Real-time control of an urban groundwater well field offline simulations and online application

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REAL-TIME CONTROL of an URBAN GROUNDWATER WELL FIELD – OFFLINE SIMULATIONS and ONLINE APPLICATION

A dissertation submitted to
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for the degree of
Doctor of Sciences

presented by

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Abstract

This doctoral thesis presents an optimal real-time control approach for the management of drinking water well fields. The Hardhof drinking water well field in the city of Zurich, Switzerland was used for the thesis as a role model regarding an urban well field’s real-time management. The real-time control algorithm is based on a hierarchical concept with fuzzy logic controllers controlling technical installations as local task. By controlling defined criteria the attraction of potentially polluted water from the city is kept small. The controllers’ parameters are adapted according to a superordinated optimal goal criterion. This criterion requires the minimization of infiltration water, simultaneously minimizing energy needs. The hierarchical algorithm is used together with a three dimensional finite element variably saturated subsurface flow model, including aquifer-river interactions, natural recharge and lateral inflow, to simulate the impact of the daily management of the waterworks on the groundwater flow field. The control method adapts the allocation of bank filtrated water for the supply of twelve injection wells and three artificial recharge basins, with an abstraction rate given by the daily demand of drinking water.

Two control criteria were used: The first one uses head gradients and the second the delineation of well catchments by path lines. The methods were first tested in offline simulations for the period January 2004- August 2005 and revealed that (1) historical management decisions were less efficient compared to optimal hierarchical control results and (2) the spatial distribution of artificial recharge should be clearly different from the historical one.

Next, the methodologies were applied and tested at the control center of the well field in online mode. For the application of the real-time control concept use is made of the Ensemble Kalman Filter method which updates the groundwater flow model with the help of online groundwater head data of 87 measurement points. The results of the applied test indicate that the electrical conductivity of the water abstracted in the wells decreased. The decrease of the electrical conductivity indicates a reduced water inflow from potentially contaminated sites as long as the groundwater management was optimised with the proposed methodology. It can be concluded that the simulation and the application prove the feasibility of the real-time control concept.
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1 Introduction

1.1 Real-Time Management of Urban Well Fields

Groundwater resources supply drinking water for cities in many parts of the world. Yet, aquifer depletion due to excessive pumping, salinization in semi-arid and coastal areas, and different kinds of contamination may threaten these valuable water resources. Leakages of chemicals, leaking sewers or oils spills on rail roads or highways may contaminate the water and make it unsuited for drinking. Nearby old waste disposal sites might produce toxic solute which can be transported with the groundwater.

All these threats lead to the question whether it is useful in general to pump groundwater for drinking water purposes in large cities. On the other side, it is attractive to abstract drinking water close to large cities because this limits the transportation costs and very often large cities are located near a river, which naturally recharges an aquifer. If groundwater is pumped in an urban area with multiple pollution sources, the operation requires a good quality control of the abstraction processes or the monitoring of protection zones. With this thesis a methodology of quality control is presented which has been put into practice for the safe pumping of drinking water in the city of Zurich, Switzerland. The methodology is of interest for a large class of cases involving sites that are relatively close to a larger contamination source that has not been removed by remediation.

Drinking water consumption in Zurich comprises up to 46 million m³ per year. The drinking water supply of Zurich originates from three major sources: 75 % is water from Lake Zurich, water from springs contributes 7% to 11%, and groundwater contributes a fraction of about 15 %. (WVZ, 2002). The Hardhof well field is situated outside of the post-war city developing area. The growth of residential and industrial quarters close to the Hardhof well field led to increased contamination risk.

Meanwhile, the HACCP concept (Hazard Analysis and Critical Control Points) (WHO, 2010) was incorporated as legal obligation by Switzerland (EDI, 2010) and requires for all producers of drinking water to guarantee the quality standard of the supplied water at any time. The old concept to secure groundwater quality consisted of defining protection zones in order to avoid input of contamination from the subsurface close to the wells thus allowing for some pre-warning time.
However, the possible inflow of polluted water from different parts of the aquifer must not only be monitored but also be controlled and prevented.

