UNIVERSITY OF AGDER

Uncertainty analysis of hydro-meteorological forecasts

By

Karl Kristian Grythe and Yukun Gao

Supervisors:

Ole Christoffer Granmo, Bernt Viggo Matheussen, and Jarand Røynstrand

Thesis submitted in Partial Fulfillment of the

Requirements for the Degree Master of Science in

Information and Communication Technology

Faculty of Engineering and Science

University of Agder

Grimstad

May 2010

Abstract

Meteorological and hydrological forecasts are very important to human's life which concerns agriculture, industry, transport, etc. The Nordic hydropower industry use and develop hydrological forecasting models to make predictions of rivers steam flow. The quantity of incoming stream flow is important to the electricity production because excessive water in reservoir will cause flood and the loss of hydropower energy. Therefore the accurate prediction will help the managers decide the optimal production level in the reservoir at the current time. If for instance the predicted runoff exceeds the limit of water that the plant can process, then it is possible to increase production early so the water level does not get higher than the edge of the reservoir.

In our project, we are studying the uncertainties which come from both meteorological and hydrological forecasting systems, and propose a new error correction methodology to reduce the uncertainties in the forecasted runoff.

We study the uncertainties in the meteorological data, and then evaluate the accuracy of the meteorological data. Then we feed the meteorological data into a hydrological forecasting system, called the "OHBV model" with forecasted meteorological data. Later we run the model again with observed meteorological data. By running the model twice with different input we evaluate the performance of the OHBV model, and find the level of improvement expected when having a more accurate weather forecast. The OHBV model is also referred to as "OHBV" for short.

At last we focus on error correction that are algorithms used to improve the runoff forecast based on statistics. We test the existing error correction method, called the "Powel algorithm", and we identify how much of the error it could reduce. The error reduction is found by comparing the runoff forecast with the observation of stream flow runoff. Furthermore, we propose our own error correction method, referred to as "Yukun&Karl algorithm", and finally evaluate the performance of the new method.

Our results show that the main part of the error comes from the HBV model in the first forecast, while when using observation data as input into the model the output improves most for last days where the weather forecasts have higher uncertainty. Weather forecasts have errors, but have gone through much refinement the latest years, and until the HBV model performs better, this is not where the main focus should be. Since the OHBV model give high errors even in the prediction with the least of uncertainty (in the 1 day ahead in forecast), this should be investigated and improved.

Error correction algorithms are applied after the model itself, and are used to give an overall improvement, though it sometimes can make the individual error larger. The best improvement by correction is in the "1 day ahead "runoff forecast, but after 4-5 days the Powel correction generally causes more errors than it can correct. The developed "Yukun&Karl algorithm" works up until the 8th day. The error corrections algorithms counter some of the effects from the simplification of hydrological systems in the OHBV model, but error correction is only based on the statistics of the input forecast. Error correction is a

quick and relative simple way to improve the forecast, but as any “quick fix” it has its limitations, and can only improve forecasts some. The findings can result in further development of error correction and improve the prediction of runoff. Error correction can also be used in other fields, as long as the data used have statistical probabilities that can be exploited.

Preface

This master thesis is submitted in partial fulfillment of the requirements for the degree “Master of Science in Information and Communication Technology” at the University of Agder, Faculty of Engineering and Science. This project was proposed by Agder Energi A/S, and carried out under the supervision of the external contacts Bernt Viggo Matheussen and Jarand Røynstrand at Agder Energi A/S, and Associate Professor Ole-Christoffer Granmo at the University of Agder. The hydrological model application together with runoff and historical meteorological data was provided by Agder Energi A/S.

First of all, we wish to thank Bernt Viggo Matheussen for the inspiration and direction in our thesis. Even though he has been busy with his work, he has helped us in meetings and other times when we have problems or questions. We also wish to thank Professor Ole-Christoffer Granmo for his assistance and inspiration in meetings through the whole project period. At last but not least, we wish to thank Jarand Røynstrand, for his suggestions in our meetings.

Grimstad, May 2010

Karl Kristian Grythe

Yukun Gao

Contents

Uncertainty analysis of hydro-meteorological forecasts 1
Abstract 2
Preface 4
1 Introduction 10
1.1 Background and motivation 10
1.2 Definition of the problems 11
1.3 Previous work 11
1.4 Claims 12
1.5 Research approach 12
1.6 Contribution 14
1.7 Assumptions and limitations 15
1.8 Geographic study area 16
1.8 Target audience 17
1.9 Report outline 18
2 Meteorological and hydrological forecasting system 19
2.1 Introduction to hydrological forecasting (HBV model) 19
2.1.1 Brief concept of hydrological forecasting 19
2.1.2 HBV model 22
2.2 Meteorological forecasting systems (EC, GFS) 24
2.2.1 European Center 24
2.2.2 Global Forecasting System 24
3 Uncertainties study in meteorological forecasting system 25
3.1 Introduction of OHBV model in Skjerka 25
3.1.1 The weather stations near and inside the catchment 25
3.1.2 Selecting and comparing data from the OHBV model 25
3.2 Uncertainties in precipitation and air temperature forecasts 26
3.2.1 Uncertainties in precipitation 26
3.2.2 Distribution of uncertainties in air temperature 32

3.2.3 Precipitation error of days with > 1mm observed. 37
3.3 Conclusions of weather forecasting uncertainties in Skjerka 39
4 Uncertainty study of inflow forecasting 40
4.1 Study of OHBV model predictions 40
4.1.1 Error distribution of the predictions ran with forecasting meteorological data 40
4.1.2 Error distribution of the predictions run with observed meteorological data 41
4.2 Improvements study 43
4.2.1 Definition of improvement 43
4.2.2 Formula of the Uncertainty on OHBV model 43
4.2.3 Quantify the improvements from observed meteorological data 46
4.2.4 Discussion 47
5 Error corrections of the HBV predictions 48
5.1 Error in original HBV model 48
5.2 Powell Algorithm 51
5.2.1 Formula of Powell Algorithm 51
5.2.2 Data selection 52
5.2.3 Distributions of the uncertainties of the predictions after Powell algorithm 53
5.2.4 Improvements study of the predictions after Powell 56
5.2.5 Error correction conclusions 57
5.3 Yukun&Karl Algorithm 58
5.3.2 Formula of Yukun&Karl algorithm 59
5.3.3 Improvements study of the predictions after Yukun&Karl algorithm 61
5.4 Comparisons of Powell algorithm and Yukun&Karl algorithm 62
5.5 Conclusions on error correction 67
6 Overall conclusions and further work 68
7: Sources/links 69
8: Appendix 70
8.1: DIV ABREVIATIONS in report and files 70
8.2 Powel error Prediction (Document from Agder Energy A/S) 71

Figure List

Figure 1. Catchment illustration 16
Figure 2. Weighted height bands 17
Figure 3. The water cycle 19
Figure 4. HBV model structure 22
Figure 5. Average precipitation error with days at Juvann weather station 26
Figure 6. Juvann precipitation 27
Figure 7. Precipitation distribution 28
Figure 8. Precipitation error 1-10 day common distribution 29
Figure 9. Precipitation error curve 30
Figure 10. Juvann precipitation error and the standard deviation of error. 31
Figure 11. Temperature curves at Juvann. 32
Figure 12. Temperature error distributions at Juvann. 33
Figure 13. Combined temperature error distribution Juvann 34
Figure 14. Temperature error curves at Juvann. 35
Figure 15. Average absolute error, mean error, and standard deviation of temperature error at Juvann. 36
Figure 16. 1 Day ahead precipitation error. 37
Figure 17. 5 Days ahead precipitation error 38
Figure 18. 10 days precipitation 39
Figure 19. Error in OHBV predictions, run with forecasted weather data 40
Figure 20. Error in OHBV predictions, run with observation weather data 41
Figure 21. Improvement def: Distance weighted value 43
Figure 22. Improvement def: Ideal prediction 44
Figure 23. Improvement def: Four realistic situations 45
Figure 24. OHBV Improvement from observation input 46
Figure 25. Mean OHBV error improvement from using weather observation as input 47
Figure 26. Historical OHBV forecast, stream flow runoff and error. 48
Figure 27. OHBV historical properties: Correct the error from the day before 49
Figure 28. OHBV historical properties: Multiplying with a factor 50
Figure 29. OHBV Error after Powel with a=0.2 53
Figure 30. OHBV Error after Powel with a=0.5 54
Figure 31. OHBV Error after Powel with a=0.8 55
Figure 32. Error in OHBV and after Powel (0.2,0.5,0.8) 56
Figure 33. Powel with the best of the parameter selected 57
Figure 34. ATAN function 59
Figure 35. Amplifying function 60

Figure 36. Yukun&Karl Algorithm Improvement distributions.. 61
Figure 37. Yukun&Karl versus original OHBV forecast. 62
Figure 38. Comparison of OHBV error corrections.. 63
Figure 39. 1 Day OHBV runoff with error correction... 64
Figure 40. 5 Day OHBV runoff with correction... 65
Figure 41. Yukun&Karl algorithm with poorly chosen parameters... 66

Table List

Table 1. Average mean and standard deviation of OHBV forecast error............................... 41
Table 2. OHBV errors and by using forecast and observation data as input, respectively. 42
Table 3. Example of data file with OHBV calculated runoff and error values......................... 44
Table 4. OHBV improvement from using weather observation data as input........................ 46

1 Introduction

1.1 Background and motivation

In the Nordic countries, there is a rich fresh water resource in mountains, which can be used for power production. The electricity power grid in the Nordic countries connects across borders and ties all the member countries together. Companies involved in electricity trading, can buy and sell power in the great public grid. The electricity price is basically decided by supply and demand, which means the price is always changing. The companies wish to sell the electricity for the highest price possible. For a hydroelectric power station, having enough capacity of water at that moment, to be able to produce power is very important. But the question is not as simple as just storing as much water as possible, because, the capacity of a reservoir is limited. If the reservoir is full, and at that moment, runoff is coming, then the company may lose production. The predicted power production can be sold in advance to ensure a stable supply of power.

To solve these many issues, there have been developed hydrological forecasting systems to predict the stream flow that enter the reservoir. This is a difficult and error-prone task, partly because of the inaccuracies in the hydrological models themselves, but also because the models to a large degree are fed with input that is noisy, such as meteorological forecasts. A hydrological forecasting system requires good meteorological data to calculate the stream flow, so both hydrological and meteorological systems are necessary to complete the forecasting task.

1.2 Definition of the problems

Daily hydrologic forecasts of river stream flow are of major importance in hydropower scheduling. Typically, the forecasts are produced by forcing weather data (precipitation and air temperature) into a hydrological model that calculates the stream flow response. The quality of the stream flow forecasts is dependent on errors in the weather predictions, model parameters, model structure and historical observations of precipitation, air temperature and stream flow. If we are to improve the forecasting quality it is important to understand and quantify the various sources of uncertainty in the forecasting methodology.

The objective of this master thesis is to identify and quantify the sources of uncertainty in a hydro-meteorological forecasting system. Based on the findings from the analysis a method for reduction of uncertainty in the forecasts will be proposed.

1.3 Previous work

Numerous scientists around the world are constantly working on improving forecast methods within the meteorological and hydrological sciences. The stream flow forecast uncertainty is due to several sources: uncertainty in forecasted input data, for instance, calibrated precipitation and air temperature, uncertainties in internal states in the hydrological model, uncertainty in model parameters, observation measurement error and errors in the hydrological model structure. [1] To correct the prediction error, there are also many mathematic methods, e.g. Powel algorithm. [2]

1.4 Claims

Our claims:

1) The main cause of error in the runoff forecast lies in the hydrological model, secondly the error comes from the weather forecast.
2) An improvement in the size on 2-7m^3 can come from improving the weather forecast, mainly when getting further ahead in the forecast.
3) Our findings suggest that error correction cause general improvements and should be implemented especially in the first 5 days forecast.
4) The existing Powel algorithm performs positively, but does not improve after day 5, so it should only be used to correct the first 5 days.
5) The proposed algorithm called "Yukun&Karl" improves more than the Powel algorithm in the first days, and also extends the improvement period up until day 8. In the last two days (9 and 10), the uncertainty is quite big and it is very hard to correct it statistically.

1.5 Research approach

To quantify uncertainty in precipitation and air temperature forecasts, we look up the precipitation and air temperature information from the meteorological forecasting data. We take the temperature forecast and subtract the temperature observation and put the errors of the first (second, third: etc.) day together in one vector, and then study the distributions. Afterwards, we do the same thing with precipitation data. ("First day" from here means 1 day ahead in the forecast, since we do not focus on single values, only assemblies of forecasts with same distance in time according to the last known observation at that time)

To quantify uncertainty in inflow forecasts, we first run the OHBV model with observed meteorological data (feed the model with observed precipitation and air temperature), then rerun the model with forecasted meteorological data. Secondly, we subtract the observed runoff from the forecast to find the error values. Then we study the distribution of these error values. Afterwards, we define the term "improvement", which is the absolute value of forecasting error minus the absolute value of observation error". Eventually, we study the improvement of the error. How large the improvement is, show how much uncertainty could be reduced from weather forecasting system.

To study and test the Powel algorithm, we compute the prediction by following the Powel calculation steps. Then we put the prediction together with observed runoff in Figure 32, to compare them.

After testing the Powel algorithm, we propose our own error correction algorithm. The corrected predictions are calculated and added to the Powel performance figure, to show the comparison of the result from the two methods in Figure 38.

The individual steps:

1. Give a short presentation of a hydrological forecasting system.

2. Give a short presentation of the various types of short range (1-15 days) of meteorological forecasting system.

3. Quantify uncertainty in precipitation and air temperature forecasts.

   a) Compare historical weather predictions against real observations of precipitation and air temperature.
   b) Study the statistical distributions of the error found in (a).

4. Quantify uncertainty in inflow forecasts.

   a) Rerun historical stream flow forecasts with historical weather predictions. Quantify uncertainty by comparing forecasts and real stream flow observations.
   b) Rerun historical stream flow forecasts with real observations of precipitation and air temperature. Quantify uncertainty by comparing forecasts and real stream flow observations.
   c) Compare the statistical distributions of the uncertainty found in (a) and (b).

5. Study and test the existing error correction, Powell algorithm.

6. Propose a new error correction algorithm.

1.6 Contribution

Our work is consisting of analyzing error in both meteorological and hydrological models by using the computational tools in Matlab. We have also tested the existing Powel error correction algorithm on the OHBV predictions. A new mathematic method has been proposed by us, and it is tested to be useful in terms of the error correction. It is improving further ahead in the forecasts and also better than the Powel, even when running Powel error correction several times with different parameter “a” and using the best of the values. Another contribution is clarifying the sources of uncertainty, and also quantifying the level of uncertainty in both meteorological and hydrological models. In addition testing the performance of the Powel method and developing our own correction method. The results could contribute to further research, as well as practical implementations in hydrological systems reducing the error, and clarifying the main sources of uncertainty.

1.7 Assumptions and limitations

Comments according to the original objectives: Due to limitations in the dataset the objective concerning seasonal variations, had to be dropped. It was also originally intended to study assembly weather forecast, but together with Agder Energy AS it was decided to rather focus on the 10 days (short time) weather forecasts.)

Originally we had had data for from 4th, May, 2009 until 31st, January, 2010. Unfortunately there where periods of data missing, so the weather forecast and HBV forecast is run on data in the period of June, July, August and September of 2009. In other words summer conditions, where results are not influenced by frost and snow accumulation. Snowmelt is considered relatively small, and has not been a main focus. The forecast and observation data are provided by Agder Energy A/S and the results apply to a possible practical implementation.

There are only 52 days with more than 1mm precipitation in the 4 months period, and therefore some of the figures are affected by noise.

Due to poor performance of the HBV model in middle of the period (precisely from the 6th of July 2009 to 21st of August), we have decided to run the error correction analyze without this part.

1.8 Geographic study area

The study area in our project is described as a Catchment where the HBV model is applied. It is located up Mandal River in the southern part of Norway. The name of the catchment is “Skjerka”.

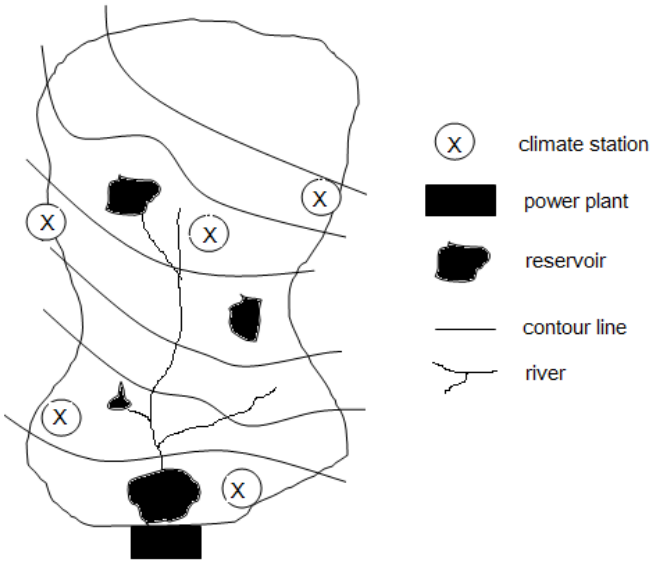

Figure 1. Catchment illustration

Figure 1. Illustrates a catchment (in our case Skjerka). A catchment is a closed area, and the area is then divided into 10 elevation bands. The climate stations are in and around the catchment at different height in terrain (within a corresponding band), and provide the observation data to compare with the weather forecasts. The stream flow (water runoff) may take different paths (and depths in the ground), before it generally pour into the rivers and end up in the reservoir. Then the power plant uses the runoff to produce electricity.

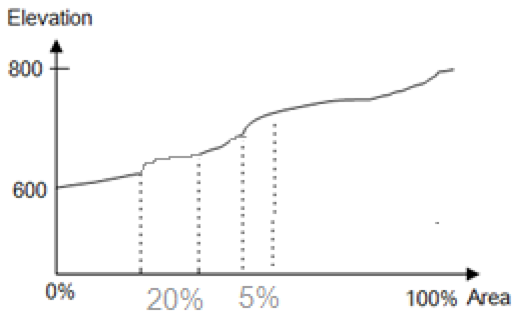

Figure 2. Weighted height bands

The 10 bands are weighted in percentage of the total area, and are involved in the runoff calculation in OHBV model. Each band will have the same number of height meters from top to bottom, but will therefore have a different sized area (weight in % compared to the total area). One reason for this is the temperature decrease when moving higher in the mountains. The elevation of Skjerka catchment area is from 600 M to 800 M.

1.8 Target audience

The target audience of this thesis is mainly teachers and students in academia, as well as engineers working in the hydro power industry.

1.9 Report outline

The first chapter covers the introduction, while in chapter 2. "Introduction of meteorological and hydrological forecasting system", it is first given a presentation of two meteorological forecasting system, European Center (EC), and Global Forecasting System in USA (GFS). Then the hydrological model which is applied for the Nordic countries, called the "HBV model" is introduced. We also mention the actual implementation called "OHBV model" used by Ager Energi A/S (and which is therefore also the model used in our thesis.) In chapter 3, "Uncertainties study in meteorological forecasting system", the objective is to quantify the uncertainty of using meteorological data which comes from the meteorological forecasting system "European Center". The uncertainty study will focus on two aspects: the air temperature and precipitation.

