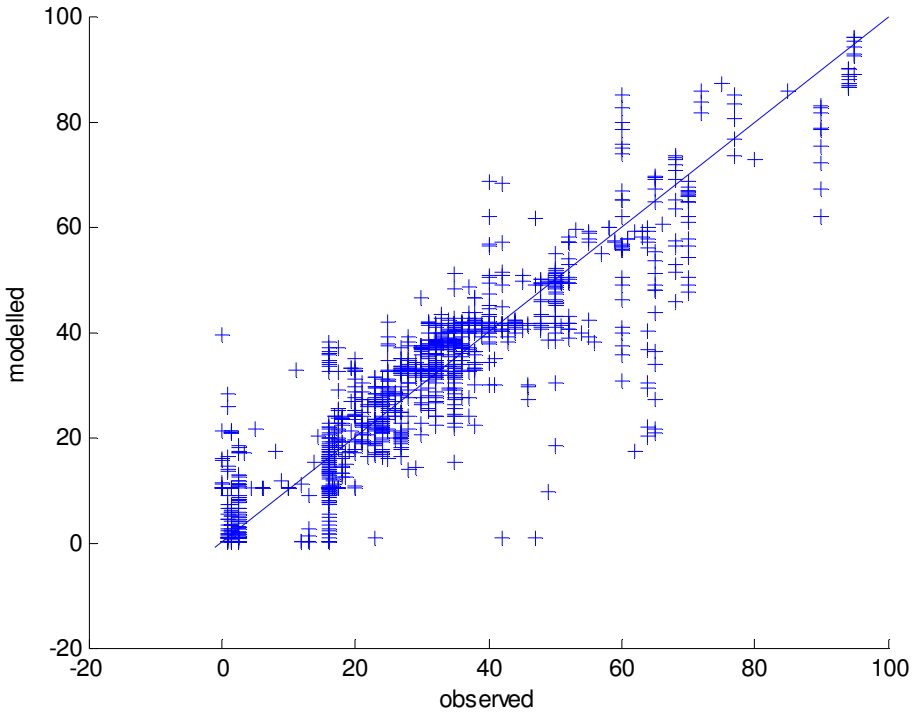

Figure 8. Scatter plot of observed versus the simulated flow during the validation period.

7.2 Flow diversion scenarios

7.2.1 Effects on the outflow at Norrström

Three sub-basins with different topographical characteristics: Kolbäcksån, Arbogaån and Fyrisån, where selected for a deeper study to evaluate the potential of using eco-flooding as a method for flood control. In this part of the thesis the flow diversion was only done in one stream at a time and the result was then compared to the flow reduction achieved when the peak flow was reduced in the other two sub-basins.

The figures 9, 10 and 11 shows the effects on the outflow at Norrström when a part of the highest flows in the three streams, Kolbäcksån, Arbogaån and Fyrisån are diverted and temporary stored.

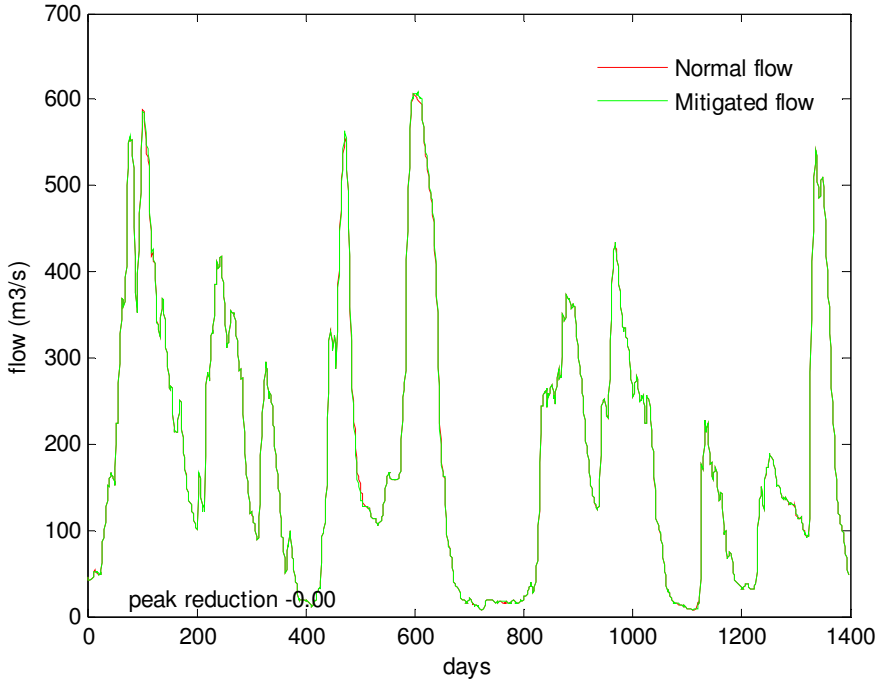

Figure 9. Flow reduction at Norrström when the eco-flooding mitigation strategy is used in the sub catchment of Fyrisån. A storage volume of 10^7 m^3 is used and the diversion rate is 20% of the cresting peak.