Online-sensors are used more and more in the recent years for the monitoring of aquifers and the operation of wells. These sensors transfer head data, temperature or chemical data, e.g. electrical conductivity, of the groundwater and can be considered as highly valuable for the monitoring of well fields. Still, an operating real-time control system for the management of urban well fields did not exist until now. A real-time system should consist of three parts: The real-time transferred data, a model that is updated with these data, and a control algorithm calculating the necessary pumping (or protective infiltration) rates at current time or in the future.

When assessing the interest in real-time control as a measure for groundwater resources management, the yearly number of relevant publications shown in Figure 1 could be an indicator. The selected publications mainly deal with water quality monitoring or remediation processes in the field using measurement devices that communicate data in real-time. Since the year 1994 the number of publications per year is stagnant either indicating low public interest in real-time control of groundwater or a scientific gap for this topic.

![Figure 1: Yearly number of records for the term: “real-time control” AND “groundwater” in the Web of Science.](image)

However, real-time control methods can contribute to an optimized well management as they present a good technical measure to operate a well field under daily changing natural conditions and demand conditions, complying with quality constraints regarding the drinking water.

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In order to create a real-time management system and implement it, a KTI project was started between the Institute of Environmental Engineering (IfU) at the Swiss Federal Institute of Technology Zurich, the Zurich Water Supply (Wasserversorgung Zürich) and the engineering company TK Consult AG as project partners. Two parts were ready, when the work for this thesis was started in summer 2006: Inside the Hardhof well field and the surrounding aquifer dozens of boreholes with measurement devices were available, delivering daily measurements of head, electrical conductivity and temperature. Second, a three dimensional groundwater flow model was established calculating the three dimensional flow field for transient boundary conditions and forcings, such as leakage from the river, pumping rates, and artificial recharge. In addition to that, a concept for the real-time model had been tested with a synthetic case study using the Ensemble Kalman Filter (EnKF), (Hendricks Franssen and Kinzelbach, 2008) and (Hendricks Franssen and Kinzelbach, 2009). The third part, the design and implementation of the real-time control approach had yet to be done.

1.2 Main Objective and Working Steps

The general objective of the thesis was to develop and to test a real-time control system for the Hardhof well field management. The working steps to achieve this goal were the following:

1. The first step was to choose a control algorithm that would fit the requirements of a real-time management for a groundwater well field in a city, where polluted groundwater has to be kept away from the pumping wells.

2. The second step was to define control criteria that could be derived from the signals/output of the already established sensor network and groundwater model. These control criteria which would be based on the flow model should indicate the origin of water.

3. The next step was to couple the already established groundwater flow model with the real-time control algorithm in order to simulate possible scenarios.
4. Results of simulations with two control criteria were evaluated. Simulated historical management decisions were to be compared with the outcome of optimal real-time control.

5. The simulative performance of alternative control methods coupled with the model had to be compared with the control approaches that were about to be applied for the real-time management of the well field.

6. The online-application of the real-time control methodology had to be supervised and conducted in the well field’s control center.

7. The results of the simulated real-time control methodology and its online-application should be presented and discussed in publications.

1.3 Outline

The thesis starts out in Section 2 with a site description of the Hardhof well field supplying necessary information on the aquifer and the well field itself. The necessary real-time data is collected by sensors at measurement points within the well protection zone and in other parts of the aquifer. These devices are described in Section 3. Section 4 explains the reason why an optimal control of the well field is necessary. Although artificial recharge is used to create a hydraulic barrier in the head protection zone around the well field, water which could transport contaminants still keeps flowing into the horizontal wells.