In chapter 4, "Uncertainty study of inflow forecasting", we use observed and forecasted meteorological data separately as input into the OHBV model, and then comparing the two outputs to quantify the uncertainty. In addition, we give a conclusion to the OHBV model performance. In chapter 5, "Error corrections of the HBV predictions", we first test the existing error correction method called "Powell algorithm". It is interesting to identify how much improvement it can make, and use that as a benchmark to compare our developed method with. Then we will present the new error correction method called "Yukun&Karl" algorithm, and compare the new algorithm to the existing one. We need to identify the advantages and disadvantages of these two algorithms, and finally give a conclusion to our overall findings.

2 Meteorological and hydrological forecasting system

2.1 Introduction to hydrological forecasting (HBV model)

2.1.1 Brief concept of hydrological forecasting

Hydrology is the study of the movement, distribution, and quality of water throughout Earth, and thus addresses both the hydrologic cycle and water resources. [3] The water cycle, also known as the hydrologic cycle, describes the continuous movement of water on, above and below the surface of the Earth. [4] Water resources are described as the resources of water that can potentially be used by humans.

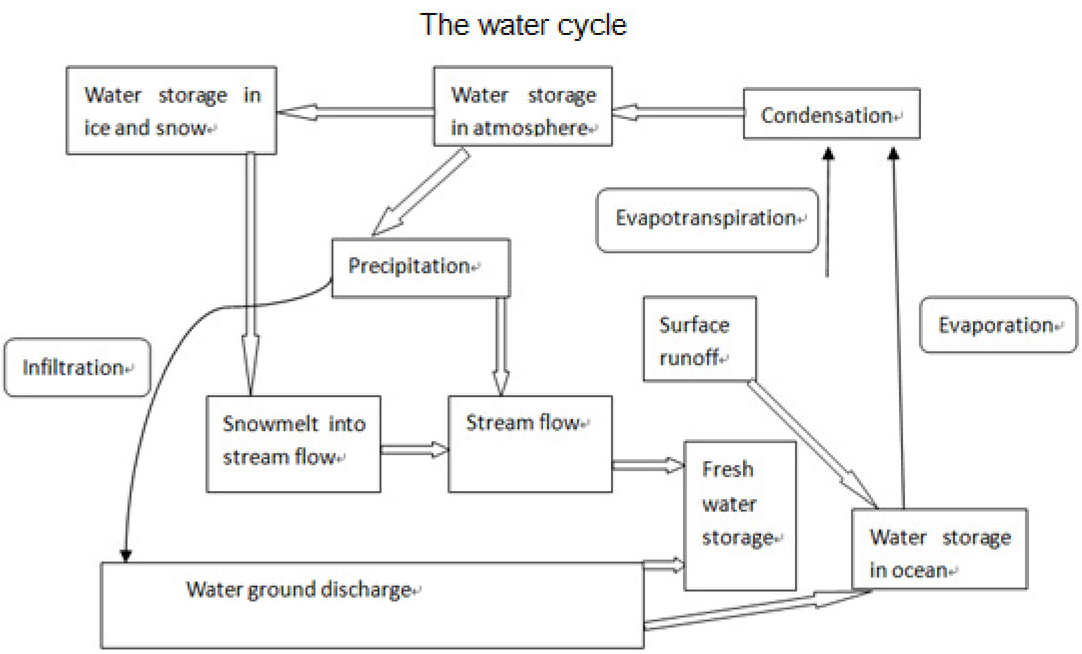

Figure 3. The water cycle

In the Figure 3, the sun, it provides almost all the energy to the Earth, drives the movement of water. The water is heated by the sun, and then evaporates as water vapor into the air. The water can also be transpired by plants, which is called Evapotranspiration (ET). Snow and ice can sublimate into the air even in low temperatures. The water vapor is rising into the atmosphere, and then cooled down and condensed into clouds. The water contained in the clouds then move, and finally falls down from the sky as precipitation. Precipitation can fall as snow, rain, hail, etc, part of the precipitation falls back into the oceans. Snow can be accumulated as ice caps, glaciers and snow packs. Ice caps and glaciers can store ice for thousands of years. Snow packs will start to melt when the average air temperature is above zero degrees. When the water flows over the ground as surface runoff, a portion of the runoff enters rivers, which move water towards lakes or oceans. Ground water can come up in springs if there is sufficient fall in the terrain. Together with the runoff the spring water is stored as fresh water in lakes, which could be used for electricity production. But not all the runoff goes into the rivers, some water infiltrates deep into the ground and stays there for long time or discharges into the oceans. In an enclosed mountain catchment though, most of the water will at one time enter the stream.

Hydrologic forecasting is used to forecast the hydrologic status in the future based on the observations in the past combined with weather forecasts, by using analysis and mathematical statistic methods. Usually, the forecasting in two weeks is called mid-term; while prediction above fifteen days is called long-term forecasting. The content of hydrologic forecasting includes the volume of runoff, water stage, ice condition, trends of flood or draught, etc. In our project, we are interested in the volume of runoff, which decides the water level in the reservoirs. This is because stream flow runoff is most the critical factor influencing the electricity production.

Many forecasting systems are established in the world today by using different models. They have different complexity and accuracy, but together they complete the tasks of hydrologic forecasting. Basically, the hydrological forecasting system is created to find out how much water is coming at each moment in time. Hydrological measurements are the methods to measure the precipitation (rain fall and snow fall, etc), evaporation, soil moisture, river flow, groundwater, water quality, and so on. The hydrological analysis consists of precipitation analysis, evaporation calculations, river flow analysis, rainfall-runoff relationships, etc. And the engineering applications cover the usage of hydrological forecasting systems, for instance, flood routing and water resources management.

Usually, the mountain regions are the main distributions to the water cycle as well as of complex meteorological patterns. In terms of their role as “water towers", mountain regions form an important supply of fresh water to the lowlands. [5]

Many hydro-geological surveys are provided by hydropower development in Norway (Håland and Faugli among others). [6] In Nordic countries, snow is a decisive factor affecting hydrologic forecasting system and it plays a vital role in the water resources in many parts of the world. Snow cover is a major component of water storage, and changes in its extent, depth, and snow-water equivalent will have an impact on the runoff in mountain areas.

Another important factor affecting snow accumulation is wind. Strong winds in winter affect both snow depth and distribution which affect the snow-water equivalent. The snow packs in shadow will last longer than those directly affected by the suns radiation. The melting water can stay in surface soil. The surface soil moisture and the exchange of heat and moisture between the land surface and the atmosphere are of very importance in Hydrological forecasting system.

The evaporation process consists of two main consecutive stages. In the first stage, when the soil is wet and conductive enough to supply water at a rate to evaporation, the evaporation is limited by external meteorological conditions. During the second stage, the evaporation rate is limited by the rate of moisture delivery from the soil toward the evaporation zone. [7] In the reverse direction, the water can infiltrate down deep into the ground where the water may stay for a long time.

2.1.2 HBV model

The HBV model was developed in Scandinavia to analyze river discharge. This was the first major application of HBV, and it has since gone through much refinement. "It comprises the following routines: Snow routine, Soil moisture routine, Response function, Routing routine."[8]

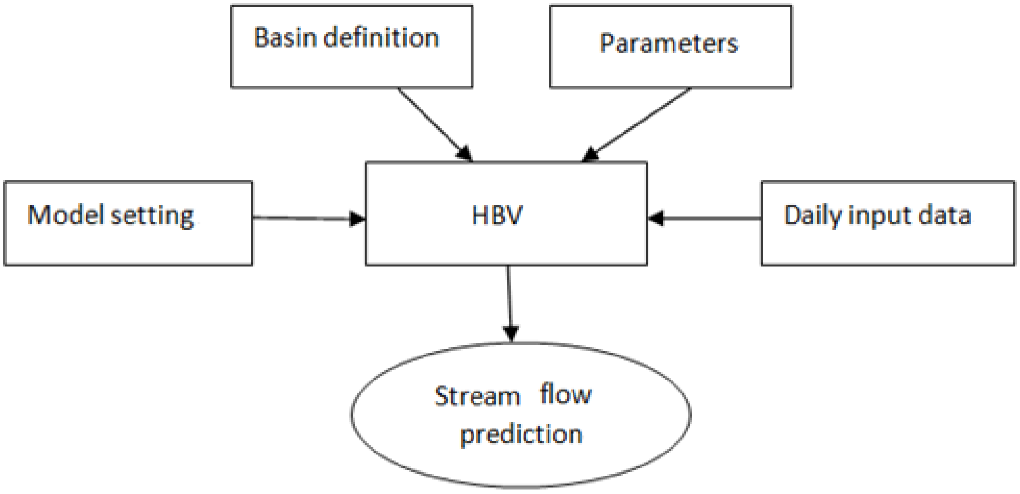

Figure 4. HBV model structure

In the Figure 4, the definition of a catchment is a closed area of mountains. At the edge of the catchment, all the water will go to different streams due to the elevation, but for those streams inside the border all the water will generally go to one main stream or reservoir. In the HBV model, many factors in mass balance are involved as a simplification of the water cycle, for example, ET, rainfall, runoff, and so on. The HBV model catchment definition describes the catchment, and it can describe the size, height and properties like delay etc. Daily input data is air temperature and precipitation which come from weather forecasting centers. There are several states and parameters used to compute the discharge. If a good performance is expected, then the parameters and states are supposed to be optimized.

The HBV model is a precipitation runoff model, which includes several important parameters. The general water balance in HBV model can be described as:

$$P - E - Q = \frac{d}{dt}\left[SP + SM + UZ + LZ + lakes\right]$$

HBV prediction calculation formula

[9]

Where:

P = precipitation
E = evapotranspiration
Q = runoff
SP = snow pack
SM = soil moisture
UZ = upper groundwater zone
LZ =lower groundwater zone
lakes = lake volume

Usually, several elevation bands are used together in the HBV model. Each catchment is divided into zones according to altitude, lake area and vegetation and so on. The model is normally run on daily values of rainfall and air temperature, and daily or monthly estimates of potential evaporation. Input data are precipitation, air temperature and estimates of potential evapotranspiration.

As mentioned there are close links between meteorology and hydrology, because the HBV model needs predictions of temperature and precipitation for simulations. Furthermore, at the regional scale, the exchange of moisture and heat between the land surface and the atmosphere determines the low level atmospheric humidity and temperature fields, which in turn has an impact on regional weather and climate. [10]

2.2 Meteorological forecasting systems (EC, GFS)

2.2.1 European Center

European Centre is an international organization supported by 31 countries in Europe. The principal objectives of the Centre are: first off, the development of numerical methods for medium range weather forecasting; second off, the preparation, on a regular basis, of medium range weather forecasts for distribution to the meteorological services of the member states; third off, scientific and technical research directed at the improvement of these forecasts; eventually, collect and store appropriate meteorological data.

EC provides operational medium range and extended range forecasts. In addition, the EC makes available a proportion of its computing facilities to its member states for their research; and assists in implementing the programs of the World Meteorological Organization; provides advanced training to the scientific staff of the Member States in the field of numerical weather prediction; makes the data in its extensive archives available to outside bodies. [11]

EC's forecast products include medium range forecast, ocean wave forecast, monthly forecast, seasonal forecast, ocean analysis, monitoring of the observing system. The member countries can order real-time data and predicted data from the EC. Besides, the center also provides weather forecast for normal customers such as daily weather prediction. In the medium range forecast, EC operates a deterministic forecasting system providing weather predictions for 10 days. "It comprises a 4-dimensional variation data assimilation system (4D-Var), the high resolution global model and the 51 member Ensemble Prediction System (EPS) at 40 km resolution." [12] EC's forecasts are used in this thesis.

2.2.2 Global Forecasting System

The Global Forecast System (GFS) is a global numerical weather prediction computer model run by NOAA with worldwide probability of precipitation forecast and climate. [13] This mathematical model is run four times a day and produces forecasts for up to 15 days in advance, but with decreasing accuracy over time. Hence, in hydrological forecast, it is widely accepted that prediction beyond one week is not very exact. The first 7 days are run in more detail, while the 8-15 days forecast is more accurate. [14]

This is the only global model for which all output is available, for free use over the internet (as a result of U.S. law), and therefore is the basis for smaller private weather companies. The predictions are ensemble data based on the probability of precipitation. The GFS is not used in this thesis, and is only mentioned as a reference of another forecasting system.

3 Uncertainties study in meteorological forecasting system

3.1 Introduction of OHBV model in Skjerka

3.1.1 The weather stations near and inside the catchment

In the Skjerka catchment the weather forecast is compared with the 6 meteorological measuring stations. They are named after the closest place or lake. There is Juvann, Langevann, Navann, Orevann, Sjavasskn and Storevatn.

One important thing to remember, is that the weather forecasting positions in Skjerka is not necessarily identical with the weather measuring positions or representative as an average for the area. We have chosen to compare with the weather forecast for each station based on geographic coordinates, but there could be local variations in height above sea level etc. Therefore some calibration is needed, and the meteorological data which is used as input into OHBV model is not exactly as the local conditions even with a good forecast for that position. Due to this situation, some extra uncertainty is added to the meteorological forecasting data.

3.1.2 Selecting and comparing data from the OHBV model

Comparing forecast data with observation: To avoid using a day with high runoff and high error only in some of the forecast, we decided to compare the data a little differently than what was the original plan. Now we use the forecasts for the first 10 days as input only, but do not compare with the observation values of those days, even though they exist. (In the beginning of the period these values come from the last 10 days of the previous month) This way it is also easier to plot the curves under each other since all the observation dates used in the comparison have 10 corresponding forecast errors.

3.2 Uncertainties in precipitation and air temperature forecasts

3.2.1 Uncertainties in precipitation

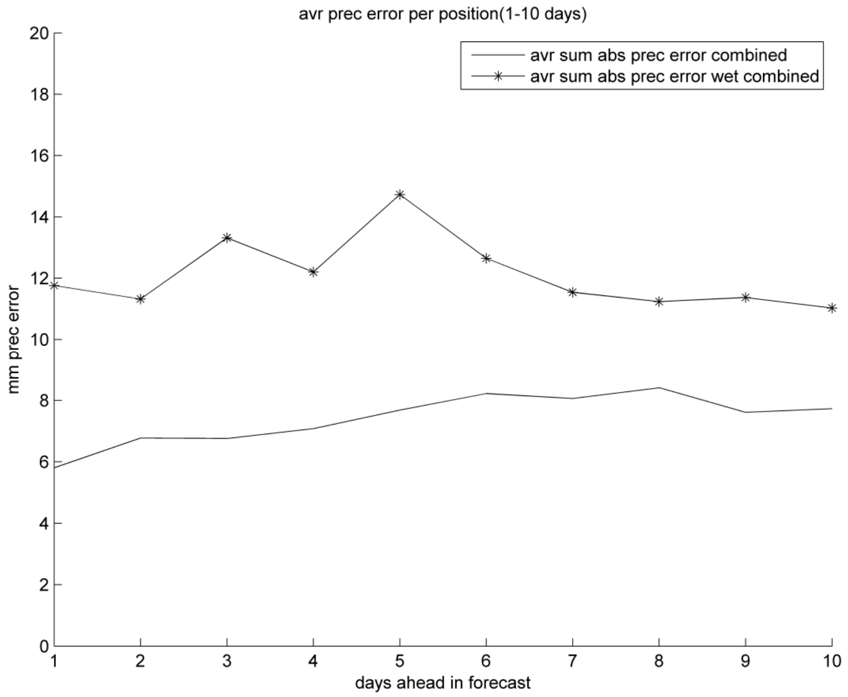

Figure 5. Average precipitation error with days at Juvann weather station.

There are only 52 wet days in the period and the precipitation error for wet days is over 1 mm in average, but the period is relatively short. It is simple to calculate the “standard error” which is a measure of how accurate the results are. You divide the standard deviation with the square root of “n” number of independent samples. Our 52 wet days are not entirely independent, since there is a higher possibility to get the same conditions at one day in time as the previous (say it starts to rain in the evening continuing into next day, or raining several days after each other). So we will have a somewhat higher actual “standard error” than we calculate. The average standard deviation is about 11, but we use 12 since want to find the worst case. 12mm/square root (52 days) = 1,67mm. This explains the errors in the top curve which is very much affected by noise. The lowest curve showing wet days include more values and is therefore less affected by noise, since the standard error calculation include the number of samples under the divider. Worst case standard error then is: 8mm/square root (122 days) = 0.72. Similar noise is not so present in the HBV model output, except for a slightly lower error in day 10 than in day 9(namely 7.32 m^3/s and 7.26 m^3/s).

Figure 5. Shows error in precipitation forecasts averaged over the 4 measure positions in the catchment. The highest curve marks the days with more than 1 mm precipitation, while the

lowest includes all the days in the period. Since we have a relative small area, both forecasts and observations are correlated (similar values in all 4 places), so even averaging over 4 positions we get a noisy curve that is close to the ones for the individual places. As mentioned the days with zero precipitation will sometimes give zero error in the forecast, which makes the forecast have a lower average error. The highest curve shows that there is an average of over 10 mm in precipitation error, at days when there is more than 1 mm precipitation. Looking at the lowest curve though it looks more like the error/uncertainty in the forecast is rising with number of days ahead in forecast, which is what we naturally expect to find given the fact that it is harder to predict further into the future.

Since we had some limitations in the data, giving us a short period and we got some noise in the figures, we decided to just include the figures for the Juvann weather station. There are three other locations also which have measurement of precipitation, and we have also calculated and used those data later to make error distributions, like in chapter 3.2.3 when we investigate the wet days using the data from all the 4 weather stations. (As mentioned the different weather stations are close together they have similar data, and figures.)

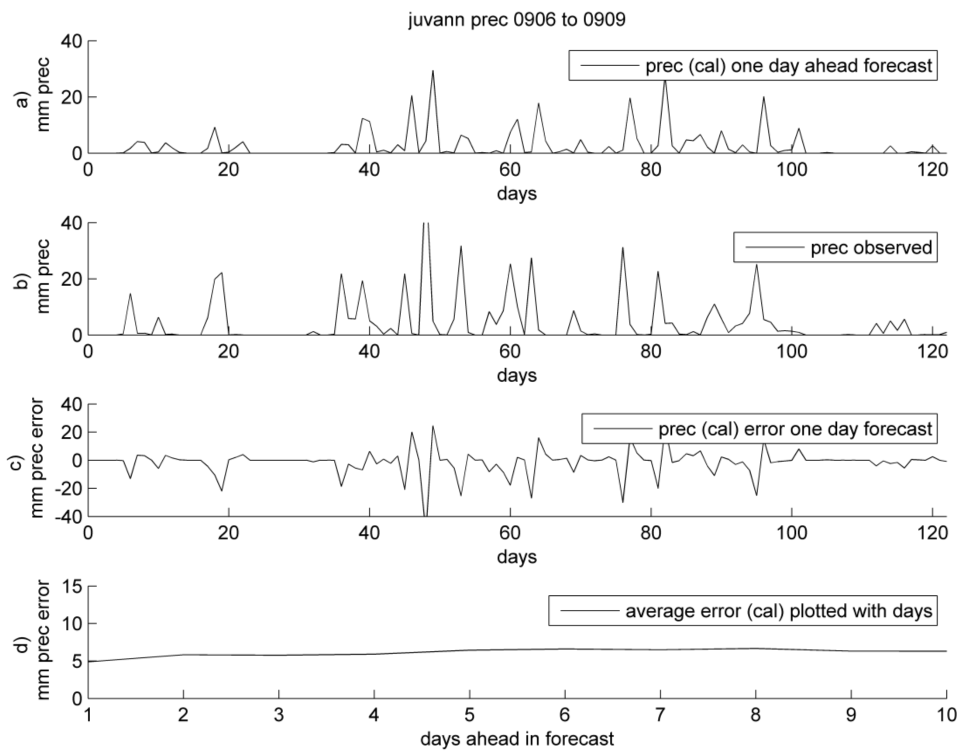

Figure 6. Juvann precipitation

Figure 6.a) shows the calibrated precipitation forecast for Juvann which is a sub basin of Skjerka. Each day have one value of precipitation in mm. In Figure 6.b) we have plotted the corresponding observed precipitation measured in a weather station at the Juvann location. 6.c) shows the error after subtracting observation from forecast. A positive value of error mean that there was an overestimation in the weather forecast that day, and a negative

value then shows underestimation. 6.d) Illustrates the average error which is starting at 5mm for 1 day forecast and slowly increasing. This value is affected by the number of days with precipitation compared to the days with no precipitation, as the size of the error grows in accordance with the size of the runoff.