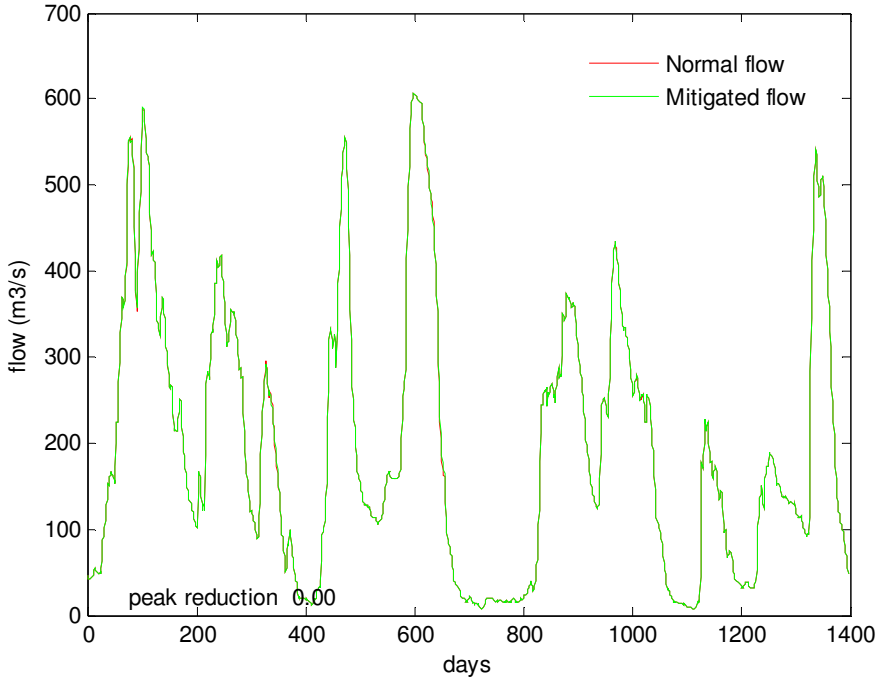

Figure 10. Flow reduction at Norrström when the eco-flooding mitigation strategy is used in the sub catchment of Kolbäcksån. A storage volume of 10^7 m^3 is used and the diversion rate is 20% of the cresting peak.

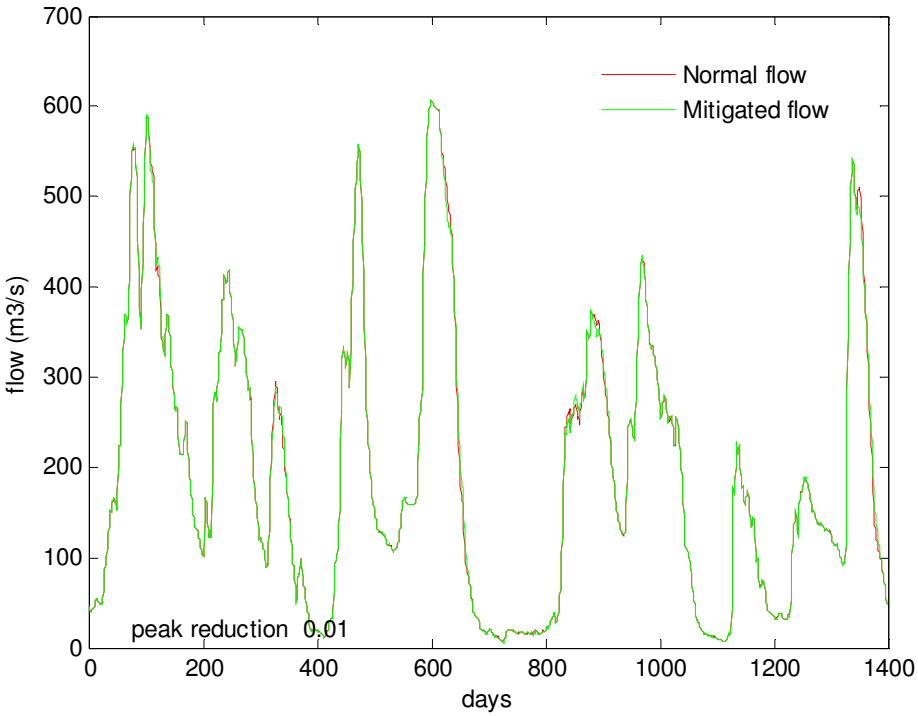

Figure 11. Flow reduction at Norrström when the eco-flooding mitigation strategy is used in the sub catchment of Arbogaån. A storage volume of 10^7 m^3 is used and the diversion rate is 20% of the cresting peak.