Section 5 introduces the already established groundwater flow model (three dimensional finite element model) and gives a short description of the Ensemble Kalman Filter (EnKF) approach to perform real-time modelling. This first part is followed by analyses which were necessary to set up the flow model. The setup of the flow and transport model with its main parameters, initial and boundary conditions is described in the different subsections. In Section 6 the general concept of the control approach is discussed. Its subchapters provide information about the chosen control criteria and control factors (i.e. artificial recharge), the design of the Fuzzy Logic controllers and the hierarchical optimal control approach. Section 7 highlights the offline simulation results with the first control criterion (i.e. Δh-criterion) and the outcomes of its online-application. After a short discussion of this criterion’s advantages and disadvantages, Section 8 introduces the model and control setup using the
second control criterion (s-criterion). It provides offline-simulation and online- application results of this control criterion as well. **Sections 9 and Sections 10** sequentially present alternative control/optimization approaches. Section 9 presents results which were obtained by a state-of-the-art approach of multi objective optimization incorporating a non-dominated genetic algorithm. This strict optimization approach uses the flow model to compute optimal artificial recharge rates. The results are compared to those computed with the hierarchical approach. In section 10 an expert system approach which was used to simulate the automatic control of the well field with the s-criterion is also compared with the outcome of the hierarchical control. **Section 11** presents simulation results of real-time control under uncertainty of model parameters. Conclusions and recommendations concerning the control approaches and control criteria and possible future working steps are given in **Section 12** which closes the thesis. **Section 13** lists all the necessary references the thesis is built upon. **Section 14** (appendix) provides the reader with supplementary data regarding the technical structure of wells and recharge installations.
2 Site Description of the Limmat Valley Aquifer and the Hardhof Well Field

2.1 Geographic Setting

The upper Limmat valley aquifer, Figure 2, is located in the city of Zurich, Switzerland. River Limmat originates from Lake Zurich (1) as an outflow. Its discharge is regulated by a weir at Platzspitz (2) (the confluence of Limmat and Sihl) and varies, with peak discharges in summer due to precipitation runoff and snow melt. The river bed is partly artificial and partly restored. The Limmat tributary Sihl (3) which originates from Lake Sihl runs parallel to the south eastern boundary of the Limmat aquifer in direction north-north-east and discharges into river Limmat (4). The groundwater flow regime has the direction of south-east to north-west with slopes of 0.001 to 0.006. Highest gradients are observed upstream close to the lake. The Hardhof well field (5) is situated at the northern fringe of the aquifer. Industrial areas (6) are in close neighbourhood today, as well as the tracks of the Swiss federal railways and the highway.

Figure 2: Aerial view of the city of Zurich and the upper Limmat Valley Aquifer. (1) Lake Zurich; (2) Weir Platzspitz; (3) River Sihl; (4) River Limmat; (5) Hardhof well field; (6) Industrial area; (7) City center; (8) Boundaries of aquifer (model).
Figure 3 shows the driving mechanisms for the groundwater flow: The rivers Limmat and Sihl supply the aquifer with surface water. Lateral inflow is produced by hill slopes in the North (Hönggerberg) and in the South (Uetliberg). Natural recharge at the surface is possible in some parts. But urban sealing generally prevents the precipitation from directly entering the aquifer. In the North-West a (theoretical, i.e. modelled) prescribed head contour marks the boundary between upper and lower Limmat valley aquifer. In the Hardhof well field, abstraction and artificial recharge dominate the groundwater flow. However, the main driving force of the groundwater flow regime is the river Limmat and its leakage, which supplies the groundwater body with surface water via natural bank filtration.

Figure 3: Three dimensional projection of the upper Limmat valley aquifer model. After TK Consult (2010).

2.2 The Hardhof Well Field

The Hardhof well field contributes with about 15% to the drinking water supply of Zurich, compared to 75% of lake water. It is the main facility serving for the Zurich Water Supply company (Wasserversorgung Zürich) as head quarters and hub for the distribution. From here all abstracted water is mixed with conditioned lake water and then pumped into the drinking water supply network. Figure 4 gives an overview on the Hardhof well field.
To protect the four drinking water wells A, B, C, and D bank filtrate is abstracted first from 19 bank filtration wells referred to as vertical wells and is then artificially recharged in three recharge basins I-III and infiltration wells referred to as S1-S12. The larger part of the bank filtrate is diverted to basins I-III aligned from East to West whereas the minor part is used for the supply of the infiltration wells. The recharge is supposed to create a water mound with gradients that point from the well site to the city domain in order to force the vectors of the flow field in this area to point westwards. This hydraulic mechanism can also be called a hydraulic barrier. Thus, the inflow of water from the city domain is supposed to be avoided. The main reason for this specific arrangement of recharge basins and infiltration wells is the protection of the well site. Several potential dangers are threatening south of the recharge works: The highway A1 that passes only 50 meters south of the recharge basins is the major transport artery between Zurich and Berne. Additionally, 500 meters further south the tracks of the Swiss federal railways run to the busiest train station of Switzerland. Both, highway and railway represent a potential of hazardous accidents and possible pollution of the drinking water resources. Although recharge operations are well performed in general, measurements of electrical conductivity in the abstraction wells (especially the wells C and D) show a fraction of the pumped water originating from the city domain. This fraction depends
on mechanisms which will be explained later in sections 4 and 4.1. Technical data of horizontal wells, recharge basins and infiltration wells are supplied in the appendix. Figure 5 shows a schematic drawing of the horizontal wells’ design.