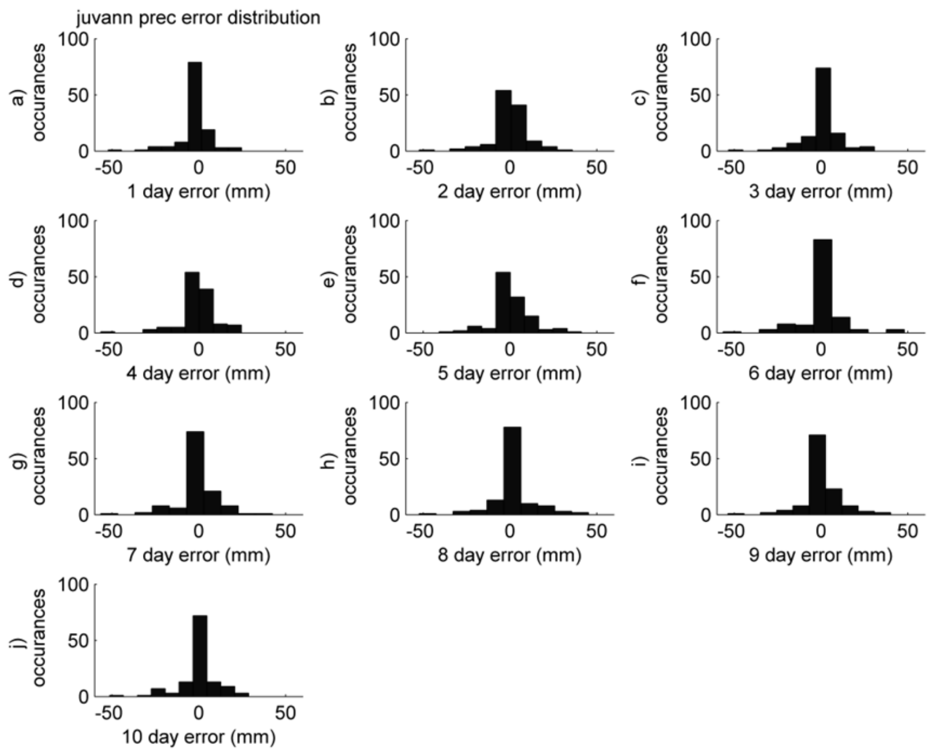

Figure 7. Precipitation distribution

Figure 7.a)-j) Illustrates the precipitation error distribution for Juvann. The standard deviation increases with the number of days ahead in the forecast. (Again the days with little precipitation gives a small error resulting in the peaks at zero.)

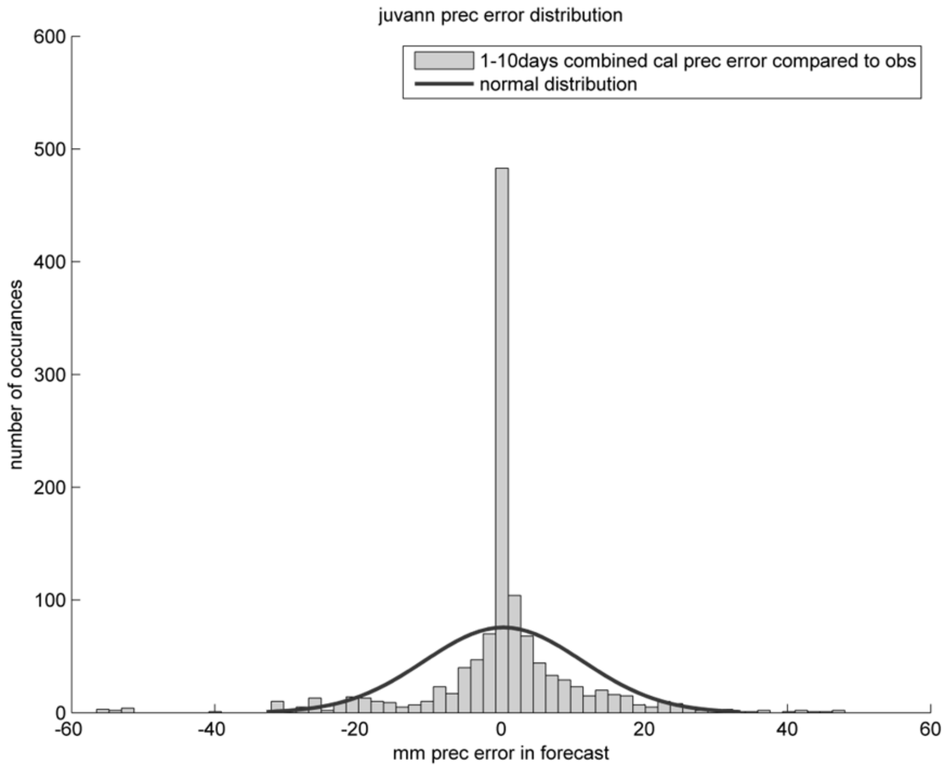

Figure 8. Precipitation error 1-10 day common distribution

Figure 8.shows the common distribution of Figure 7.a)-j) together with the normal distribution. The errors are decreasing moving from 0 towards 30mm. We can get an impression of overall the error size.

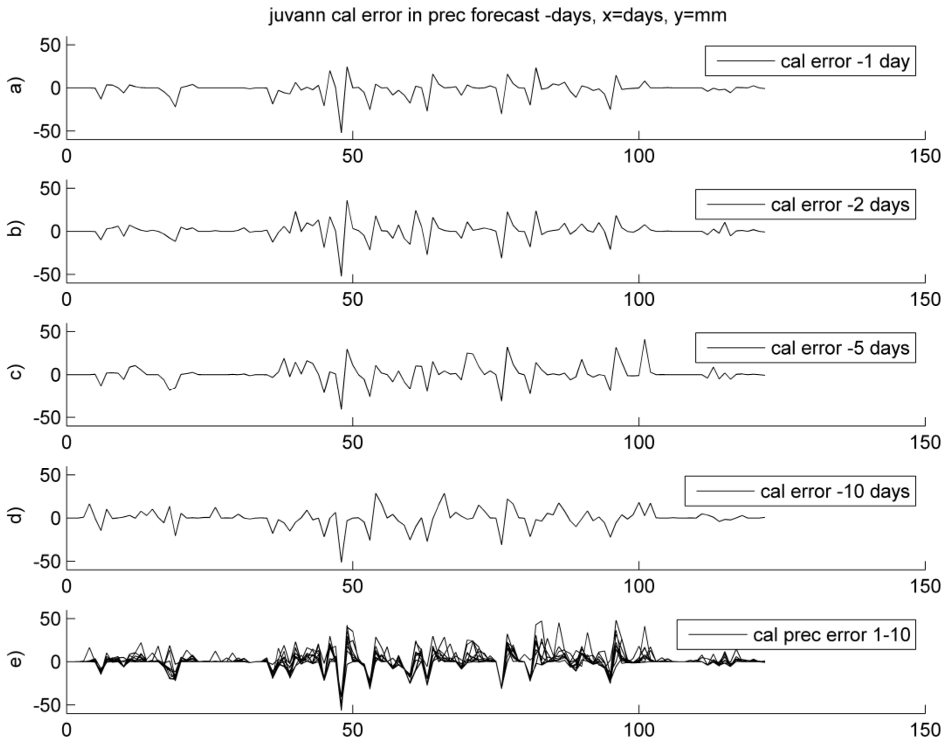

Figure 9. Precipitation error curve

In Figure 9, the precipitation error curves are shown for some of the ten different forecast lengths (1, 2, 3, 5 and 10 days forecast) at Juvann. The forecast error vary some as time goes by from 1 day ahead to 10 days ahead, getting larger. Figure 9.a) with curve of 1 day ahead should in theory have an absolute mean error closest to zero, compared with the other days, finally 10.e) show all the curves together giving an impression of how much the forecast error vary in time.

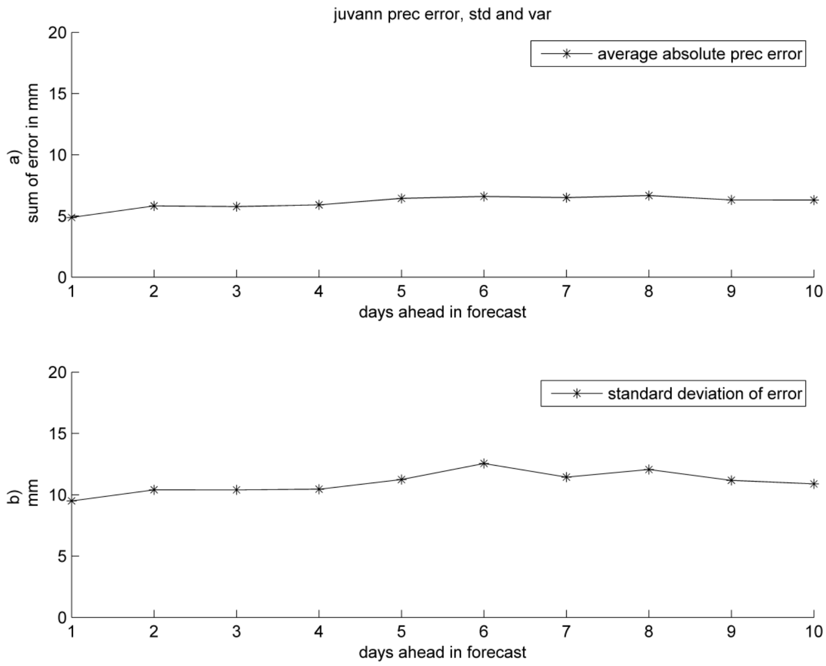

Figure 10. Juvann precipitation error and the standard deviation of error.

Figure 10.a) Illustrates the average absolute precipitation error with days ahead in the forecast, the result show a slow increase in error when further ahead in the forecasts. We also tested the error in uncalibrated forecasts and got similar results with a little bigger error, showing that the calibration is improving the forecast. The measurement error (inaccuracy in measuring precipitation) will have similar influence on the error making the errors larger over all 1-10 day forecasts. Figure 10.b) show the standard deviation that have little change as forecast length increases.

3.2.2 Distribution of uncertainties in air temperature

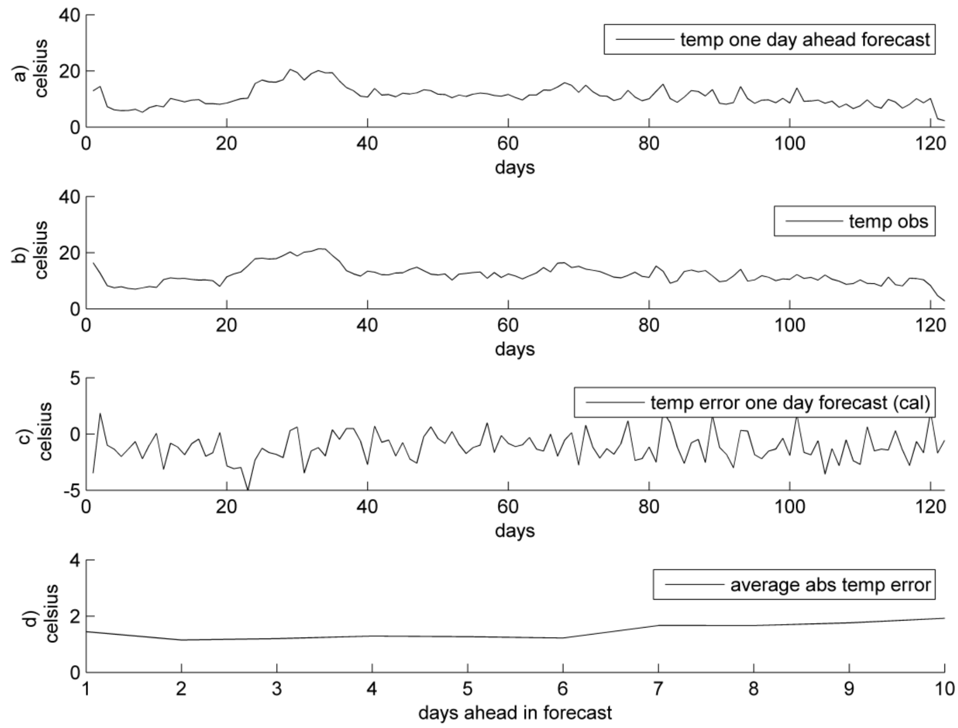

Figure 11. Temperature curves at Juvann.

The temperature forecast in Figure 11.a) show the forecasted temperature in Juvann for each day in the period 06-2009 to 09-2009 represented by one average value per day. The observed temperature in the same period is plotted under in figure 11.b). The error is found by subtracting the observed temperature from the forecast. A positive value of error in the curve in Figure 11.c) shows overestimation in the forecast, while a negative show underestimation. Figure 11.d) illustrate an average error of ca 2 degrees Celsius for the 1-10 days ahead.

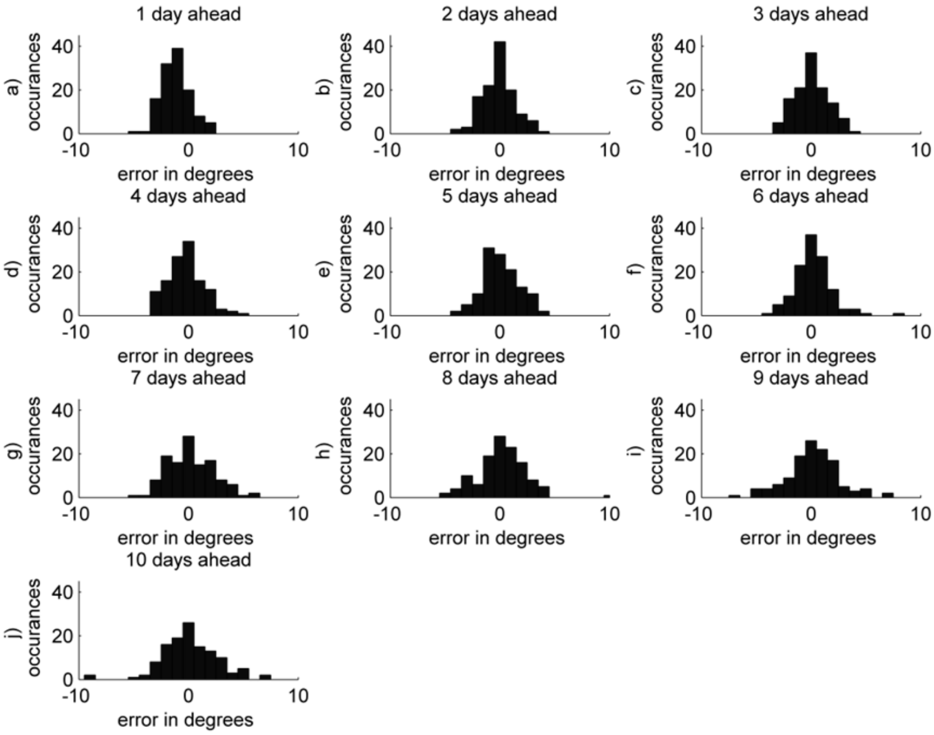

Figure 12. Temperature error distributions at Juvann.

Figure 12. shows the distributions from the curves in Figure 11.c), and because the temperature can get negative, thus the value is always varying. We therefore do not get the same peaks in the distributions as we did from the precipitation distributions. The distributions change little, but as expected the spread is going up as time increases

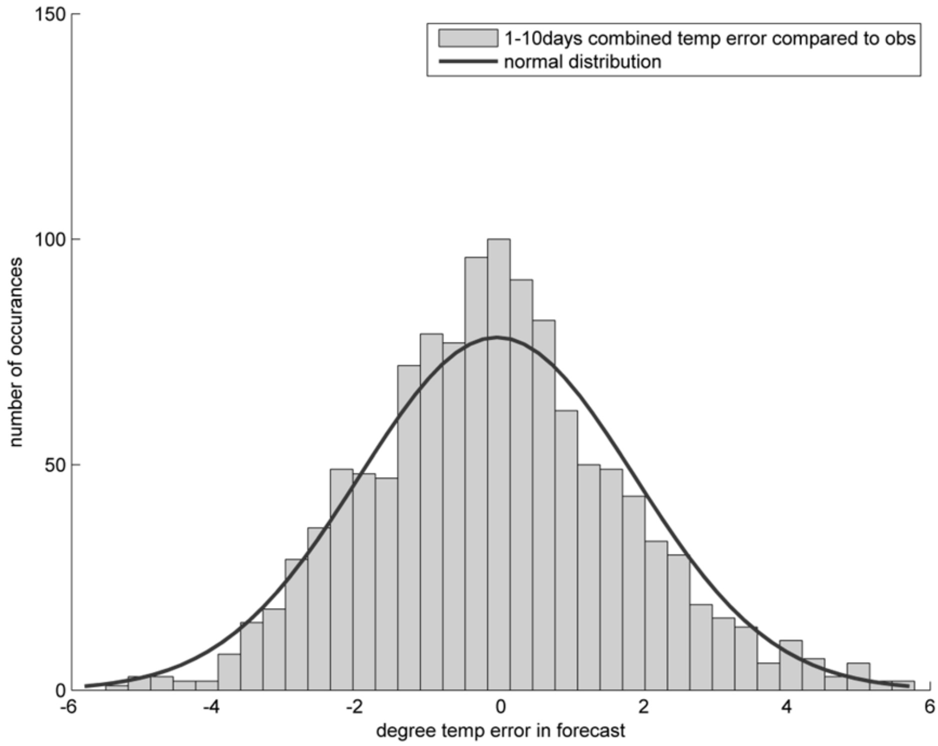

Figure 13. Combined temperature error distribution Juvann

Figure 13.shows the common distribution of figure 12, and the main part of the error in the temperature forecast is smaller than 2.5 degrees. It is possible to see that the error distribution is close to the normal distribution with the mean values close to zero which tell us that the temperature forecast is correctly calibrated.