As it can be seen in the figures 9 to 11 is any effects on the outflow from Mälaren hardly noticeable when only diverting water in one of the sub basins. When diversion was made in Arbogaån a small peak reduction is achieved but the effect is still very moderate. On basis of these results is it therefore difficult to see if the characteristics of the three different catchments had any impact on the response to the eco-flooding diversion.

An extension of the eco-flooding strategy to include diversion in most of the major recharge-streams simultaneously will not increase the flow reduction much (see figure 12). Only a small peak reduction, approximately 1%, is achieved. The storage volume used were 10 000 000 m^3 in each sub catchment. It is probably not a realistic storage size but that is the size required to get a visible effect. This is completely in line with previous studies on Lake Mälaren (SOU, 2006) which state that the best way of controlling the water level of the Lake is by affecting the outlet.

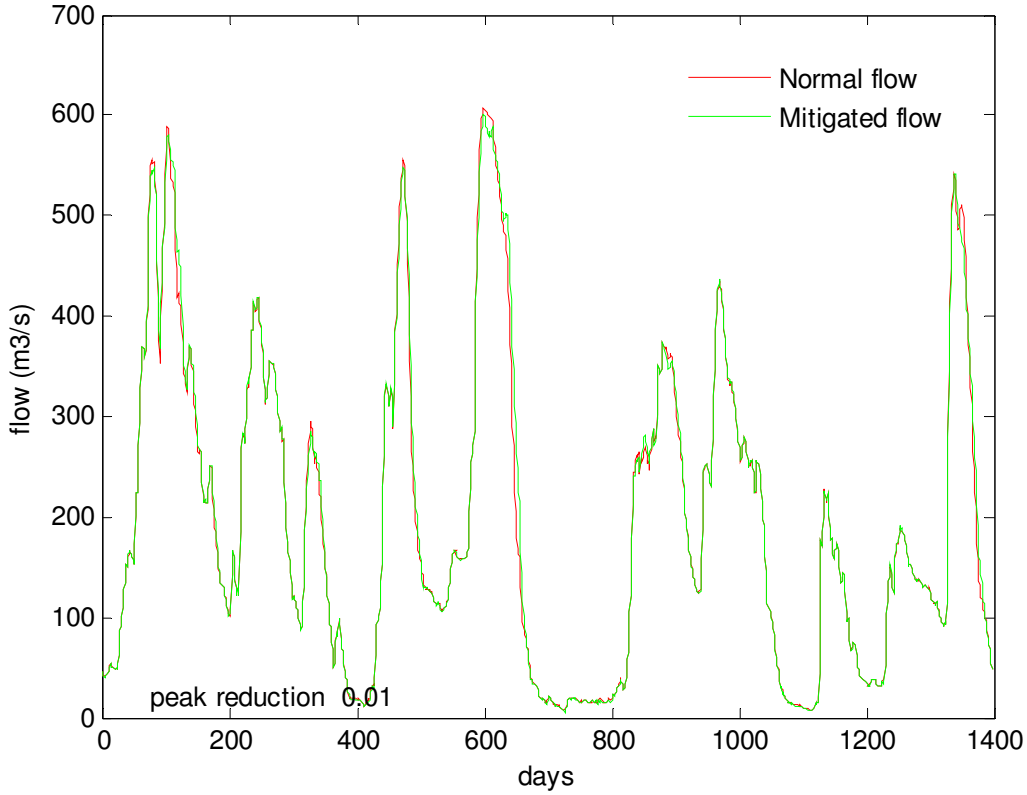

Figure 12. Flow reduction at Norrström when the eco-flooding mitigation strategy is used in all the major recharging streams. A storage volume of 10^7 m^3 is used in each catchment and the diversion rate is 20% of the cresting peak.

The hydrographs in figure 12 show that the flow peaks actually can become higher when using the eco-flooding diversion, if the water is returned at the wrong time. The outflow from Mälaren is affected by a combination of all the inflows and the time lag between them and the outflow. Since the peaks in the sub basins don't have to be simultaneous in different parts of the watershed the flood wave in one sub basin can have passed when the flow in Mälaren peaks. If the regulation is only based on the situation in sub-catchments, like in this model, is it possible that stored water is returned to a recharging stream at a time where it will be added to the natural flow peak of Lake Mälaren and aggravates the situation. It is therefore important that any temporary diversion is based on a proper regulation-schedule for diversion and return that is based on the catchment as a whole and not just the sub basin where the diversion is made. Even when if the temporary storage is only supposed to be used as a local flood control method in a small sub catchment.