Figure 5: Scheme of the horizontal well design and picture of the interior of the well shaft (WVZ, 2010).

2.3 Geological Settings

Several geological studies (drillings) have been carried out to analyse the underground structure in the Hardhof area (WVZ, 2006). The drillings (Figure 6) revealed that the resulting geological profiles could be classified into three categories: Profiles with a single layer (category 1, green dots) are mostly located south of the Hardhof. They can be characterised by relatively high hydraulic conductivities with no layering of soils and a homogeneous structure.

Drillings of category two are mainly found inside the Hardhof area and one at Limmat River. They indicate layering of soils into at least two different layers of different hydraulic conductivity. The coarser material has been deposited over finer sediments. Thin layers of silt or sand may contribute to heterogeneous soil structures. The flow paths may be strongly affected by possibly creation of preferential flow paths in horizontal and vertical direction. The surface of the Hardhof area itself has been sealed by the Zurich Water Supply to protect the well field from surface pollution. The sealing has a depth of 80 cm.

Drillings of category three can be found north of the Limmat and at a distance of 500 meters south of the Limmat River. Areas marked with red dots are characterised by urban activities in the past. The surface shows soils partly contaminated by construction materials such as wood debris and bricks.
Figure 6: Geological categories of drillings (Baatz, 2010).
3 Measurement Devices of Head, Electrical Conductivity, and Temperature

The Zurich waterworks have 87 piezometers available with a high spatial density in the Hardhof area (Figure 7). Kaiser (2010) assumes the density of dozens of boreholes with piezometers (Figure 8) within an area of less than 1 km² to be considerable as one of the highest in Europe.

Figure 7: Map (Swiss coordinate system) of piezometer locations in the Limmat valley aquifer (WVZ, 2010).

The groundwater head measurements are made with solid state pressure transducers and communicated mostly by a 4-20 mA signal via cable (79 cases) (Figure 8) by SMS (2 cases) (Figure 9) mobile phone (6 cases), and directly stored in the data warehouse, or on an FTP server that is accessed by the Zurich waterworks. Daily meteorological data are automatically downloaded by FTP from a MeteoSwiss website. River discharge measurements are obtained from the electricity company EWZ by a cable connection. Groundwater EC and temperature measurements are made with a TetraCon 96A-4 measuring cell (Figure 10) with four graphite electrodes. The instrument is stored in the boreholes of the piezometers beneath the groundwater level and measures temperature and electric conductivity between 10 to 75 degrees Celsius with an accuracy of 0.1 and 0.5.
per cent respectively. Electrical conductivity varies with temperature. The reference value of measured electrical conductivity is automatically set to 20 °C.

Figure 8: Borehole of a piezometer with signal cable (Baatz, 2010)

Figure 9: SMS Data logger for data communication (WVZ, 2010)

Figure 10: TetraCon 96A-4 measuring cell for EC and temperature (Baatz, 2010)

Figure 11: Meteorological station (rain gauge and wind speed) (WVZ, 2010)
4 An Imperfect Hydraulic Barrier

4.1 The Identification of City Water

The artificial recharge in the recharge basins and infiltration wells leads to a synergetic effect: First, its purpose is to elevate the groundwater level, which would otherwise be drawn down permanently due to the abstraction of the horizontal wells and therefore cause infractions on buildings near the well field. Second, the artificial recharge of the bank filtrate provides an additional natural filter effect in the underground, when the water passes the masses of gravel, coarse grained sand and silt. When pumped in the horizontal wells, the water already possesses drinking water quality. No further conditioning (except chlorination) is necessary. The third purpose (which was described in chapter 2.2) is to maintain a hydraulic barrier in order to prevent a possible inflow of water from the city. Figure 12 shows the assumed principle of the natural recharge and artificial recharge. The ideal situation would be a perfect hydraulic shortcut of the horizontal wells with the natural bank filtrate water from river Limmat and the artificially recharged water from the basins and infiltration wells.