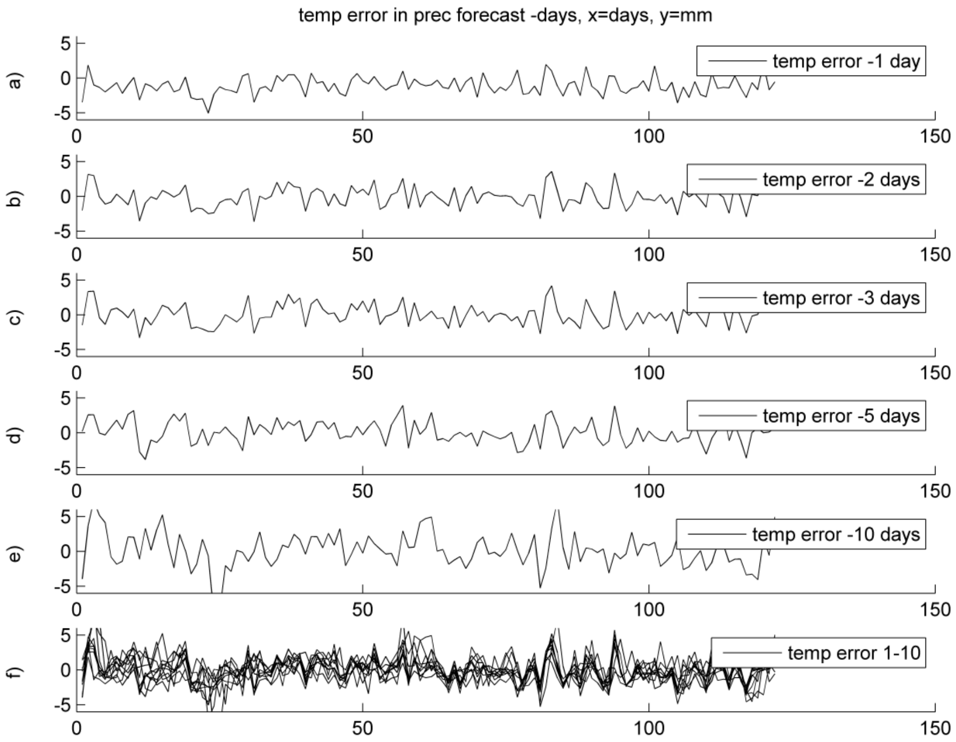

Figure 14. Temperature error curves at Juvann.

Figure 14.a)-e) shows the temperature error curves according to the length in the forecast., while Figure14.f) show the combination of the curves for day 1-10 and the size of the errors increase little. Interestingly one observation is that the temperature forecast varies a lot all the time, more than the precipitation variation changes in time in Figure 9.

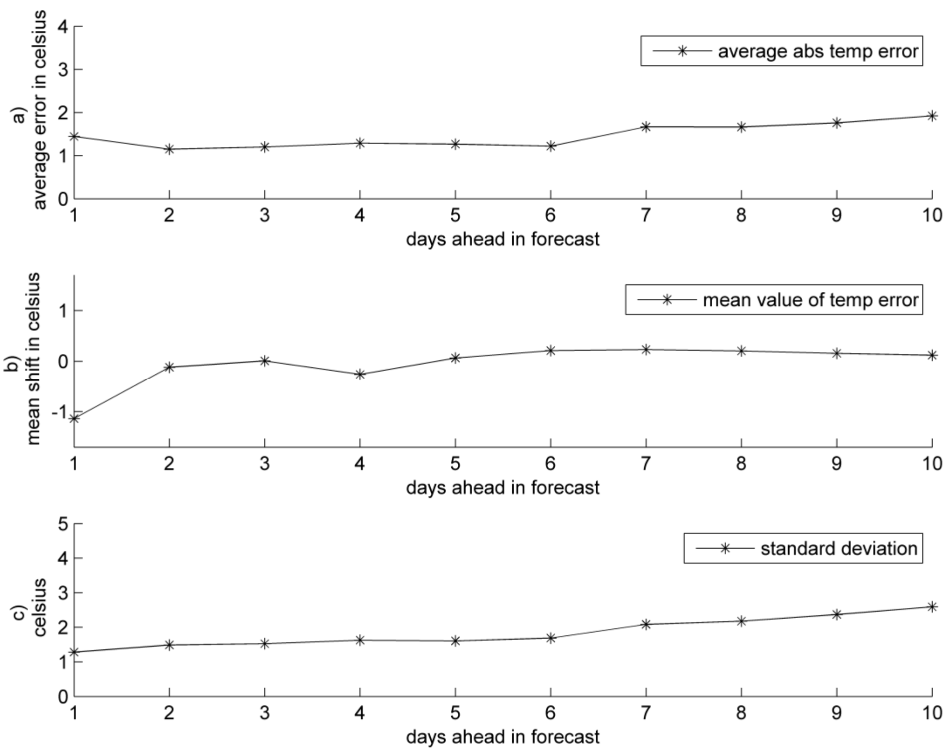

Figure 15. Average absolute error, mean error, and standard deviation of temperature error at Juvann.

In Figure 15.a) the average error in the temperature forecast is rising slightly with days, but stops at ca. 2 degrees Celsius. 15.b) shows the mean of the error which can tell us if there is a general over or underestimation. Except for day 1, the mean error is close to zero. As expected the standard deviation increases with the number of days ahead in the forecast, seen in Figure 15.c).

3.2.3 Precipitation error of days with > 1mm observed.

Wet days = more than 1 mm precipitation, Dry days = more than 1 mm precipitation

We chose to study the precipitation further since it is the most important factor deciding the runoff. (Temperature distributions shown earlier are also very close to normal distribution)

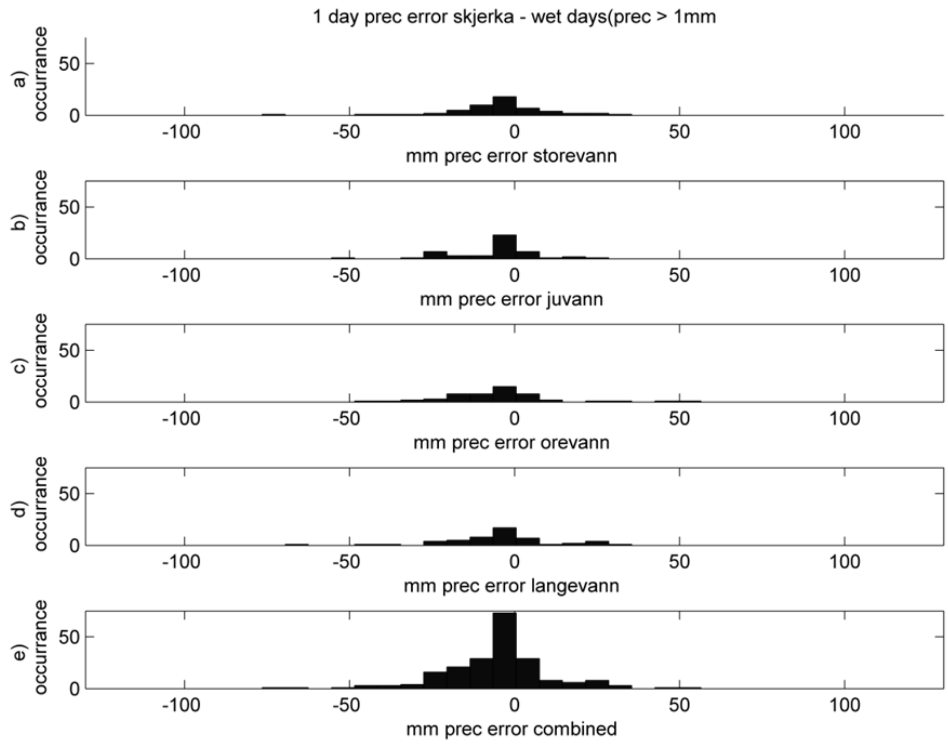

Figure 16. 1 Day ahead precipitation error.

Figure 16.a)-d) shows the precipitations error for the "wet days" (observed precipitation > 1mm) in the four positions in the Skjerka catchment, Storevatn, Juvann, Orevann and Langevann. In the "one day ahead forecast" we find that there is a negative shift or bias in the distribution for the 4 positions combined in Figure 16.e) This negative error("underestimation of rain in summer") could be reduced by using better calibration that increase the forecasts slightly.

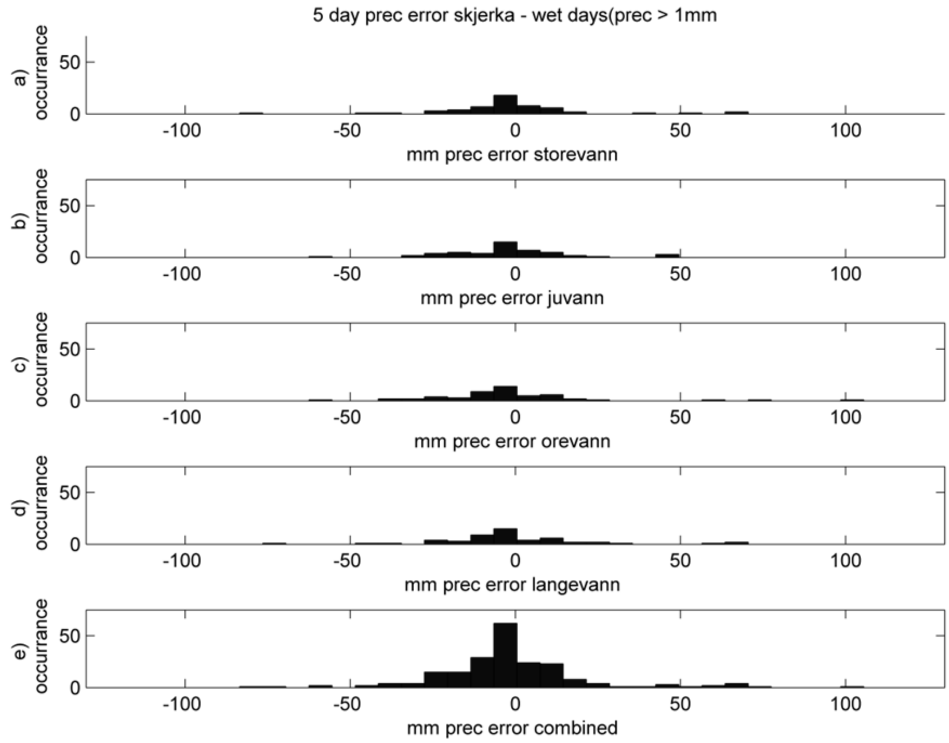

Figure 17. 5 Days ahead precipitation error

In the 5 day forecast in Figure 17.e) we do not find the same underestimation in precipitation forecast. Compared to 16.e) we see a lower bar at zero and a higher spread.

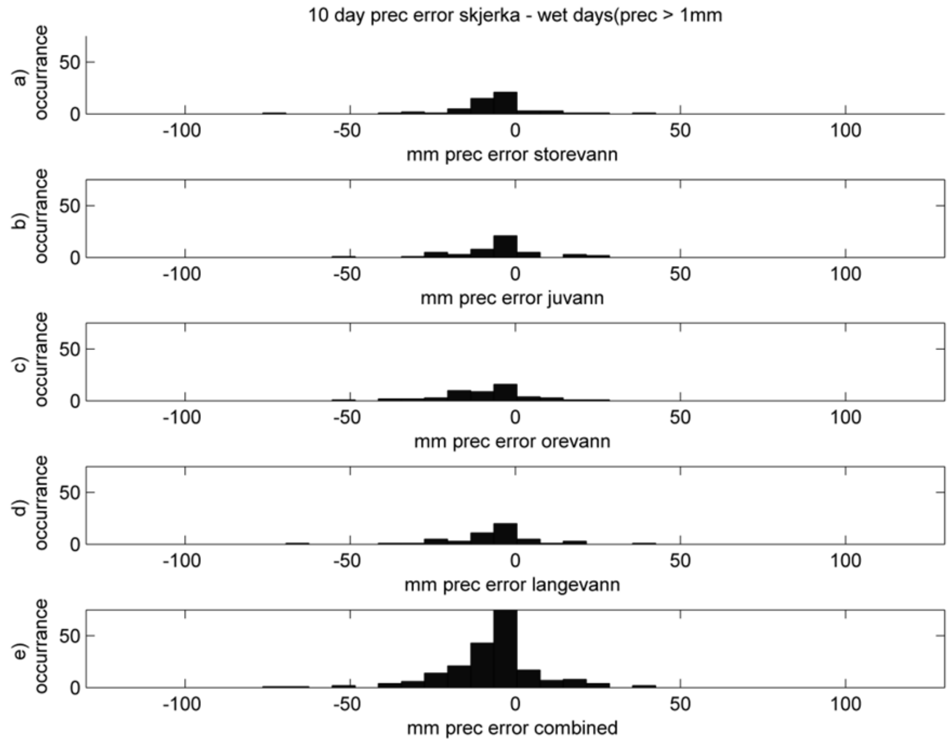

Figure 18. 10 days precipitation

In Figure 18.e) in the 10 day forecast there is again a clear underestimation, since several of the forecast show clear average underestimation of precipitation, this will probably affect the runoff forecast giving an underestimation there also.

3.3 Conclusions of weather forecasting uncertainties in Skjerka

In the summer period the temp error is between zero and 5 degrees, and small enough that we consider it to contribute in little runoff error. The precipitation error for wet days has a high uncertainty, but the underestimation seen in Figure 18. (the 10th day forecast) might be countered with better calibration of weather forecast data. Since the weather forecast always will have error caused by simplification and estimation, and already is very complex there are limitations to the level of improvement. When running the HBV model with observation data it is clear that even then the HBV model still have a high average error. Therefore it is more important to focus on improving the HBV model and the using error correction.

4 Uncertainty study of inflow forecasting

After quantifying the uncertainty from the meteorological forecasting system, we feed these data into the OHBV model, and compare the difference of predictions with forecasting meteorological data and observed one.

4.1 Study of OHBV model predictions

The OHBV model records the hydrological state of the Skjerka in "state values" These values are very important to the runoffs calculation, because, if the state file has inaccuracies, the OHBV model will give higher errors in the predictions after. We run the OHBV model with historical observed weather data, and also with the 10 days forecasting data from the EC. After we have obtained these two different runoff forecast, we can compare them to see how much improvement is gained by removing the error in the weather forecasts completely. We have not recalibrated the model parameters, which may have an effect on the performance after changing the quality of the input, since this is not covered by this thesis.

4.1.1 Error distribution of the predictions ran with forecasting meteorological data

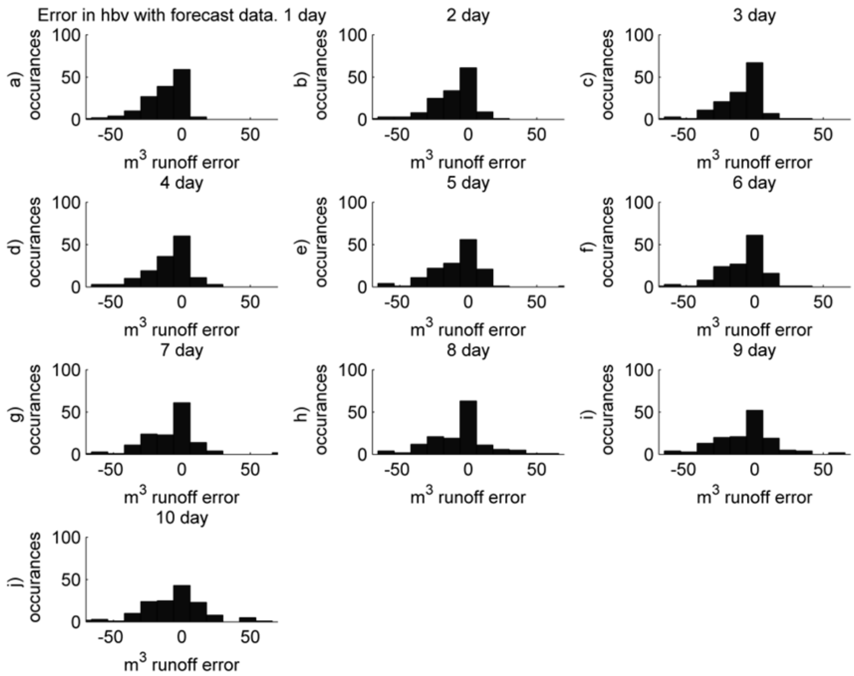

Figure 19. Error in OHBV predictions, run with forecasted weather data

As expected due to the findings in the precipitation forecast there is a visible negative shift in the runoff forecast generated by the HBV model when using the weather forecast as input.

The average mean error of the HBV prediction when run with forecast meteorological data is from 15 to 18. But since this is before any correction is applied, so it may come closer to zero if the error correction part goes well.

Days ahead	mean_hbv_error_forcast	std_hbv_error_forcast
1	15.5914	20.5172
2	15.1434	21.2564
3	14.8423	21.5643
4	14.9273	21.7384
5	15.6582	22.7427
6	16.4841	27.6727
7	16.7708	25.4232
8	16.8797	25.3568
9	18.6676	28.6518
10	18.5756	26.9349

Table 1. Average mean and standard deviation of OHBV forecast error.

4.1.2 Error distribution of the predictions run with observed meteorological data

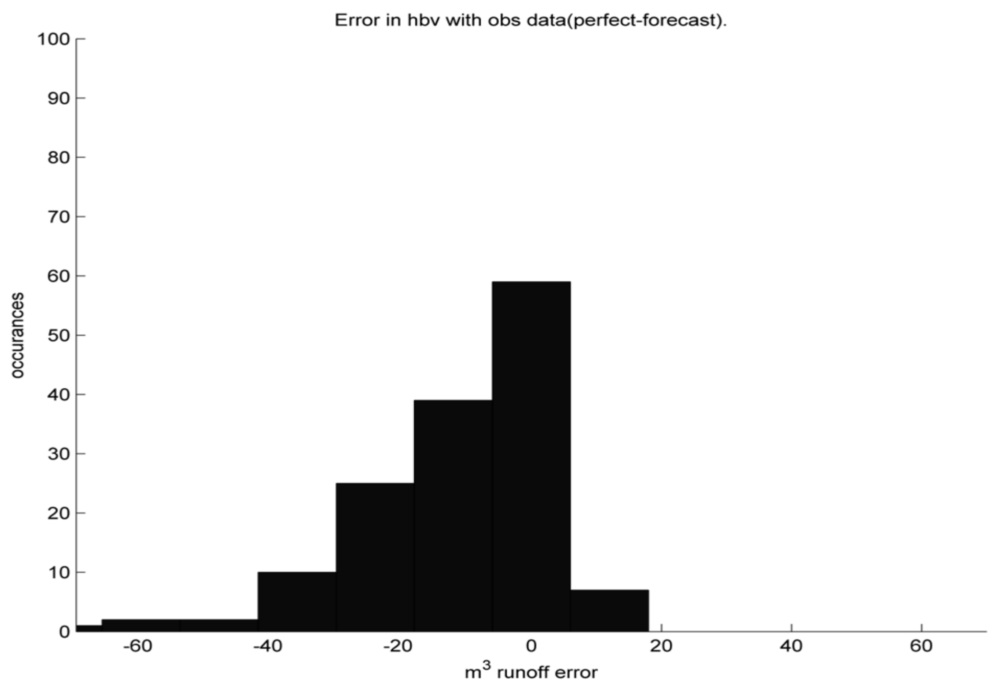

Figure 20. Error in OHBV predictions, run with observation weather data

Running the HBV model again with observations of temp and precipitation we would expect that the negative shift would be smaller than when running with forecast data, this is actually not the case, which may indicate that the relative small error in precipitation forecast does not have such a big impact on the final HBV forecast as we had expected. Instead of ten distributions we get one since runoff observation is fixed for a certain date, as well are observation of precipitation and temperature. The mean error from HBV forecast run with observation data is around 13m^3 while the standard deviation of the error is 19, in other words close to the one day forecast (the improvement is shown in Figure 25). Substituting weather forecast with observation data before running the HBV model gave little change in the terms of improving the forecast.