7.2.2 Modelling effects of a temporary diversion in the catchment of Kolbäcksån.

Kolbäcksån has a much smaller catchment (3100 km^2) compared to the catchment of Mälaren (22600 km^2) used in the previous scenarios and should therefore be a more suitable location for studying the effects of the temporary water storage. Although it would even in a relatively small catchment, like this one, be necessary to use very large surfaces if any significant peak reduction is to be created with the eco-flooding methodology. Figure 13 show the predicted flow mitigation in Kolbäcksån River during six different scenarios. Three different sizes of the hypothetical detention basin were used and flow was reduced by either 10 or 20 percent.

When using a storage volume of 5 000 000m^3 only a modest effect is achieved (fig. 13a), because the storage would be filled after only a day. Larger reservoirs would obviously enhance the usefulness of this method of during prolonged flows, but to reduce the largest peaks by 5% a storage of 20 000 000 m^3 is needed (see fig 13c and 13f) which corresponds to a flooded area of 20km^2 if assuming a 1m storage depth. Peak reduction is in this study defined as the percentage difference between the top of the peaks in the hydrographs of the unchanged and the mitigated flow.

Figure 13 also show that the benefits from using off-line storages as a mean for flood control to a great extent are affected by the way in which the flow reduction is implemented. There is a tradeoff between the size and duration of the diversion (Sanders et al., 2006). To large diversion rates will initially give a good flow reduction, but it can not be maintained during the entire peak since the reservoir will be filled up. The opposite occurs if the diversion rate is to low; diversion will be maintained during the entire scenario but is to low to be meaningful. Optimizing the flood control is a hence of great importance for the mitigation success. As have been pointed out by Sanders et al., the knowledge of the flood hydrograph in advance a benefit when setting up the diversion scenarios in a study of this kind. A real-time diversion is a much greater engineering challenge that would require a detailed flow forecast to identify the optimal timing and diversion rates for each individual flood wave.

It can also bee seen in figure13 that the downstream flow reduction is much smaller than the size of the diversion. This can partly be explained by bad optimizing of the flow diversion. But even with the largest storage size and using the lower diversion rate, the flow reduction is clearly smaller than the diversion (fig. 13f). This indicates a large lateral inflow downstream of the hypothetical reservoir.

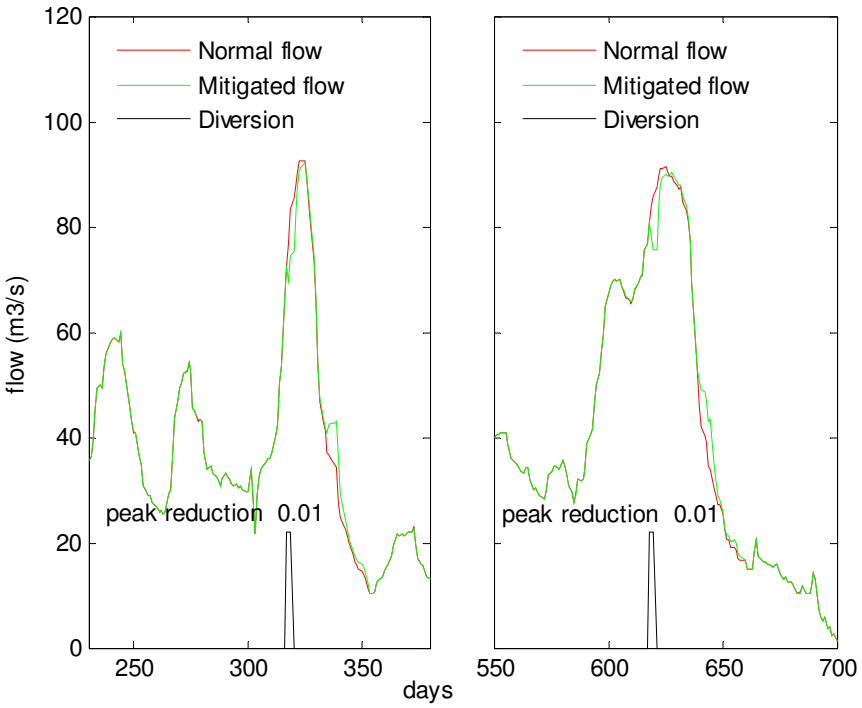

Figure 13a. Reduction of flow in Kolbäcksån when a part of the flow peak is diverted to an off-line storage. Storage volume is $5 \cdot 10^6$ m^3, diversion rate 20%.