Figure 12: Idealized picture of the dynamics of bank filtrate water from the river and bank filtrate water from the basins and infiltration wells, after WVZ (2010).

However, almost four decades of well field operation with the artificial recharge concept have shown that such a picture is idealizing the situation. An important study on the hydrogeology of the Hardhof was carried out on behalf of the Zurich water works in 1992 (Jäckli, 1992). The main subject of the study concerned the contaminants in the Herdern land fill waste disposal site that is in the neighborhood of well C at a distance of about 250-300 m. The outcome of interest for this thesis concerns the electrical conductivity in the groundwater.
Before 1992 it was assumed that this waste disposal site had an influence on elevated values of electrical conductivity in the pumped water of wells C and D. Water samples were taken at different places of the field and their electrical conductivity was measured. These point measurements were used for an inverse weighted interpolation, Figure 13, of isolines of electrical conductivity.

![Figure 13: Map of interpolated isolines of electrical conductivity in the groundwater. The isolines for electrical conductivity of 400 mS/cm (red) and 500 mS/cm (green) are drawn after Jäckli (1992).](image)

One of the recent studies carried out by the Swiss Federal Institute of Aquatic Science and Technology (Eawag) in 2001 for the Zurich water works (Kaiser, 2001) showed a specific spatial distribution of electrical conductivity (EC) with elevated values between 500 μS/cm and 700 μS/cm in some parts of the city domain (here, EC is always reported for a reference temperature of 20°C) and low values between 200 and 270 μS/cm (showing an annual cycle) for the river Limmat. EC values between 250 μS/cm and 300 μS/cm were measured in the bank filtration wells which supply the water for artificial recharge (Kaiser, 2001). The EC values measured in the four horizontal wells give an indication of the percentage of city water (CW). Wells A and B are mainly supplied by infiltrating river water and artificially recharged water and therefore the measured EC is relatively low. The measured EC in wells C and D is larger, which is indicative of a more elevated fraction of CW.
Figure 14 shows one outcome of the mentioned study: The definition of “city water” was achieved via extrapolation of measurements of tracers in the groundwater at different places, in this particular case Freon. It yields an electrical conductivity of about 370 μS/cm for the city water. This value is considered as a mean value including the elevated values of the Herdern site.

![Graph showing the identification of city water](image)

**Figure 14: Identification of city water (Kaiser, 2001): linear regression function of water samples between measured Freon concentration and electrical conductivity from different locations.**

Table 1 shows the calculated percentage of city water in the four horizontal wells A, B, C, and D according to Kaiser (2001). The values show that wells A and B get a big fraction of bank filtrate water from the river and a minor fraction of city water, whereas the wells C and D get a relative high percentage of city water.

**Table 1: Identification of city water in horizontal wells: For every one of the horizontal wells A, B, C and D the origin of water was calculated with a regression function, see Figure 14.**

<table>
<thead>
<tr>
<th>Well</th>
<th>Bank filtrate water from river</th>
<th>Bank filtrate via recharge basins</th>
<th>City water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well A</td>
<td>91 %</td>
<td>5 %</td>
<td>4 %</td>
</tr>
<tr>
<td>Well B</td>
<td>70 %</td>
<td>24 %</td>
<td>6 %</td>
</tr>
<tr>
<td>Well C</td>
<td>36 %</td>
<td>34 %</td>
<td>30 %</td>
</tr>
<tr>
<td>Well D</td>
<td>34 %</td>
<td>38 %</td>
<td>28 %</td>
</tr>
</tbody>
</table>

Additional tracer tests with Eosin (Wyssling, 2007) also indicate that especially wells C and D pump a considerable amount of water from deeper layers in the aquifer (which might be city water). This shows that the barrier concept created by the artificial recharge does not
completely avoid city water and needs to be improved. The Zurich water works’ management saw a discrepancy between the main objective, i.e. the requirement of 0% city water according to the HACCP standards in all wells on one side and the reality of fractions of city water in the well domain on the other side.