Days ahead	mean_hbv_error_forcast	std_hbv_error_forcast	mean_hbv_error_obs	std_hbv_error_obs
1	15.5914	20.5172	-13.4148	20.5837
2	15.1434	21.2564		
3	14.8423	21.5643		
4	14.9273	21.7384		
5	15.6582	22.7427		
6	16.4841	27.6727		
7	16.7708	25.4232		
8	16.8797	25.3568		
9	18.6676	28.6518		
10	18.5756	26.9349		

Table 2. OHBV errors and by using forecast and observation data as input, respectively.

The forecast has a negative shift seen in Figure 20, even when the model is run with weather observation (“perfect forecast”) this proves that that the underestimation is coming from the OHBV model and not the forecast. When using observation data as input in the HBV model, we expect to be closest to the 1 day “mean_hbv_forecast” results, since that is the most accurate runoff forecast, and the weather forecast used as input is also closest to the weather observation.

4.2 Improvements study

4.2.1 Definition of improvement

The first problem is the definition of the improvement. That is how we can state that there is an improvement or not when changing the OHBV prediction. The OHBV prediction only has three situations which is the prediction is over observed runoff; the prediction is under observed runoff; and finally the prediction is equal to the runoff. The third situation is the perfect prediction, because it gives us the results we want that there is no error. But the first and the second situation have different meanings in reality. The first situation occurs when the incoming stream flow is the expectation, the second one occurs when the water amount is beyond the estimation. Both two situations are uncertainties in the predictions. We generally do not distinct the two, but are only interested in the size of the error.

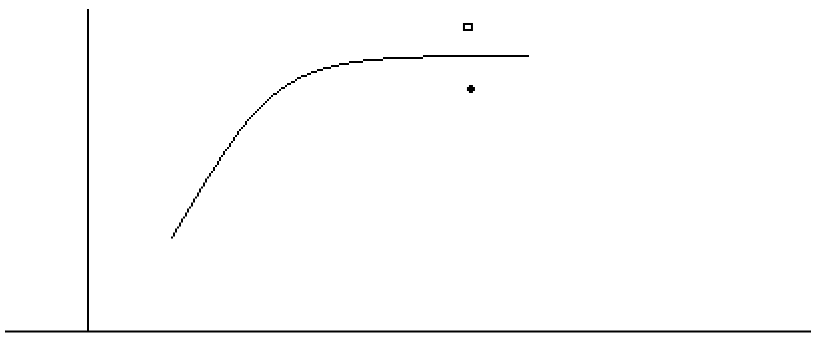

Figure 21. Improvement def: Distance weighted value

In Figure 21., the two predictions have the same uncertainty. That is they have the equal absolute value. (They have the same distance to the observed value.)

4.2.2 Formula of the Uncertainty on OHBV model

This is how we could compute the numerical uncertainty. Since we have run the OHBV with forecasting meteorological data, and then rerun with observed meteorological data, we can separately compute uncertainties about each of the two predictions. As we expected, the prediction with observed meteorological data should be better than the prediction that use forecasting input, because we have removed the uncertainty in weather forecasting system.

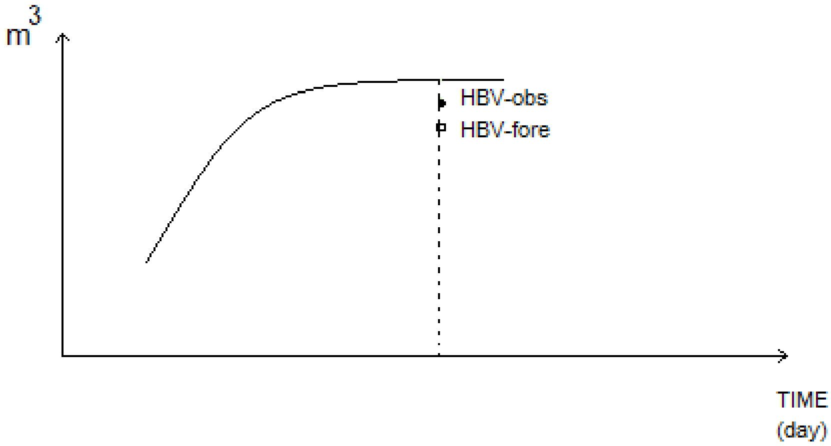

Figure 22. Improvement def: Ideal prediction

In Figure 22, we expect that HBV prediction with observed meteorological data should be closer to the observed runoff (black line) than those with forecasting meteorological data.

Hence, we have such formula that computes the uncertainty:

- Uncertainty from the weather forecasting system = |HBV_fore – Obs_runoff| - |HBV_obs – Obs_runoff|

This uncertainty is just the errors which come from the weather forecasting system. If using weather observation is improving the runoff forecast, then the uncertainty should be above zero. If the uncertainty result is equal to zero, that means we get the same OHBV prediction with forecasting meteorological data and observed meteorological data. In other words, it means there is no improvement in uncertainty. Poor performance in the HBV model, or little error in weather forecast could cause such situations.

	A	B	C	D	E	F	G	H	I	J
1		openhbv fore	obs_runoff	openhbv obs m	D-value fore-obs		D-value obs-obs		D-Uncertainty from mete	
2	2009050600	24.42092	49.56877667	24.27569	-25.14785667	25.14785667	-25.29308667	25.29308667	-0.14523	
3	2009050700	20.38936	44.89234789	28.66006	-24.50298789	24.50298789	-16.23228789	16.23228789	8.2707	
4	2009050800	31.69236	49.50515397	32.13293	-17.81279397	17.81279397	-17.37222397	17.37222397	0.44057	
5	2009050900	42.99707	57.37737357	29.11107	-14.38030357	14.38030357	-28.26630357	28.26630357	-13.886	
6	2009051000	46.87993	55.80689898	28.13546	-8.92696898	8.92696898	-27.67143898	27.67143898	-18.74447	
7	2009051100	39.51813	44.41849873	23.19061	-4.900368731	4.900368731	-21.22788873	21.22788873	-16.32752	
8	2009051200	31.79764	34.84915903	21.44379	-3.051519032	3.051519032	-13.40536903	13.40536903	-10.35385	
9	2009051300	27.50739	29.97731805	20.37971	-2.469928052	2.469928052	-9.597608052	9.597608052	-7.12768	
10	2009051400	25.00989	26.6530774	18.89846	-1.643187396	1.643187396	-7.754617396	7.754617396	-6.11143	
11	2009051500	24.04579	23.09871073	17.25012	0.947079274	0.947079274	-5.848590726	5.848590726	-4.901511452	
12										
13	2009050700	19.12909	44.89234789	28.66006	-25.76325789	25.76325789	-16.23228789	16.23228789	9.53097	
14	2009050800	28.66542	49.50515397	32.13293	-20.83973397	20.83973397	-17.37222397	17.37222397	3.46751	
15	2009050900	39.65311	57.37737357	29.11107	-17.72426357	17.72426357	-28.26630357	28.26630357	-10.54204	
16	2009051000	40.78488	55.80689898	28.13546	-15.02201898	15.02201898	-27.67143898	27.67143898	-12.64942	
17	2009051100	34.40976	44.41849873	23.19061	-10.00873873	10.00873873	-21.22788873	21.22788873	-11.21915	
18	2009051200	28.08864	34.84915903	21.44379	-6.760519032	6.760519032	-13.40536903	13.40536903	-6.64485	
19	2009051300	24.93114	29.97731805	20.37971	-5.046178052	5.046178052	-9.597608052	9.597608052	-4.55143	
20	2009051400	23.61796	26.6530774	18.89846	-3.035117396	3.035117396	-7.754617396	7.754617396	-4.7195	
21	2009051500	22.4023	23.09871073	17.25012	-0.696410726	0.696410726	-5.848590726	5.848590726	-5.15218	
22	2009051600	19.27072	21.36319634	15.40432	-2.092476339	2.092476339	-5.958876339	5.958876339	-3.8664	
23										

Table 3. Example of data file with OHBV calculated runoff and error values

In this Table 3, column B is OHBV prediction which is run with forecasting meteorological data. Column C is observation runoff, column D is OHBV prediction which ran with observed meteorological data. Column E = B – C which is difference value; column G = D- C. F and H are absolute value of E and G. Then we can get the uncertainty from the weather forecasting system which is column I.

As we expected, the prediction with forecasting meteorological data should be worse than the prediction with observed data. But the opposite situation can also happen.

From the whole table, we have several occasions as followed:

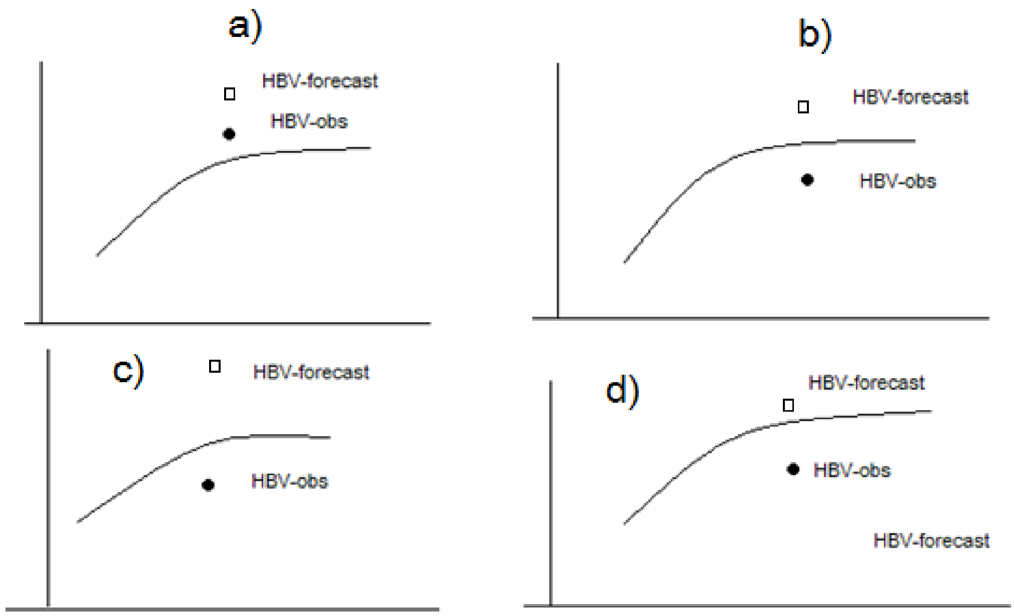

Figure 23. Improvement def: Four realistic situations

Figure 23a), the prediction with forecasting meteorological data is bigger than the observed data. The improvement from using observation data is positive.
Figure 23.b), the prediction with forecasting data is above the observed runoff, at same distance as forecast with observation input. The improvement is zero.
Figure 23.c), Compared to the OHBV(forecast), the OHBV(observation) is much closer to the observed runoff, so the improvement is also positive.
Figure 23.d), the prediction with observed meteorological data is further from the observed runoff, so the improvement is negative.

So we have it at last:

Uncertainty (error) from the weather forecasting system
= |HBV_fore – Obs_runoff|- |HBV_obs – Obs_runoff|

4.2.3 Quantify the improvements from observed meteorological data

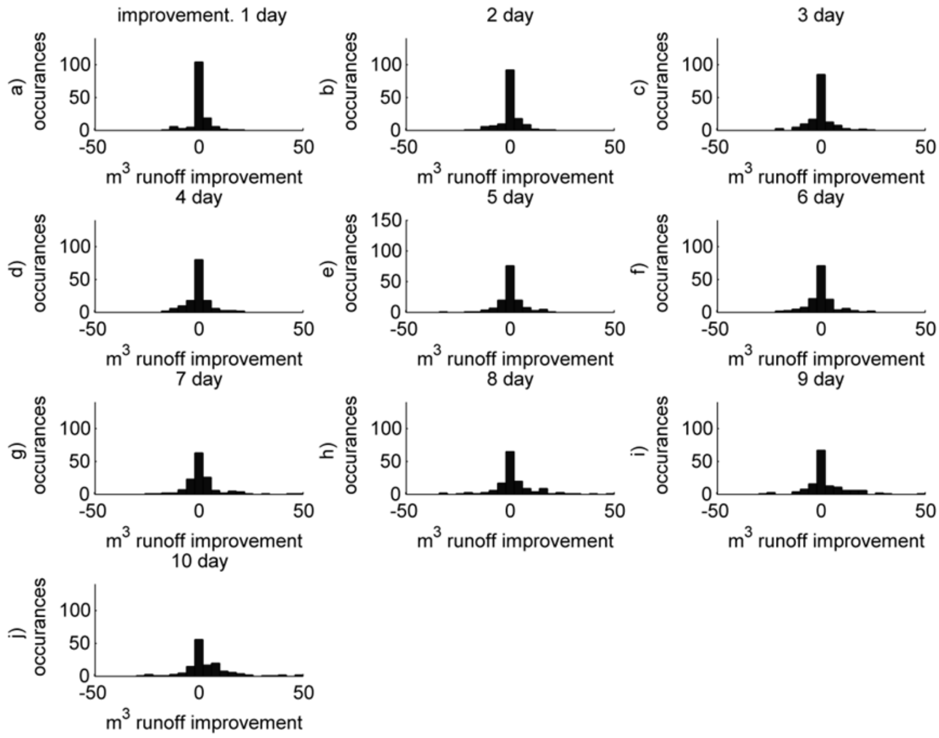

Figure 24. OHBV Improvement from observation input

The improvement in the HBV output from using observed weather data instead of weather forecast is small seen in the distribution, though clearly visible in Figure 24.h)-j) . The size of the improvement is shown in figure 25. The values can also be found in Table 4.

Days ahead	mean value of improvement	std improvement
1	2.3806	4.4035
2	2.9057	4.9641
3	3.4896	5.9345
4	3.5831	5.6905
5	4.0855	7.6276
6	5.4989	13.4162
7	5.8322	11.4160
8	6.2853	10.5949
9	7.3219	14.4483
10	7.2613	11.3987

Table 4. OHBV improvement from using weather observation data as input.

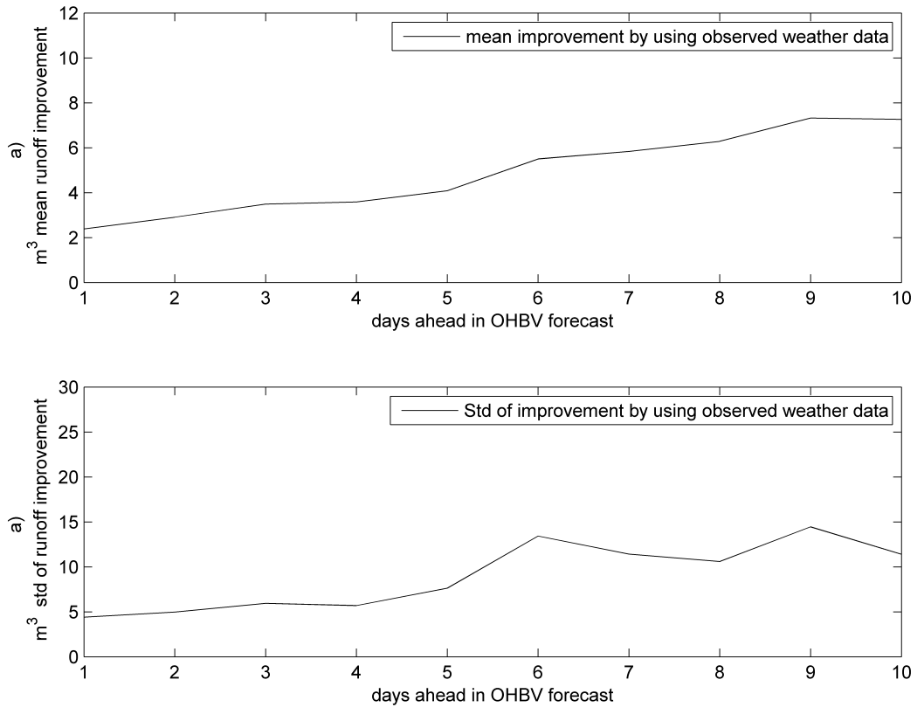

Figure 25. Mean OHBV error improvement from using weather observation as input

The mean improvement and the standard deviation of the improvement of error is rising with days ahead. Values are found in Table 4.

4.2.4 Discussion

If the weather forecasts improve the predictions, there will also be an improvement of the HBV predictions in the area of 2-8 m^3/s, as it is currently implemented. While the original error lies between 15-18 m^3/s therefore more that 10 m^3/s error comes from the model and is still there even when using very good weather forecasts. Both the model and the weather forecasts have room for improvement, but our result show that the error from the OHBV model simplification is the main contributor for the shortest forecast, and at day 10 they will be more equally contributing.

5 Error corrections of the HBV predictions

5.1 Error in original HBV model

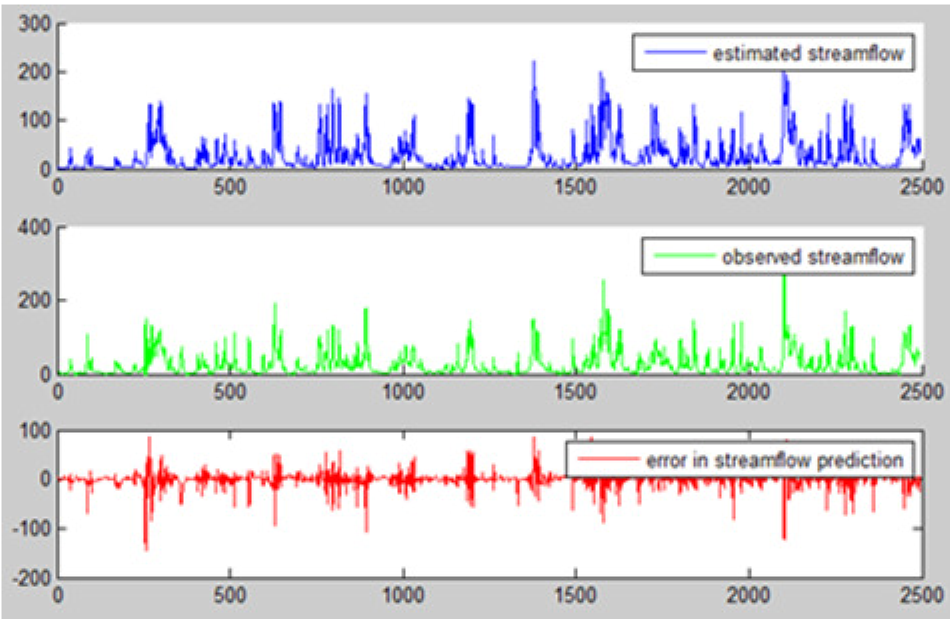

Figure 26. Historical OHBV forecast, stream flow runoff and error.