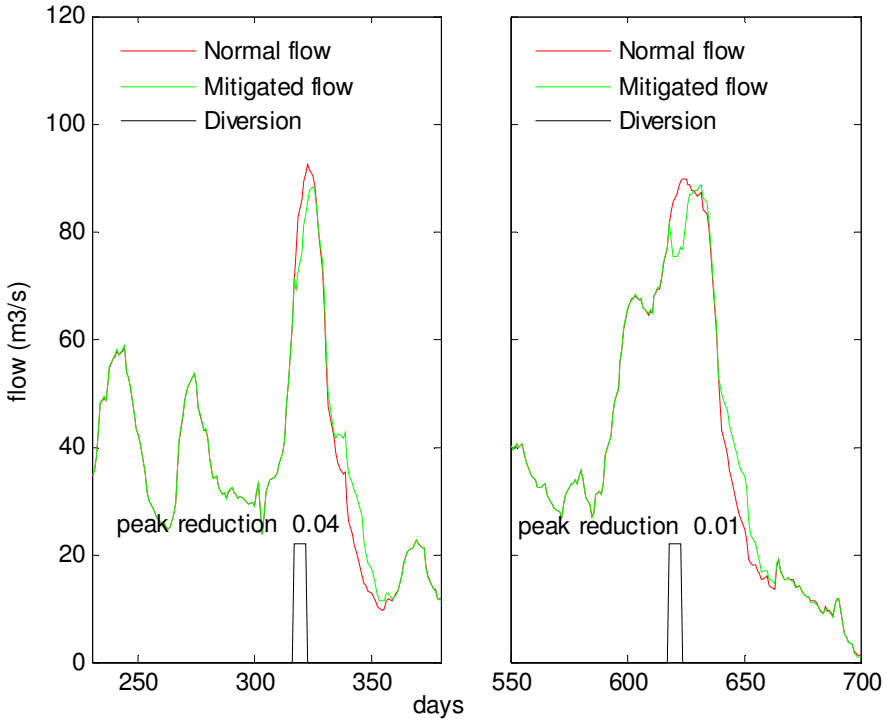

Figure 13b. Reduction of flow in Kolbäcksån when a part of the flow peak is diverted to an off-line storage. Storage volume is 10^7 m^3, diversion rate 20%.

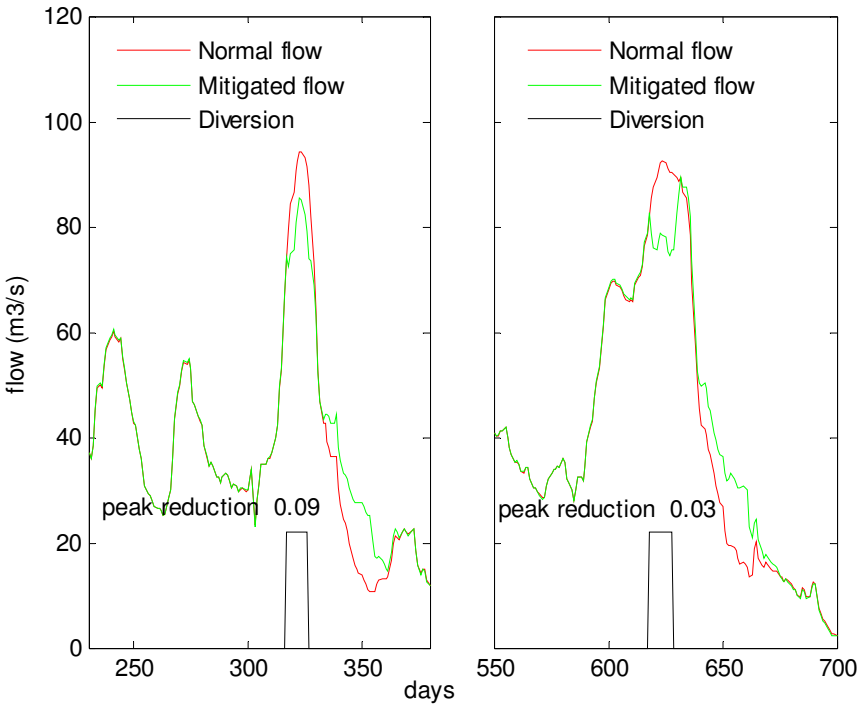

Figure 13c. Reduction of flow in Kolbäcksån when a part of the flow peak is diverted to an off-line storage. Storage volume is $2 \cdot 10^7$ m^3, diversion rate 20%.