The outcomes of the studies led to the motivation to develop a 3D finite element groundwater flow and transport model (Hendricks Franssen et al., 2011) in order to understand the main processes such as flow regime, solute transport and heat transport and later to combine it with the Ensemble Kalman Filter and real-time optimization methods for a better day-to-day well field operation. Besides an improved or even optimal well field operation an additional advantage of a real-time optimization of the well field operation would be the avoidance of costs regarding future studies for the analysis of contamination extent and dynamics threatening the horizontal wells.

Regarding the design of the control concept the conclusions of the presented analysis leads to the question how to choose control state and control factor. As the design would be purely based on the flow model (a control simulation that uses electrical conductivity as control criterion not being possible at present) it would be best to attach the operation of necessary artificial recharge rates to head differences or to the delineation of well catchments with the path line method. Still, the measurement value of electrical conductivity in the water pumped in the wells could be used as an indicator of hydraulic effects caused by artificial recharge or high pumping rates.

4.2 Analysis of Historical Data

Data of the time period January 1997- May 1998 were analysed in order to evaluate historical effects of abstraction and artificial recharge on the inflow of city water. This time period was chosen because the infiltration wells S7-12 were not built yet and well C would most likely attract city water. Data series of abstraction, artificial recharge, and electrical conductivity in the pumped water were selected to analyze the cross correlation. Figure 15 shows the time series of measured electrical conductivity (EC) $\sigma_{wellC}$, the ratio of recharge in basin II and the abstraction rate in well C, and the head difference $\Delta h_{3247-3417}$ between the measured heads at the piezometers 3247 and 3417 which are situated south of well C. The ratio $ratio_{II/WellC}(k)$ is calculated with equation (4.1)
\[ \text{ratio}_{\text{II-wellC}}(k) = \left| \frac{Q_{\text{II}}(k)}{Q_{\text{wellC}}(k)} \right| \]  

with artificial recharge \( Q_{\text{II}}(k) \) in basin II at discrete time step \( k \), and the pumping rate \( Q_{\text{wellC}}(k) \) in well C at time step \( k \). The time period starts with 1st of January 1997 and ends after 469 days (1 day = one time step \( k \)) at 14th of April, 1998.

During this time period an elevated value of electrical conductivity was measured in well C in the second half. This was due to an unbalanced ratio of artificial recharge and abstraction. In the year 1997 the infiltration wells S 7-12 did not exist and therefore the artificial recharge in basin II was the sole measure to produce an elevated head south of well C which was fully exposed to the inflow of city water. Since late July 1997, more water was pumped than recharged. The ratio \( r_c(k) \) was then falling beneath the 1:1-ratio (red dashed line) to 0.3 for a time period of ca. 70 days. This led to an observed effect of a rising electrical conductivity in well C with a maximum value of 380 \( \mu \text{S/cm} \) on day 285. As the EC is an averaged signal over ten days, peak values can not be recognised. The measured data (see appendix) show values of about 390 \( \mu \text{S/cm} \) approaching the alarm value 400 \( \mu \text{S/cm} \). An overstepping of the alarm value would lead to the switching off of the well’s pump in the control center (WVZ, 2010).

In order to analyse whether the assumption that an unbalanced ratio leads to elevated values of EC is correct, we use the cross correlation function (Equation 4.2)
to calculate the correlation between the discrete data of $ratio_{HI/wellC}$ and $\sigma_{wellC}$ in well C, $l$ is the total number and $k$ the discrete time index. Figure 16 shows the function values. The result is a maximum anti-correlation of -0.75 indicating that a low ratio leads to high EC values in the well with the lag time of about 5 days representing the transport time between pumping well and infiltration basin.