It clear that the estimated stream flow will have errors, they come from simplification in the model compared to real life system, errors in weather forecasts both temperature and also HBV model parameters that can be calibrated to fit local conditions. In dry periods there is less error since runoff cannot be negative, both predicted and observed stream flow runoff goes towards zero.

There are two things we wish to investigate after looking at the runoff figures. It is limited what we can do with this data for the whole period 2002-2009 since each day has only one value of prediction based on weather observations. (It's basically what 1 day HBV forecast would produce if the weather forecast was 100% accurate) we cannot see how the forecast change from 10 days ahead to 9 days ahead as we do in our shorter period, but since we do have long dataset run with observation it is interesting to investigate some properties. Since the HBV model has states giving dependence in time, and the catchment also has delay(precipitation that come in one day might give runoff in 3 days), error in one forecast could influence the next, as well as there will be "trends" where runoff is going up and later down.

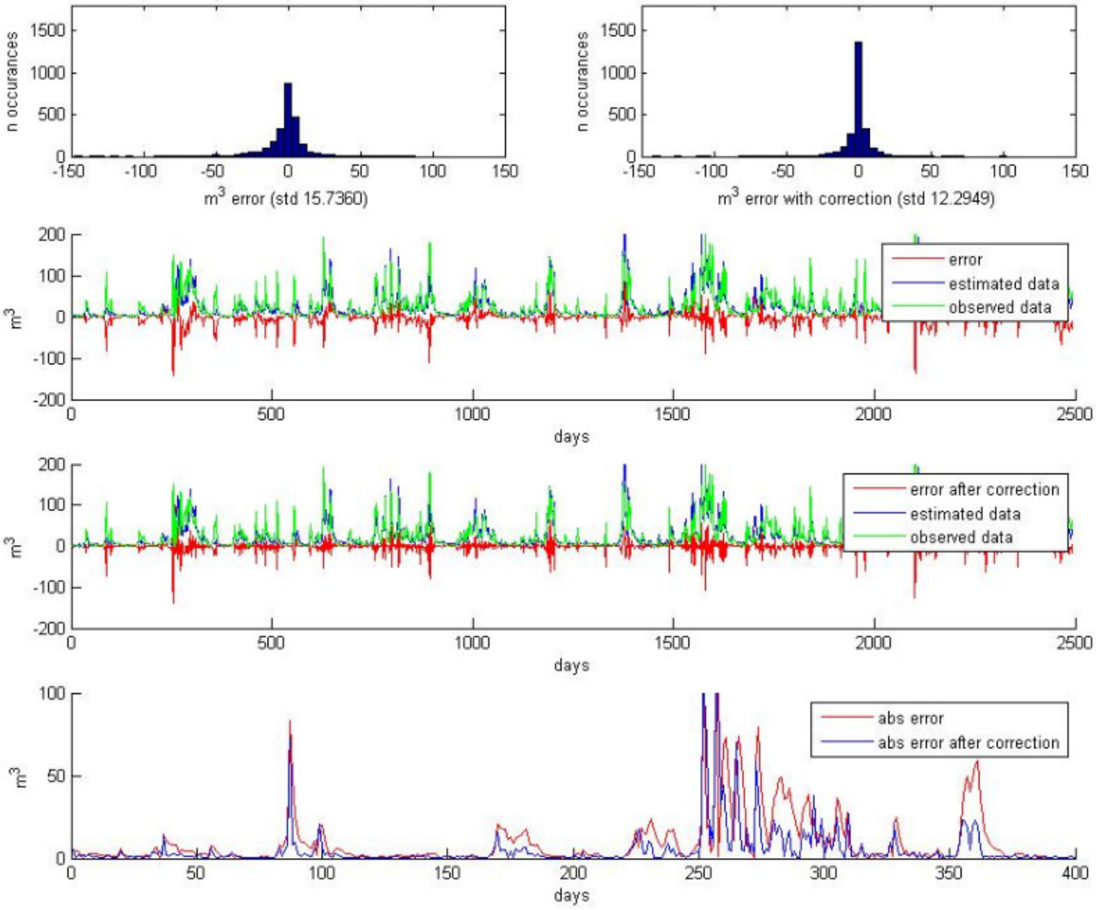

Figure 27. OHBV historical properties: Correct the error from the day before

Using a correction of about 0.7 multiplied with yesterdays error gives an improvement of 48% compared to the error in the original forecast. Strangely it seems that 0.68 is best when there was underestimation the day before, while 0.71 is best in case of overestimation.

It could be that the model output has a little higher or lower average output than it should. Looking at the figure there is a clear underestimation in the forecast, since the error in red is generally below zero. Using correction also influenced from 2 days before did not improve the runoff forecast significantly (a factor of 0.04 could be used)

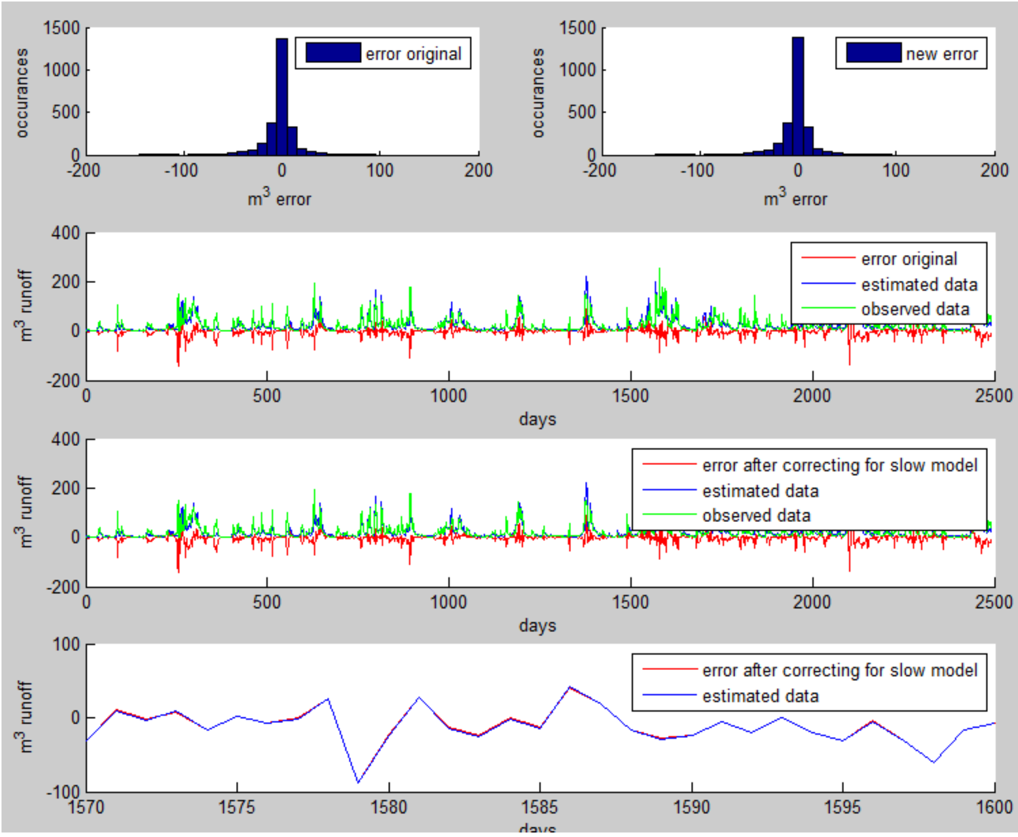

Figure 28. OHBV historical properties: Multiplying with a factor

Using a multiplication/dividing factor based on if forecast was higher or lower than last (yesterdays) runoff observation to counter if the model works too slowly. That is we have an estimated "positive trend" which mean that the amount of water coming to the power station is rising. Seen as red in the figure the error after the change is very close, but it's mostly lowering the error if it differs from the original error (the red is closer to zero in figure). The best level seems to be from 10 to 133 and the best correcting factor 0.89 %. Then the error (in present compared to observation) drops from 33.82% to 26.88%.

After studying the hydrological forecast from the OHBV model, we found that many of the predictions are not close to the observation. Therefore an error correction mechanism should be added to reduce the uncertainties of the predictions. Instead of establishing such a mechanism inside the OHBV model, a new component called "error correction algorithm" is placed after. It is working independently and the only input is the OHBV model predictions. The advantage is to avoid influencing the complicated process of computing discharge inside the model, and focus on the error correction algorithm only. This "black box" design makes it easier to develop, compare and improve the algorithm.

Chapter 5. gives the overview of an existing and a new developed method of error correction mechanism. First we look at Powel's error correction and its performance, and then we will develop an alternative method and finally compare them. We will present the new error correction method as "weighted ATAN error correction".

5.2 Powell Algorithm

The Powell Algorithm employs an error correction algorithm which is working parallel of the model error. Using Powel was proposed by Agder Energi, based on its relative simple implementation. It is an empirical algorithm, but it is not fully tested according to "Powel doc". Implementations of Powel funded by "Kraftvershydrologisk råd" came to the conclusion that the observations of model status are erroneous."[15]

5.2.1 Formula of Powell Algorithm

Main calculation steps are:

1. $qTrend_t = SIM_t / SIM_{t-1}$

2. $trendAttenuation_t = 1/qTrend_t$, $qTrend_t \geq 1.0$

Or $trendAttenuation_t = qTrend_t$, $qTrend_t < 1.0$

3. $qRatio_t = (OBS_t / SIM_t)^{1-a}$

4. $qFact_t = (qFact_{t-1})^a * (qRatio_t{}^{(1-a)}))\sqrt{trendattenuation_t}$

5. $SIM_t^* = SIM_t * qFact_t$ [16]

(1) A trend factor $qTrend_t$ is calculated which is discharge this time step divided by discharge previous time step.

(2) If $qTrend_t$ is greater than 1, which means an increasing of discharge, an attenuation factor $trendAttenuation_t$ is calculated: $1/qTrend_t$. Otherwise the attenuation factor is equal to $qTrend_t$.

(3) If there is a discharge observation for the actual time step, the error factor, $qRatio_t$ is calculated. $qRatio_t$ is observed discharge divided by calculated discharge. If there is no discharge observation, $qRatio_t = 1$.

Where a is the error prediction constant (calibration constant), a=<0.0, 1.0>

(4) If the error prediction algorithm is active, the calculated discharge is multiplied by $qFact_t$.

Formula Powel algorithm from attachment 8.2

5.2.2 Data selection

In the study of the OHBV predictions, we found a period of days with abnormally large errors in the predictions. And as mentioned, we can't find the exact reasons why the performance in this period was so poor. For the study of error correction, we decided to remove this abnormal data, to avoid it influencing the results of the experiment. As we expect that when the prediction is very poor, it will influence the correction in a negative way. This may seem opposite of logic since with larger error there are more room for improvement. On the other hand Powel is based on the error between last observation and forecast, and thereafter using this to improve the future forecast. Then it is important that there is a strong positive correlation between the HBV forecast and the observation. It means that if observed runoff is increasing or decreasing, and then there should be a high probability the forecast does the same. Basically Powel will try to counter errors from under/over estimation, but will sometimes introduce errors also, especially if the HBV forecast is uncorrelated with observed stream flow. The experiment date is from 5th, May, 2009 until 30th, September, 2009 without the abnormal period which is from 6th, July to 21st, August. The precipitation type within the 101 days is rain and the air temperature is always above zero.

5.2.3 Distributions of the uncertainties of the predictions after Powell algorithm

First, when parameter A is equal to 0.2, we input the meteorological data into OHBV model, and run Powell error correction on these predictions. Then use these numbers minus the observation. Finally, we got the uncertainties of the predictions.

Here, we are going to study the distributions of these uncertainties.

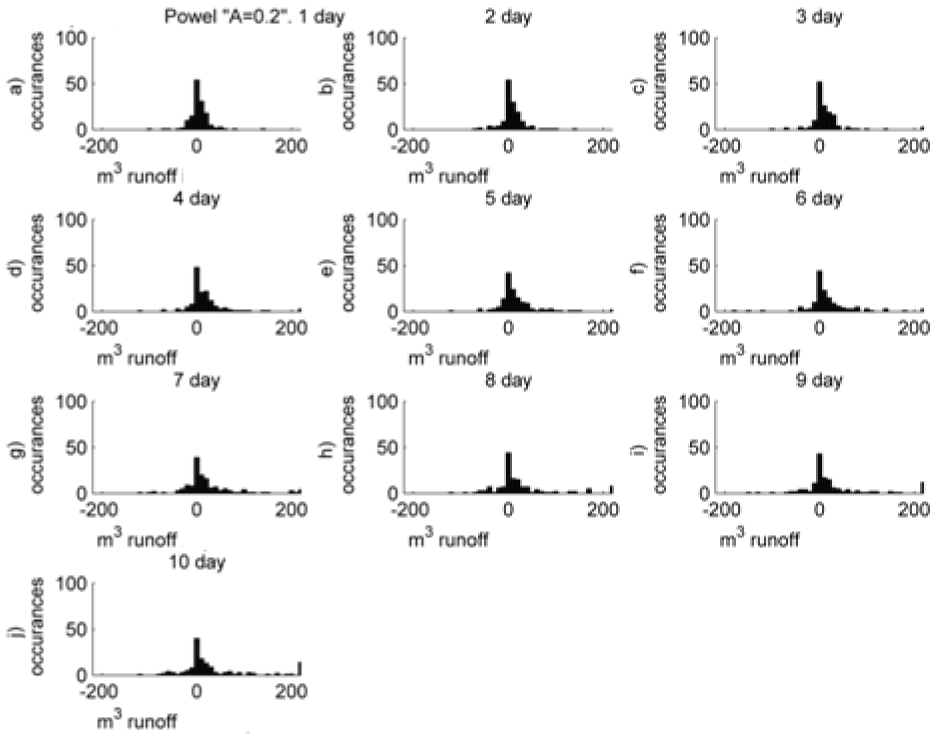

Figure 29. OHBV Error after Powel with a=0.2

Some values will occur outside the figure on the x axis, though they would hardly be visible. The most important thing in these error distributions is that the "spreading" increases. There is also a clear positive shift, which means Powel is overestimating(especially at day 5-10) See later figure with mean and standard of error after Powell is applied to conclude the Powell level of performance.

From Fig 29, we can see that in the first few days, the distribution is quite good (narrow), but after day 5, some very big positive values occur. It means that sometimes the corrected predictions are far away from the observation. Though the algorithm still corrects some error, other errors get very large. In reality, if such situations happened, then the algorithm makes no sense to use. As mentioned when investigating error in the HBV model, it would be possible to only use correction at the "medium levels of runoff", that is to avoid correcting when the runoff is at it peaks. At the high narrow peaks you get the possibility for the most extreme values, since if you underestimate at the peak Powel will add more at the next day, while in reality it was going steep down. The deciding level of how high the values could be before Powel is not used could vary for days ahead (becoming smaller). It will vary from place to place, so the most efficient way to decide the levels would be to look at the historical HBV runoff curve together with observation of runoff. The level should be decided where the error is large, at high narrow peaks. At the Skjerka catchment the HBV analysis with multiplying factor showed that the best limits where from 10 to 133 so that could be a start.

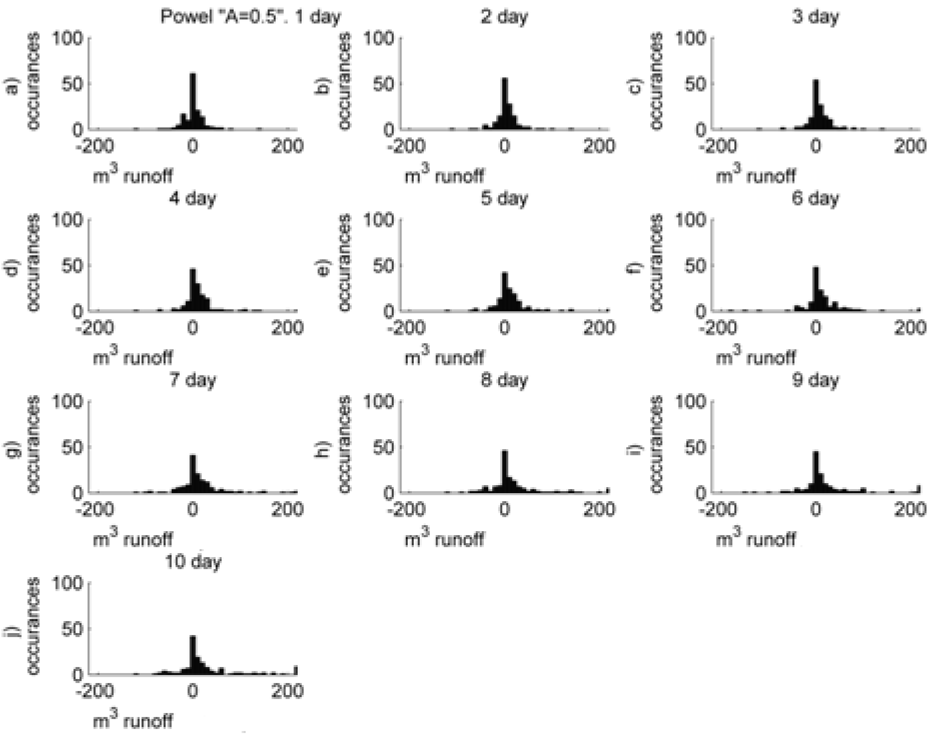

Figure 30. OHBV Error after Powel with a=0.5

When A is equal to 0.5, we can see that in the first four days, the distribution sharps are almost the same. In next four days, the positive value occurred far away from zero, it means some big uncertainties happened and the algorithm doesn't correct as much as the first four days, almost the same situation as the 0.2 one.