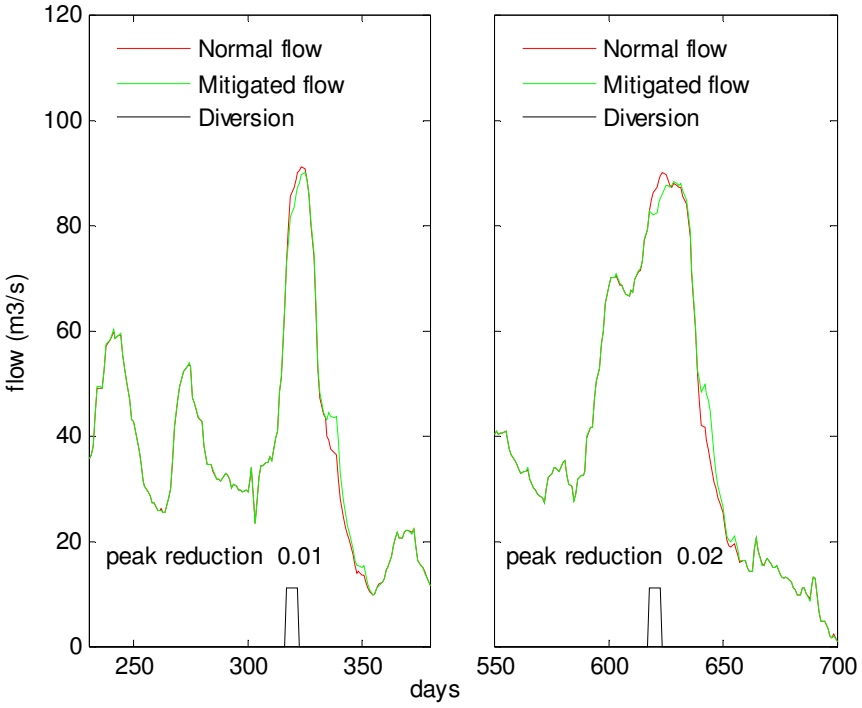

Figure 13d. Reduction of flow in Kolbäcksån when a part of the flow peak is diverted to an off-line storage. Storage volume is $5 \cdot 10^6$ m^3, diversion rate 10%.

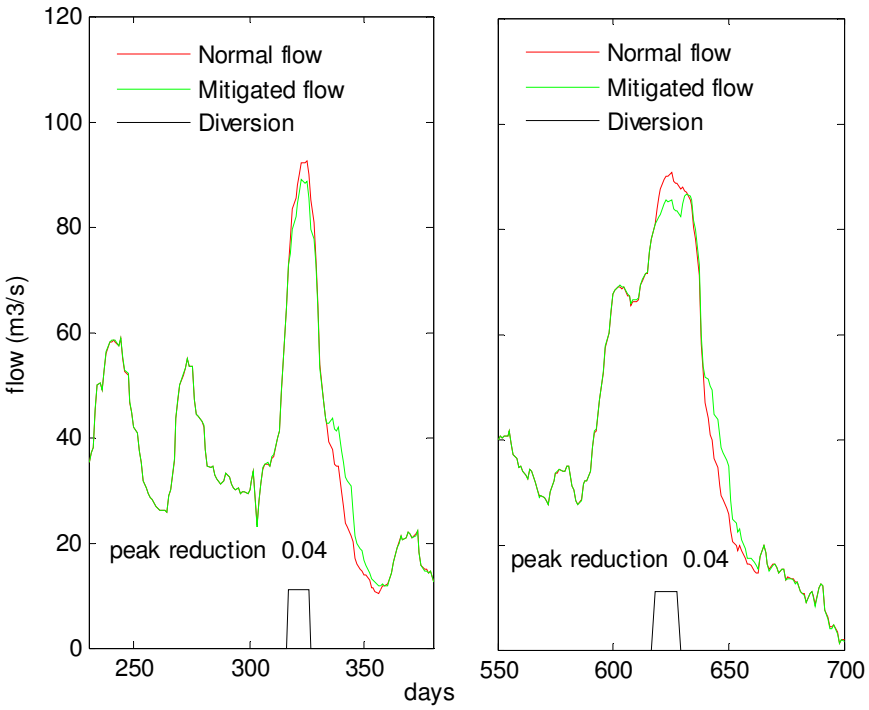

Figure 13e. Reduction of flow in Kolbäcksån when a part of the flow peak is diverted to an off-line storage. Storage volume is 10^7 m^3, diversion rate 10%.