![Cross Correlation Function](image)

**Figure 16:** Cross correlation function of ratio and measured electrical conductivity in well C.

Although the cross correlation function shows a smooth curve and not a single value due to the dispersive processes in the groundwater, it can be concluded that the amount of artificial recharge plays an important role for the protection of the well from the inflow of city water. The correlation $R(ratio_{HI/wellC}, \Delta h_{3247-3417}, T)$ of the recharge/abstraction ratio and the head difference $\Delta h_{3247-3417}$ was analysed as well.

The outcome, Figure 17, is a high and positive correlation of more than 0.7 indicating an effect of artificial recharge on groundwater heads. As the first piezometer 3247 is situated closer to well C and the second one 3417 closer to the city, a positive (or less negative) head difference would signify a local groundwater gradient that points away from the well. The higher the artificial recharge the better (more positive) gets the head difference.
The two cross correlation analyses lead to the preliminary assumption that an appropriate artificial recharge (i.e. recharge/abstraction ratio larger than 1) would keep the measured electrical conductivity in well C low. This suggestion could be checked with the analyses of data from the other wells and basins taking into consideration the range of electrical conductivity data due to the annual oscillations. However, the yearly average value of bank filtrate is ca. 275 $\mu$S/cm (Kaiser, 2001). The city water south of well C shows a constant value of 500 $\mu$S/cm, Figure 13. As the ranges of both electrical conductivities do not overlap, the conclusions from the cross correlation analysis can be considered as valid.
5 The Setup of the Groundwater Flow Model and the Ensemble Kalman Filter

5.1 Variably Saturated Groundwater Flow

The upper Limmat valley aquifer belongs to the class of unconfined aquifers. The aquifer is modelled with the software SPRING developed by delta h (SPRING, 2010). The variably saturated groundwater flow is described with the following governing equation (Engeler et al., 2011):

\[
\left( S \rho S_{op} + \rho n \frac{\partial S}{\partial p} \right) \frac{\partial p}{\partial t} - \nabla \left( \frac{\rho k k_r (S)}{\mu} (\nabla p + \rho g \nabla z) \right) = w
\] (5.1)

With \( S \) as saturation, \( \rho \) – water density, \( p \) - pressure, \( S_{op} \) - specific storativity with respect to pressure, \( n \) - porosity and \( t \) - time, \( k \) - permeability, \( k_r \) - relative permeability, \( \mu \) - dynamic viscosity, \( g \) - gravitational force, \( z \) - elevation with respect to a reference, and \( w \) as variable of sources (recharge) and sinks (abstraction).

Additional to the flow field calculation SPRING can be used to calculate advective transport (also advective-dispersive and reactive transport). The main driving mechanism of transport is movement of a solute with water passing through the pore space, called advection. The principle of water flow processes takes place along the hydraulic gradient. The average velocity of water travelling from one point in space to another can be represented by the seepage velocities \( v_s \) in equation 5.2 with \( n_e \) being the effective porosity of the medium and \( q \) being the Darcy velocities.

\[
v_s = \frac{q}{n_e}
\] (5.2)

For transport processes (advection) the effective porosity is of interest, since the effective porosity determines the pore velocity of solutes. The porosity and effective porosity respectively can be expressed by Equation 5.3.

\[
n = n_e = \frac{V_0 - V_{hygr}}{V_{tot}}
\] (5.3)

\( V_0 \) is the volume occupied by water. It may contain trapped air bubbles. \( V_{hygr} \) is the volume occupied by hygroscopic water and \( V_{tot} \) is the total volume of the soil sample. An effective porosity of 0.15 was chosen for the model.
5.2 Numerical Solution

The SPRING model is discretised in space by finite elements which possess prismatic shape while it uses time discretization by finite differences. Variables describe soil and aquifer parameters and are assigned either to elements (e.g. hydraulic conductivity) or nodes (e.g. hydraulic head). Parameters such as the hydraulic head are assigned to nodes but are defined over the whole element by the interpolation function used. The ‘basis function’ or weighting function is applied to give each node a weight. The Galerkin-method minimizes the weighted residual of a trial solution. The temporal discretisation into finite differences in time is carried out by Equation 5.4:

\[ \frac{dh_i}{dt} = \frac{h_i^{n+1} - h_i^n}{\Delta t_{n+1}} \quad (5.4) \]

\( n+1 \) denotes the time step following after the known time step \( n \) at node \( i \). \( h_i^{n+1} \) is the unknown head at time \( n+1 \). A linear extrapolation is made from the previous time step as shown in Equation 5.5.

\[ h_i^{n+1} = h_i^n + \left( \frac{\Delta t_{n+1}}{\Delta t_n} \right) (h_i^n - h_i^{n-1}) \quad (5.5) \]

Finally there are two criteria to be complied with the solution of the flow and transport model.