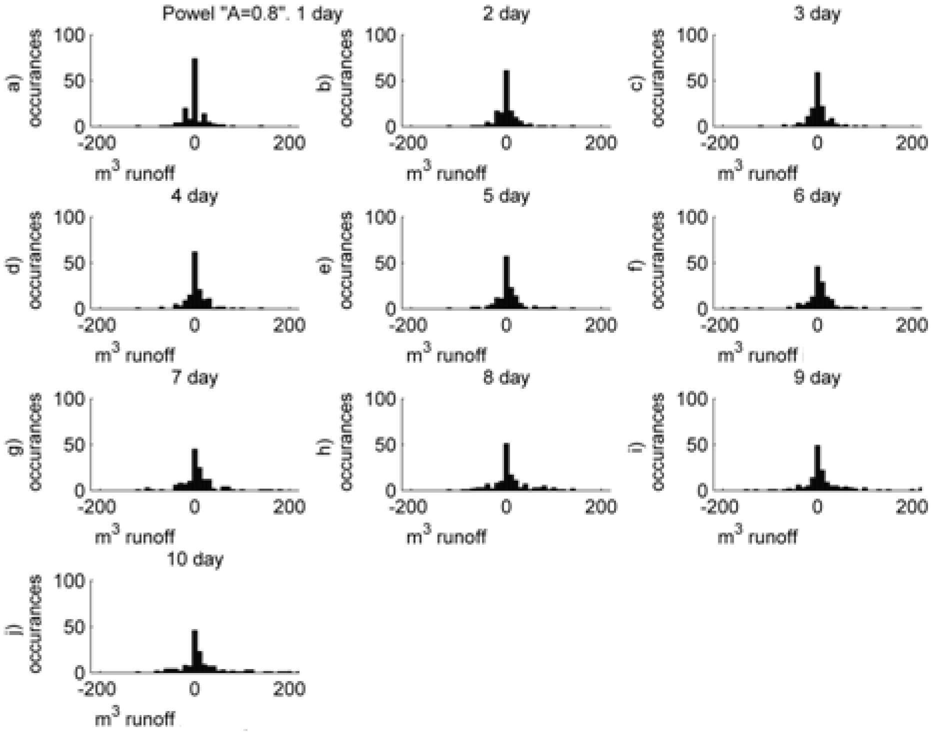

Figure 31. OHBV Error after Powel with a=0.8

Even though in the first day, the peak at zero is very high, but noise makes it look strange. If the steps where much larger it would be hard to distinct the different figures, so we kept it like this. Comparing Powel(a=0.8) figure to Powel(a=0.5) and Powel(a=0.2), we will later show that small "A" makes Powel perform best at day 1 and 2, while larger a works best for day 3+. This is easier to see from the curves below.

5.2.4 Improvements study of the predictions after Powell

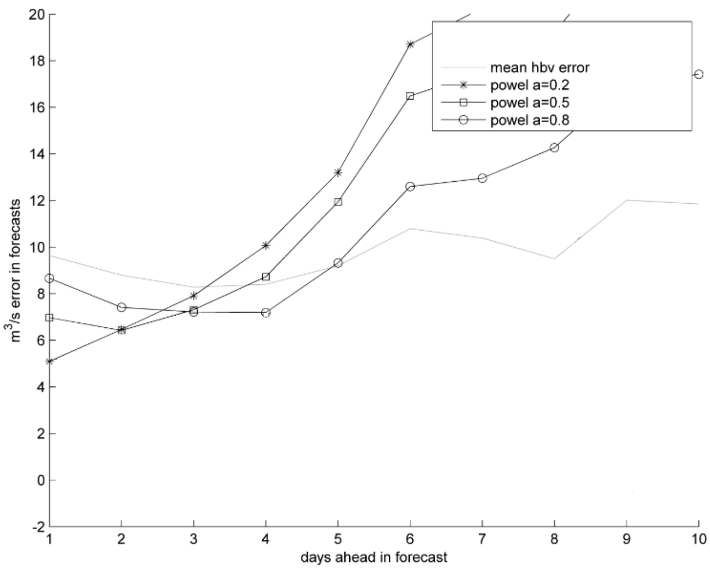

Figure 32. Error in OHBV and after Powel (0.2,0.5,0.8)

In Fig 32, it presents the general correction performance of Powel algorithm. In 4.1.1, it is presented that the adjustment of the error correction is controlled by the parameter A, which is in the intern from 0 to 1. There is not a fixed value of parameter A to predict the best results. To examine and decide the best proper value of parameter A, we tried 3 different values when A is equal to 0.2, 0.5, and 0.8 to observe the trends of improvements. After we calculated the corrected predictions, we compared the curve of Powell predictions to original OHBV predictions.

5.2.5 Error correction conclusions

From the figure 32, the curve of parameter A that is equal to 0.2 reduces the uncertainty value down to about $5\mathrm{m}^3$/s in the first day; The curve of 0.5 and 0.8 are significantly improving less than the 0.2 one. The curve 0.5 is about $7\mathrm{m}^3$/s and the curve is 0.8 about $8.9\mathrm{m}^3$/s. In the second day, the curve 0.2 improves as same as the curve 0.5, but the curve 0.8 is still worse than the other two. In the third day, the curve 0.8 improves as same as the curve 0.5, but this time, the curve 0.2 is worse than the other two. In the fourth day, the curves 0.2 and 0.5 have been beyond the uncertainty of OHBV model itself, which means they contribute nothing to the error correction. Meanwhile, the curve 0.8 still improves ca. $1.5\mathrm{m}^3$/s error. In the fifth day, the curve 0.8 has the same uncertainty as the OpenHBV model, and the other two curves, 0.2 and 0.5 have bigger uncertainties than the OHBV model. After the fifth day, the predictions after Powell algorithm error correction are much worse than the original OHBV model predictions. In other words, the Powell algorithm is only employed in 5 days at the beginning.

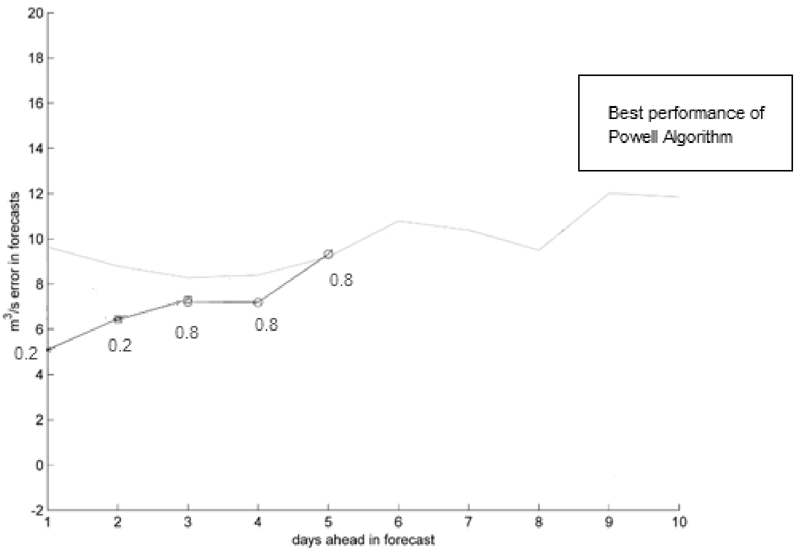

Figure 33. Powel with the best of the parameter selected

To employ the best performance of Powell Algorithm, the methodology could set different parameter A values in different days, in our case, that is A is equal to 0.2 in the first and second day, set A to 0.8 in the third, fourth, and fifth day, and nothing to correct after.

5.3 Yukun&Karl Algorithm

This is a new algorithm developed by the authors of this paper. The Powel Algorithm is an empirical method, while Yukun&Karl Algorithm is focusing on mathematical improvements.

The main idea behind our method is that from the observation and studies of distribution of the uncertainties in OHBV model predictions, that is from the first day until the tenth day, the mean values of the prediction of each day are lower than the observation discharge. This means we have a general underestimation. To solve this problem, it is needed to add some positive value to OHBV predictions within statistic methodology. The correction also needs to work in the case of overestimation, and then we need to add a negative value to the original forecast.

Another important problem it that, after observing the prediction results, we found that in first few days, the discharges have some relevance with the observation of Day 0. “Day 0” can be described as the average observed runoff of “today” and “tomorrow” is the first day of 10 days forecast. However, in the middle and last part of the 10 days forecasting, we don’t have any relation with observations, and need to rely more on the OHBV model. At last, the mean value of error in the last few days are significantly increasing and the standard deviation values are also much bigger than the previous days.

Also a very important factor in correcting the OHBV forecasts successfully is the trend of how the discharge is changing, which is a relative “stable” curve of increasing or decreasing the runoff in most situations. In a catchment with delay, there are rarely flat or rapid changes in the runoff. The exceptions are some high peaks that possibly could be excluded from correction, by setting a maximum value. Yukun&Karl Algorithm has exploited all these points mentioned above.

5.3.2 Formula of Yukun&Karl algorithm

The main steps of Yukun&Karl Algorithm are:

1. $\mathrm{Y_i}$= ATAN ($\frac{\mathrm{OpenHBV_{F(i)}-OpenHBV_{F(i-1)}}}{\mathrm{OpenHBV\_F(i-1)}}$) (i= 1,2,3,4,5,6,7,8,9,10)

2. $\mathrm{Z_i}=|\mathrm{Y_i}| * \mathrm{Y_i}$ (i=1,2,3,4,5,6,7,8,9,10)

3. $\mathrm{Error\_Correction_i} = (1+\mathrm{Z_i}) * \mathrm{Error\_Correction_{i-1}}$,when t=1 $\mathrm{Error\_Correction}_0$=OBS (i=1,2,3,4,5,6,7,8,9,10)

4. $\mathrm{Prediction_i} = \mathrm{a_i} * \mathrm{Error\_Correction_i} + \mathrm{b_i} * \mathrm{OpenHBV\_Forecast}_\mathrm{i}$ (i=1,2,3,4,5,6,7,8,9,10)

5. $\begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ a_3 & b_3 \\ a_4 & b_4 \\ a_5 & b_5 \\ a_6 & b_6 \\ a_7 & b_7 \\ a_8 & b_8 \\ a_9 & b_9 \\ a_{10} & b_{10} \end{bmatrix} = \begin{bmatrix} 0.9 & 0.1 \\ 0.8 & 0.2 \\ 0.7 & 0.3 \\ 0.5 & 0.4 \\ 0.4 & 0.5 \\ 0.3 & 0.6 \\ 0.2 & 0.7 \\ 0.1 & 0.8 \\ 0.1 & 0.9 \\ 0.1 & 0.9 \end{bmatrix}$

Formula Yukun&Karl algorithm

(1) $\frac{\mathrm{OpenHBV_{F(i)}-OpenHBV_{F(i-1)}}}{\mathrm{OpenHBV\_F(i-1)}}$ is how much percent the discharge would increase or decrease this day, NB: if $\mathrm{OpenHBV\_F(i-1)}$ is equal to zero, then no error correction for that day.

Then the percent number will go through ATAN function, which is:

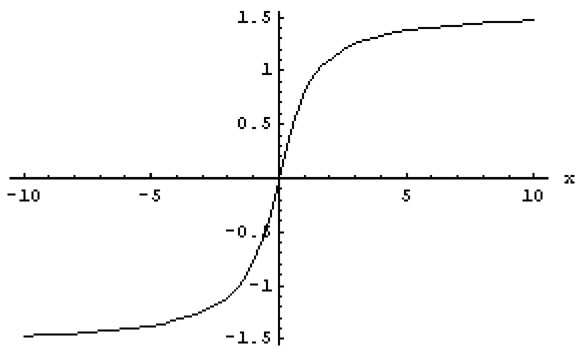

Figure 34. ATAN function

This function has a special feature at each asymptote at value $\pm\frac{\pi}{2}$, the idea behind this is for the safety of the predictions; an extreme big value will not be allowed to influence the accuracy of the final result, since the y axis growth slows down when x gets larger.

(2) After computing the internal parameter Y, it is calculated in next function in order to reform the value. The function is: $Z_i = |Y_i| * Y_i$ (plotted as y=(+,-)x^2)

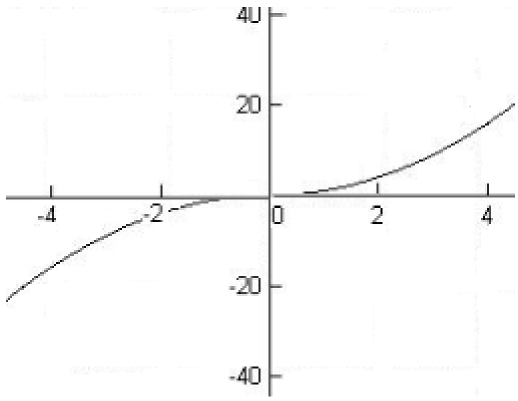

Figure 35. Amplifying function

Then we got the error correction parameter Z(in percent).
(3) Next step, it is to compute $\mathrm{Error\_Correction_i}$ for each day. At the beginning of the first day, we involve Observation runoff for calculation.
(4) Compute the final prediction for each day.
(5) The parameter matrix of a, b is not fully tested. It means there could be a better matrix which could reduce much more error than the present one.

5.3.3 Improvements study of the predictions after Yukun&Karl algorithm

As the definition of improvement in chapter 3, we compared the predictions error of each day after Yukun&Karl Algorithm correcting to the original OHBV runoff. Then here is the distribution of improvement in each day.

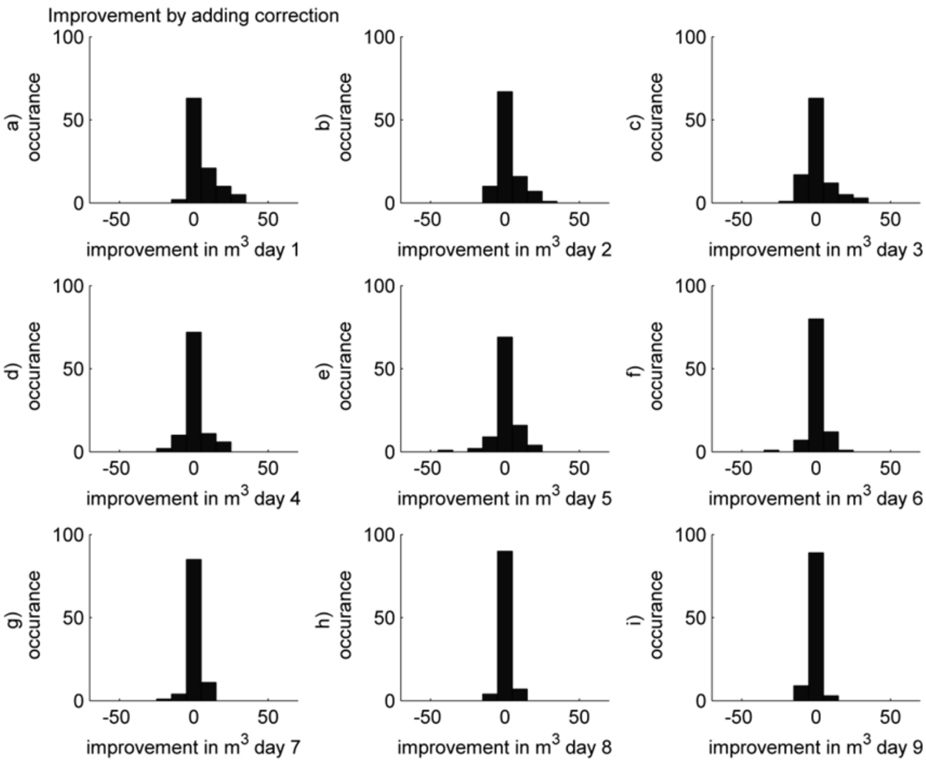

Figure 36. Yukun&Karl Algorithm Improvement distributions

The positive bars show improvements; however, the negative bars show the dates when the error correction algorithm actually makes the prediction worse. Because Yukun&Karl Algorithm is focusing on statistic improvements, it cannot guarantee an improvement every time, but only an average positive improvement. Furthermore, the bigger the size of the positive value of the improvement, the larger was the improvement on that specific error (big improvements are further from zero in the distribution). The heights of bars show the number of improvements in the interval.

From Figure 36, we can see that in the first day, the algorithm corrected significant errors. In the second day, it made some predictions worse, but only a few and the error was small. In the third day, there are more errors produced, but the average improvement is still positive. In day 4 it the improvement is better, and then the factor in the matrix makes the change so small that day 5-8 day forecasts are very close to the original HBV forecast. At day 9 and 10 it would be better not to use any correction.

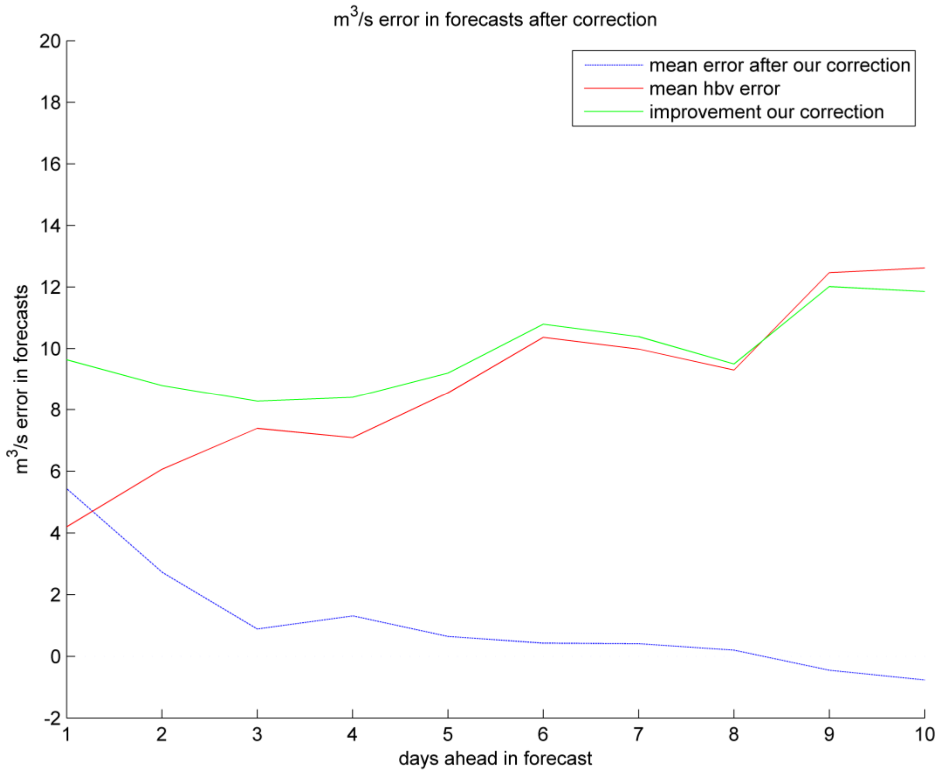

Figure 37. Yukun&Karl versus original OHBV forecast.

From Figure 37, we can see that the blue improvement curve is going down with time. The error correction algorithm reduces most errors at the beginning, but is then corrected less and less in the middle of days and almost flats out. For the last 2 days the improvement is negative.

5.4 Comparisons of Powell algorithm and Yukun&Karl algorithm

After the studies of Powell algorithm and Yukun&Karl algorithm, we can make a comparison to find out advantages and disadvantages of each algorithm, and get a final conclusion.

There are two necessary aspects to compare; the first is the error correction effect, and the second thing is complication of the operation. The first thing is how much error it could reduce, and the second thing is how much time and effort is needed to calibrate and calculate the error.

In figure 38. The Powell algorithm, Yukun&Karl algorithm, and OHBV prediction error results are plotted together.