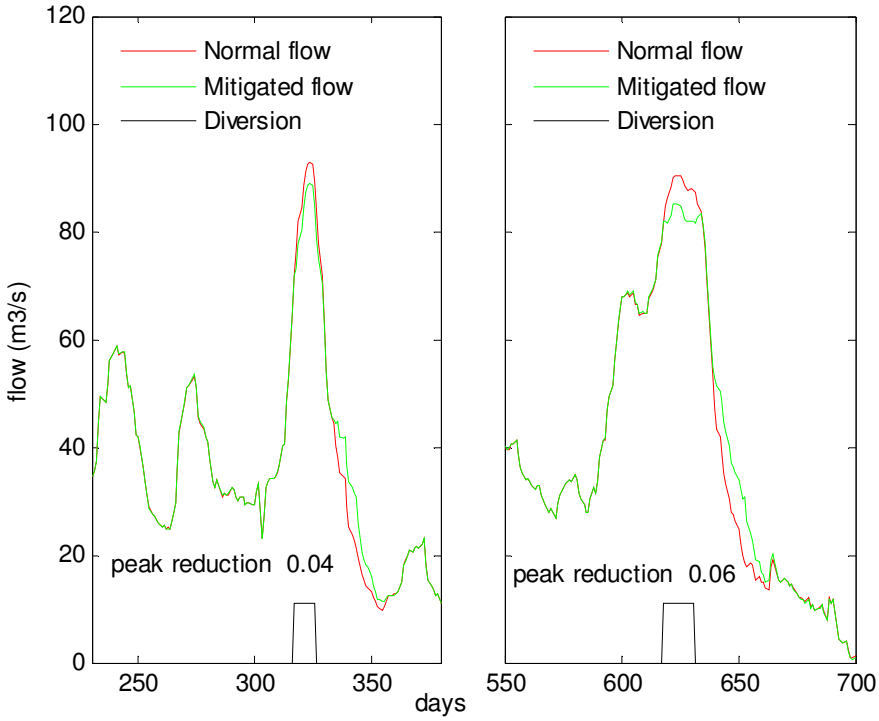

Figure 13f. Reduction of flow in Kolbäcksån when a part of the flow peak is diverted to an off-line storage. Storage volume is $2 \cdot 10^7$ m^3, diversion rate 10%.

The results of the last simulation, whose purpose was to investigate what kind of diversion rate would be required to reduce peak flow by ten percent, is displayed in figure 14. According to the modell results is a diversion rate of 25% needed to create that reduction, the storage size was in this case dimensioned to be large enough not to be filled. However; if the diversion is started earlier, at a flow rate of 73 m^3/s instead of 82 m^3/s as was used in the other scenarios, a downstream reduction of 10% can be achieved with a lower diversion rate (20%). These results once again emphasises the challenge of optimizing the reservoir management, and the benefits of having knowledge of the peak hydrograph in advance.

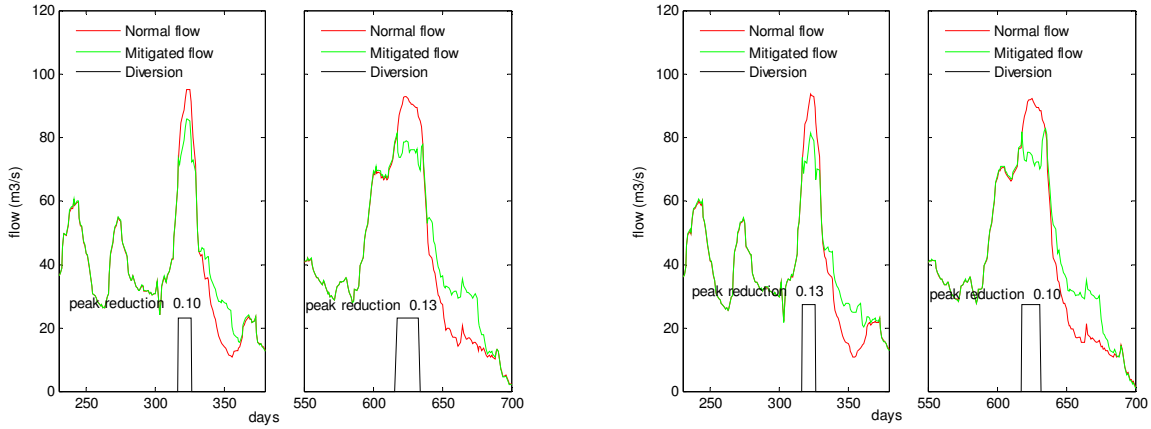

Figure 14. Flow reduction in Kolbäcksån when using a diversion rate of 25%, staring at 82 m^3/s (left) and a diversion rate of 20%, starting at 73m^3/s (right).

7.3 Evaluation of ANN as a tool for flow detention models

Since ANN is the only type of hydrological model used and very few previous studies about the subject have been made is it hard to make any qualitative comparisons between the methodology in this study and other model types such as conceptual and physical models. Instead will a principal discussion about flow detention modelling and ANN:s be made.

A strength of artificial neural networks is their capability of recognizing complex non-linear relations between input and output variables without having full knowledge about the underlying physics (ASCE, 2000b). Many hydrological applications, such as rainfall runoff models, are known to be non-linear and highly complex. They also show a large spatial and temporal variability (ASCE, 2000b). The properties of ANN therefore make it an attractive computing tool for many hydrological applications.

In contrast to the rainfall runoff process, the relationship between the outflow from Lake Mälaren and the sum of the contributing streams (weather these are mitigated or not) is a simple linear relationship, and the benefits of using ANN in this type of flow detention studies is therefore less obvious compared to some of the more common neural network applications in hydrology. Hence is it possible that a simpler numerical model could have been equally good for this purpose, although the regulation of the Lake and its recharges might be a problem in that case.

A major restriction for a successful use of ANN in flow detention modelling is the incorporation of diversion scenarios into the model. As a consequence of the neural network structure will all flow modifications have to be made through changes in the input matrix. That greatly limits the number of possible diversion scenarios; this applies in particular to the possible locations of detention basins in the model. The usefulness of an ANN in this type of study is therefore to a large extent depending on the location and number of available gauging stations.

8 Summary and conclusions

Artificial neural networks were used in this diploma work to model flow and flood mitigation using the eco-flooding strategy in the Catchment of Lake Mälaren. The idea behind the eco-flooding strategy is to retain streamflow during critical flow situations, by divert a part of the flood wave into temporary storage in the landscape. The effect of the eco-flooding diversion was studied on the catchment of Lake Mälaren as a whole and in one of the Lake's recharges separately.

The ANN was capable of predicting regulated flow reasonably well when only precipitation, temperature and upstream flow were given as inputs, The fact that information of the complex underlying physical processes is not needed is one of the main advantages of ANN models, compared to other approaches (Suther et al., 2002), In this study however, availability of data was a major restriction. It is conceivable that addition of more input variables could have improved the model performance, although adding more variables generally require larger networks which is harder to train, and also needs longer time series in the input matrix (Maier and Dandy, 2000).

Implementing diversion scenarios in the ANN model showed to be very difficult, since it had to be done through modifications in the ANN input matrix. Thus, what the ANN is simulating is flow reductions at the location were the flow measurements was made and the effects this reduction has at some point downstream of this site. Hence is the model restricted to predict effects at a few locations in the catchment, which does not have to be the locations where terrain is most favourable for flood detention. Good data availability and suitable locations of the gauging sites is therefore very important if a neural network is to be successful in this type of studies.

The results of this study indicate that achieving any significant flow reduction in the outflow from Mälaren by using upstream storages would require storage volumes that probably are unrealistic, the most suitable flood control method is instead to increase the outflow capacity as have been suggested by Klimat och sårbarhetsutredningen (SOU, 2006:94). The eco-flooding philosophy may be used to reduce flow peaks upstream in smaller sub-catchments, but very large areas would still have to be submerged. The results also indicate that a well developed diversion strategy that includes a forecasting system is needed for this type of flow retention. It should be able to predict the optimal timing for diversion of water and also be able to identify a safe return of the stored water, so that any downstream flood situations will not be aggravated.

9 Recommendations for further studies

Difficulties with implementing the mitigation strategies in the ANN-based model and the availability of data were a major restriction in this study. It is possible that other model types are better at cooping with the restrictions faced. So for a further study it might be wise to try other modelling approaches, using for example a conceptual or numerical model instead.

In this study eco-flooding was used exclusively as the only mean of flood retention within the catchment. A more realistic approach would be to simulate effects of eco-flooding in combination with improved flow detention in the existing dams and reservoirs. Although it has to be pointed out that the main purpose of these are hydroelectric power production and not flood control.

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Appendix 1 – Measuring stations

Data from the following SMHI-stations was used for the modelling in this diploma work.

Table 1. Flow series:

Station number	Station name	River	Type of flow
61-138	Övre Hyndevald	Eskilstunaån	Reg.
61-516	Övre Stockholm	Norrström	Reg.
61-1532	Kåfalla	Sverkstaån	Reg.
61-2139	Karlslund 2	Svartån	Reg.
61-2206	Dalkarlshyttan	Arbogaån	Reg.
61-2216	Åkersta kvarn	Svartån	Reg.
61-2219	Dömsta	Hedströmmen	Reg.
61-2220	Sörsätra	Sagaån	Reg.
61-2231	Almbro	Täljeån	Reg.
61-2243	Sävja	Sävjaån	Unreg.
61-2246	Ulva kvarndamm	Fyrisån	Unreg.
61-2248	Härnevi	Örsundaån	Reg.
61-2249	Åkers krutbruk	Råckstaån	Reg.
61-50116	Hallstahammar	Kolbäcksån	Reg.
61-348	Semla	Kolbäcksån	Reg.

Table 2. Precipitation and Temperature:

Station number	Station name	Data type
9600	Valla	Precipitation and Temperature
9655	Sala	Precipitation and Temperature
8460	Törntorp	Precipitation
8659	Katrineholm	Precipitation
9433	Greckåsar	Precipitation
9458	Ställdalen	Precipitation
9525	Västvalla	Precipitation
9644	Skulltuna	Precipitation
9712	Södertälje	Precipitation
9738	Enköping	Precipitation
9752	Uppsala	Precipitation
10500	Fagersta	Precipitation
9751	Uppsala AUT	Temperature