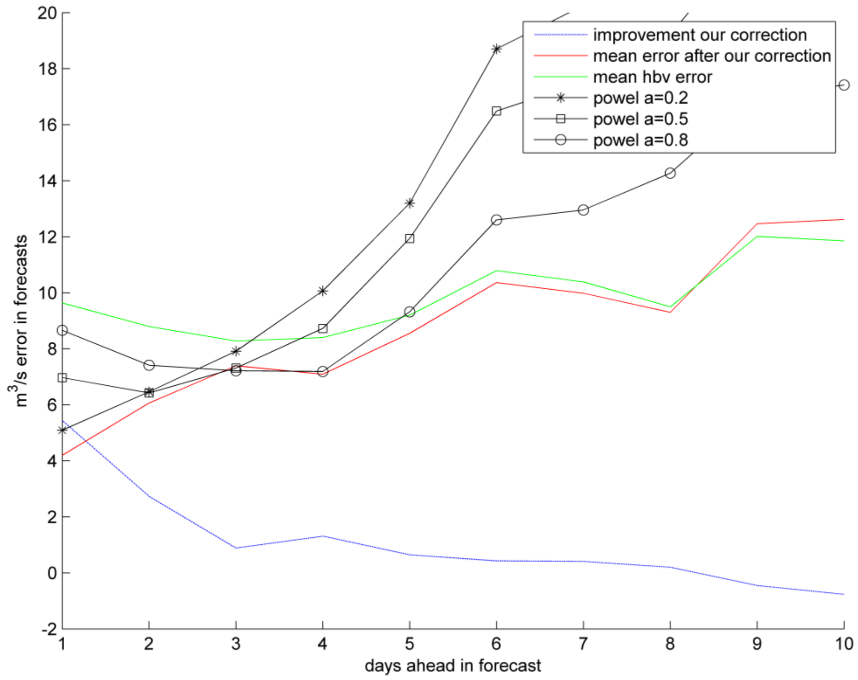

Figure 38. Comparison of OHBV error corrections

From Figure 38, we can see that, within the first four days at the beginning, Yukun&Karl algorithm is a working little bit better than Powell algorithm. In period of day 5 until day 8, Powell algorithm has very significant errors, and is making the forecast worse than the OHBV model itself, but Yukun&Karl algorithm still makes some improvement. At the end of day 9 and day 10, nothing is better than original OHBV model.

To have a clear vision of corrections, we are going to study the correction curve in the first and fifth day. The first day is the day when most of error is corrected. The fifth day is special when investigating the data in Figure 38, because in that day Powell algorithm contributes almost nothing, while Yukun&Karl algorithm is still correcting errors.

In Figure 39. we compared the OHBV forecasting runoff, observed runoff, Yukun&Karl algorithm, and the Powell algorithm with a=0.8 together within 101 days of 5 days ahead HBV forecast.

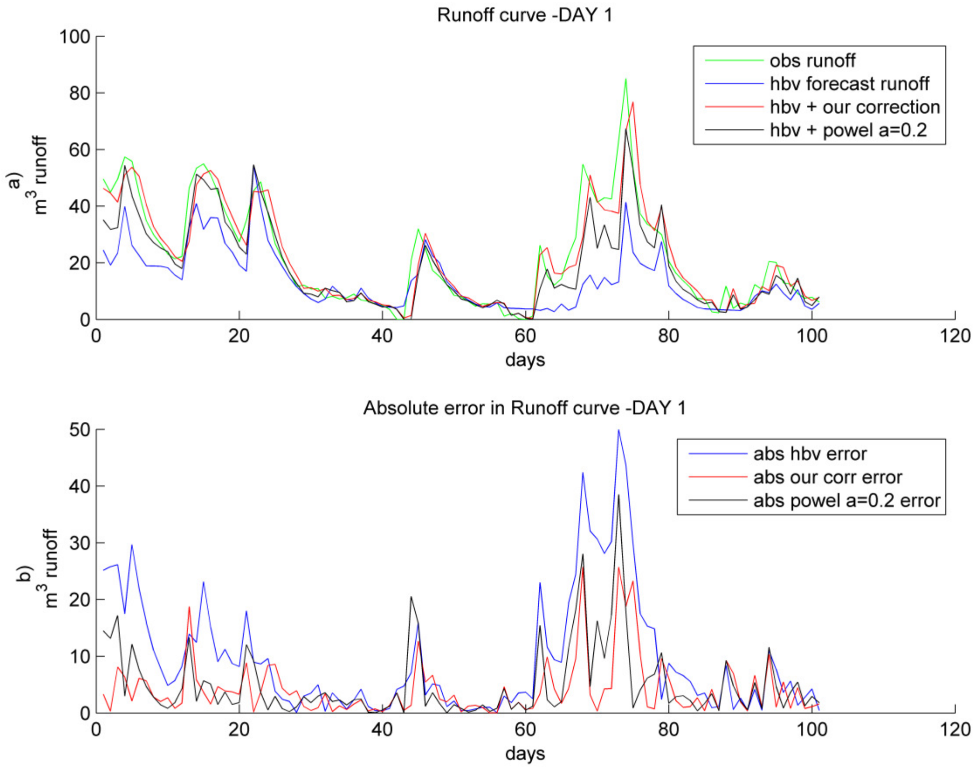

Figure 39. 1 Day OHBV runoff with error correction

In Figure 39.a), Yukun&Karl algorithm is doing almost as good as the Powel algorithm(with a=0.2) when the runoff is under $30\mathrm{m}^3$/s. The only difference is how the two algorithms work when flash flood is coming which is usually over 40 m^3/s. In picture a, around the 70th forecast, there are significant enhancements of the error correction, comparing Yukun&Karl curve to the Powel 0.2 curve.

Please notice that, around the 70th forecast, the observed runoff show a flash flood, but the OHBV model under predicts. This big error could influence the error correction as well.

From the Figure 39.b), the OHBV model sometimes produce large errors, approximate $50\mathrm{m}^3$/s. Such big amount error should not be acceptable in the final estimation. The largest errors occurs when the runoff is changing rapidly and over $30\mathrm{m}^3$/s. Most of the errors are corrected somehow, only no more than 10% forecasts are corrected even worse.

In days runoff below $10\mathrm{m}^3$/s, the average error is under $2\mathrm{m}^3$/s. Actually, the prediction after Yukun&Karl algorithm is always over $2{\sim}3\mathrm{m}^3$/s, which means, if the observed runoff is very low, and no precipitation is forecasted in the few days, it is not better to employ error correction algorithm, to avoid that small error introduced by the error correction algorithm.

The first day is corrected successfully, because we can use observation to help correcting error. The 2nd, 3rd and 4th days are not corrected as much as the first day. In fact, the prediction after 2 or 3 days at the beginning is not relative to the observation any more. So, we have to rely on the OHBV model and error correction from day 5 until day 8.

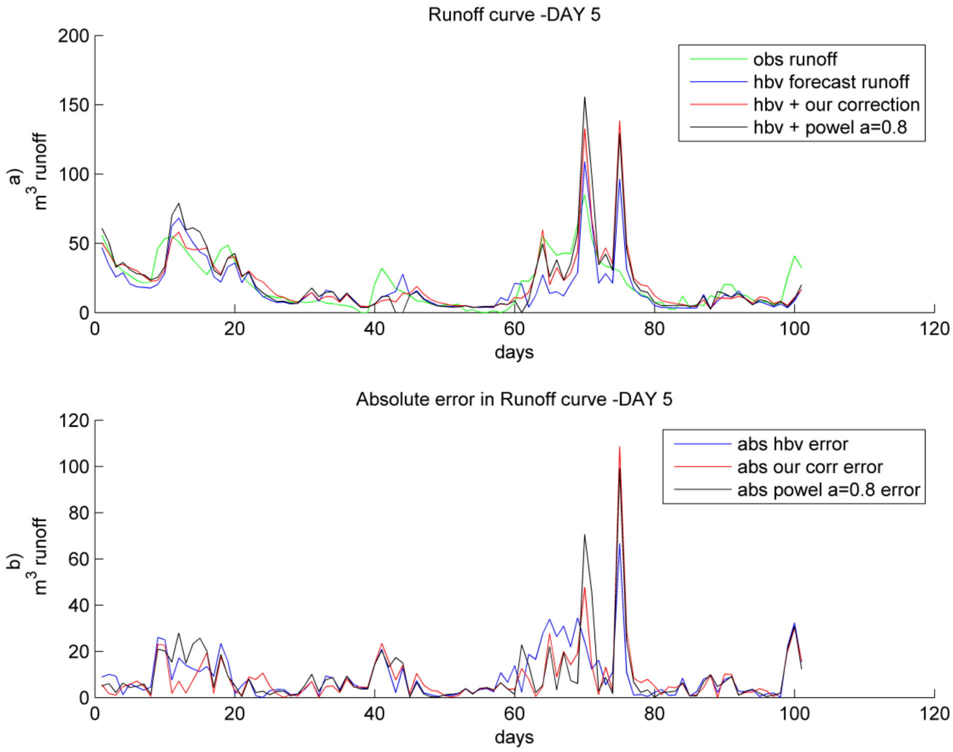

Figure 40. 5 Day OHBV runoff with correction

From the Figure 40.a), we can see that both the algorithms size of error follow the trend of OHBV model stream flow level. Proving that larger runoff gives larger error.

In Figure 40.b), around the 75^{th} forecast, the OHBV prediction have a large error similar to the 1 day error study in Figure 39.

Besides, one import thing we have to highlight is that both algorithms are controlled by parameters, and that these parameters are not fully tested, which means the parameters in our curves and figures are not optimal values. In the other words, there could be a further study on finding the optimal parameters to ensure the best error correction performance.

The level of improvement in the 6th to 8th days is under 0.5 m^3/s, which means the selection of parameters is very important. Not just for the level of improvement, but to avoid negative effects on the original error (“negative improvement”). If the parameters chosen do not fit with the properties of the data, the algorithm may make no sense to use.

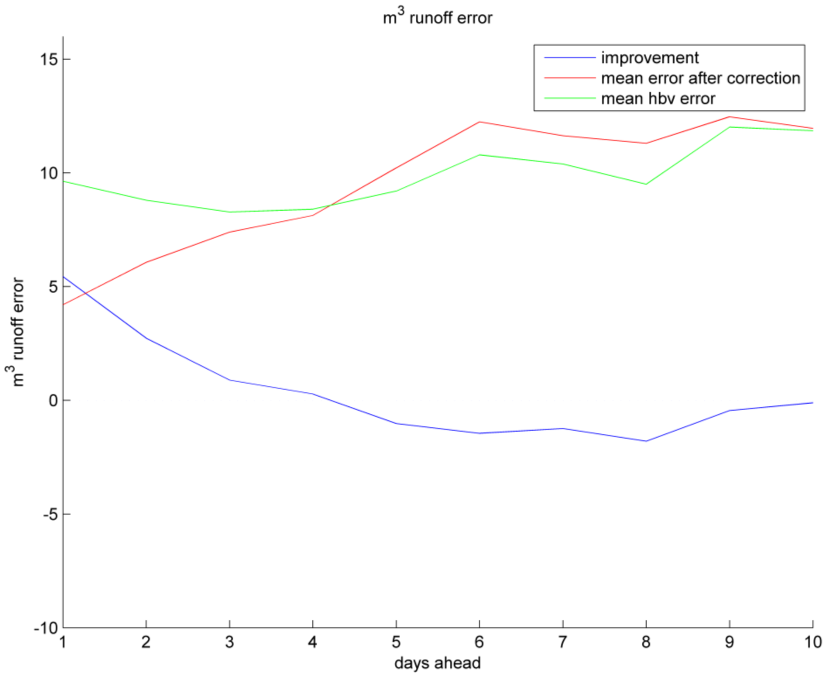

Figure 41. Yukun&Karl algorithm with poorly chosen parameters

Figure 41. Shows the result after correction if the parameters are not chosen carefully. From the fifth day, the correction algorithm do not contribute to lowering the error, but in average introduce more errors.

5.5 Conclusions on error correction

Yukun&Karl algorithm works as well as the Powel algorithm in the first four days. It is then needed to compute the Powel error correction several times each day and sort out the best values to compete with the performance of the Yukun&Karl algorithm. For our chosen values of parameter a, the best Powel performance where when using: A=0.2 for day 1 and 2 and A=0.8 for day 3 to day 5.

The biggest advantage of Yukun&Karl algorithm compared to Powel is the improvements in the middle days, which from the fifth day until the eighth day. In this period, Powel algorithm makes no sense at all. Though Yukun&Karl algorithm does not improve much of the error, but this could be a possible method to improve and then it could work even better in the future.

At day 9 and 10 in the forecasting, the growing uncertainty seems to make error correction problematic, so none of the two error correction mechanism does seem suitable to solve the error correction problems in those days.

In our result apply to general application; we can conclude that Yukun&Karl algorithm is working a little bit better than Powel algorithm.

Though it is possible to use Yukun&Karl algorithm instead of Powel algorithm, the only disadvantage is that there are more parameters to set in Yukun&Karl algorithm than Powel algorithm. In Powel algorithm, there are only 5 parameters to set, however, in Yukun&Karl algorithm, it needs 2 parameters for each day, and total 8 pairs parameters to be set, and they are independent from each pair.

Both of the algorithms works after the OHBV prediction further work could be developing a methodology which to find the optimal parameters of the algorithm.

6 Overall conclusions and further work

At last, we present several overall conclusions and the suggestions of further work.

In the summer period when the precipitation generally falls as rain, the air temperature error is between zero and 5 degrees, and contributes little to the runoff error. Precipitation error for wet days have a high uncertainty, but the underestimation seen in the 9^{th} and 10^{th} day forecast might be countered with better calibration of weather forecast data and a longer data period. The weather forecast improvement is limited, since it will always have error caused by simplification and estimation.

After running the HBV model with observed and forecasting meteorological data separately, we found that the improvement within meteorological data is not as significant as we expected. The weather forecasting uncertainty contribute to between 2 and 7m^3/s according to number of days ahead in the forecast. The rest of the error then comes from the OHBV model.

The Powell algorithm improves significantly in the first four days, but it is needed to find the best parameters “a” first. In our thesis we compute the Powel error correction with three different parameters “a”, and sort out the best values per day, e.g. A=0.2 for day 1 and 2 and A=0.8 for day 3 to day 5. Since we use historical predictions to confirm the optimal parameters, after a while, when we have new historical prediction, the optimal parameter may be obsolete and to be updated.

The Yukun&Karl algorithm is somehow similar to the Powel algorithm, but it needs two parameters for each day in the forecast, which is more than the one in Powel. The parameters for each day should be updated after a period of prediction, in case of changes in the input data properties (example is when OHBV parameters are changed). In the data we have studied, the results show that Yukun&Karl algorithm works a little bit better than Powel algorithm in lowering the error.

The biggest advantage of Yukun&Karl algorithm compared to Powel is the improvements in the middle days, which are from the fifth day until the eighth day. In this period, Powel algorithm makes no sense to use. Though Yukun&Karl algorithm does not improve much of the error in this period, it could be a possible method to improve and then it could work even better in the future. At day 9 and 10 in the forecasts, the growing uncertainty seems to make error correction problematic. So error correction mechanism does not seem suitable to solve the error problems in those two days.

A suggestion to further work is to develop an agile method to optimize the parameters for error correction. As for the OHBV model itself, it still needs enhancement in performance.

7: Sources/links

[1] Refsgaard, J.C., Storm, B., 1996. Construction, calibration and validation of hydrological models. In: Abbott, M.B., Refsgaard, J.C. (Eds.), Distributed Hydrological Modeling, Water Science and Technology Library, vol. 22. Kluwer Academic Publishers, Dordrecht, Netherlands, pp. 1 – 54.

[2] See 8.2 Powel error Prediction (Document from Agder Energy A/S).

[3] http://ga.water.usgs.gov/edu/hydrology.html

[4] http://ga.water.usgs.gov/edu/watercycle.html

[5] Climate and Hydrology in Mountain Areas, Carmen de Jong David Collins Roberto Ranzi, , ISBN-13 978-0-470-85814-1

[6] Climate and Hydrology in Mountain Areas, Carmen de Jong David Collins Roberto Ranzi, page 186, ISBN-13 978-0-470-85814-1

[7] Climate and Hydrology in Mountain Areas, Carmen de Jong David Collins Roberto Ranzi, page 85, ISBN-13 978-0-470-85814-1

[8] Bergström, S. 1995. The HBV model. In: Singh, V.P. (Ed.) Computer Models of Watershed Hydrology. Water Resources Publications, Highlands Ranch, CO., pp. 443-476.

[9] http://www.smhi.se/sgn0106/if/hydrologi/hbv.htm

[10] Climate and Hydrology in Mountain Areas, Carmen de Jong David Collins Roberto Ranzi, page 221, ISBN-13 978-0-470-85814-1

[11] http://www.ecmwf.int/about/overview/

[12] http://www.ecmwf.int/products/

[13] http://www.emc.ncep.noaa.gov/modelinfo/

[14] http://wwwt.emc.ncep.noaa.gov/gmb/moorthi/gam.html.

[15] See 8.2 Powel error Prediction (Document from Agder Energy A/S).

[16] See 8.2 Powel error Prediction (Document from Agder Energy A/S).

8: Appendix

8.1: DIV ABREVIATIONS in report and files

Abs = absolute value

EC = European center weather forecast

GFS = Global Forecasting System in USA

Mean = average value

OHBV = Open HBV (hydrological model)

Prec = precipitation

Runoff = stream flow runoff (amount of water coming)

Std = standard deviation

Temp = temperature

Var = variance

8.2 Powel error Prediction (Document from Agder Energy A/S)

The kalman filtering technique was tested and evaluated in the early versions of HBV, funded by “Kraftverkshydrologisk råd”. However, the method has been dropped when there is no unique way to update the hydrological condition based on observed discharge.

There are several methods available in order to correct the deviation between observed and simulated discharge, for instance by adjusting the water level in lower and upper zone, soil moisture content and snow reservoir. The snow reservoir may be corrected several ways, for distribution and the water content of the snow pack. However, the snow reservoir is excluded as spring seasons. During the snow free season, we may modify the water level lower and upper when there is one linear tank in model. In this situation there is a unique link between the water level in the tank and the output from the linear tank.

When the model contains both linear as well as nonlinear tanks, there is no longer a unique way to make corrections of the model status based on the deviation between the observed and calculated discharge. Available methods are several subjective combinations of analytical methods as well as some “Kraftvershydrologisk råd”. This is the reason why the latest model implementations have left the Kalman filtering technique, and rather implemented an error prediction algorithm.

The Powel Inflow model (Powel implementation of the HBV model) does not employ the Kalman filtering technique but an error prediction algorithm.

There is no feedback from the discharge deviation into the model status, but a parallel correction of the model error. The main reason behind this decision are experiences from the early implementations funded by “Kraftvershydrologisk råd” where the conclusion was that the observations of model status was erroneous, especially in the winter season.

The error prediction algorithm is an empirical technique, and it has not been fully tested. The method is logarithmic, in the way that it deals with “relative error” and not the absolute error.

Main calculation steps are:

1. A trend factor is calculated qTrend& endash; discharge this time step divided by the discharge previous time step.
2. If qTrend is greater than 1, which means an increasing of discharge, an attenuation factor trendAtt is calculated: 1/qTrend. Otherwise the attenuation factor is equal to qTrend. The reason behind this is that error correction is more safe and accurate when discharge is decreasing. The uncertainty of the error correction is greater and it is proportional to the increase of discharge.
3. If there exists a discharge observation for the actual time step, the error factor, aRatio, is calculates. qRatio is observed discharge divided by calculated discharge. If there is no discharge observation, qRatio=1.
4. The error correction factor q-cfact(t) is calculated as follow:

   q_cfact(t)=$(q\_cfact(t-1)^{a} * (qRatio^{(1-a)}))^{\sqrt{trendattenuation}}$

   Where a is the error prediction constant (calibration constant), a=<0.0, 1.0>

   If the error prediction algorithm is active, the calculated discharge is multiplied by q_cfact(t).