An important criterion when calculating advection is the Courant number. The Courant number relates the average velocity and time step \( \Delta t \) to the spatial increment \( \Delta l \). It is defined as:

\[ C_o = \frac{\Delta t}{\Delta l} u \quad (5.6) \]

The Courant number must be smaller or equal to 1 to satisfy the criterion for a stable numerical solution (explicit method). However, SPRING uses in general the mildly explicit method with \( \theta = 1/2 \) (Crank-Nicolson). Exchange or leakage between surface water and groundwater represents a natural process with large contribution to the water balance in the aquifer. Leakage is especially interesting for the Hardhof area, where 19 bank filtration wells (vertical wells) are in operation. The pumped water from these wells does not have drinking water quality due to the limited residence time within the aquifer. Therefore it is artificially recharged into the groundwater by the three infiltration basins and twelve infiltration wells as described in section 2.2. The two governing variables for leakage from a surface water body into groundwater are the hydraulic head gradient between river,
governed by river stage, and groundwater head \((h_{ext} - h_i)\) and the leakage coefficient. The present model uses a constant leakage coefficient, although Engeler et al. (2011) have shown the temperature dependency of the leakage coefficient due to changing viscosity of water. In SPRING the amount of leakage \(Q_v\) can be calculated with Equation 5.7.

\[
Q_v = L * (h_{ext} - h_i)
\] (5.7)

with \(L\) being a modified leakage coefficient per node and \(h_{ext} - h_i\) the hydraulic head gradient between river, governed by river stage, and groundwater head. Specific data of the model are provided by: Hendricks Franssen et al. (2011), Engeler et al. (2011), and Doppler et al. (2007).

### 5.3 The Ensemble Kalman Filter Approach

Although the groundwater flow model may fit well the measured head data, deviations between measured and simulated heads are not negligible. Moreover, if the calibrated model is applied in prediction mode, deviations tend to be larger, which is common when applying any calibrated model for predictions (Evensen, 1994). In order to reduce the discrepancies between measured and simulated hydraulic heads an Ensemble Kalman Filter approach (EnKF) was introduced to update the model in real-time. This approach is used for the real-time management of the well field. The assimilation of measurement data was tested beforehand in two synthetic case studies (Hendricks Franssen and Kinzelbach, 2008, 2009). The EnKF uses measurement data to update model predictions by optimally weighting measurement data and model predictions. For choosing the optimal weights it is essential to characterize the model prediction uncertainty. Details can be found in (Burgers et al., 1998), among others. In this thesis, uncertainty was dominated by the spatial variability of the hydraulic conductivity \(K\) and \(L\) and was described with the help of geostatistical methods (Hendricks Franssen et al., 2011). For online applications with the real-time control method, uncertainty of river stage values could be reduced by making use of existing predictions on the basis of a coupled regional climate- surface hydrological model (Verbunt et al., 2007). The EnKF used 100 stochastic realisations to characterize the model prediction uncertainty. Using 200 stochastic realisations only gave a small additional improvement in terms of head prediction. Given the CPU-intensity of the calculations, only 100 realisations were used. In general, the Ensemble Kalman Filter consists of the following steps:
1. The groundwater flow model is used to predict for \( t=1 \) the groundwater levels. Necessary input for these predictions are the initial states (hydraulic heads at \( t=0 \)), predicted forcings (groundwater recharge, river stages, lateral inflows) and additional static and dynamic model parameters. The Ensemble Kalman method relies on solving the groundwater flow model many times (100 in our case). In principle, any input parameter or model forcing can be stochastic. In this study, hydraulic conductivity and leakage coefficient were the uncertain parameters, as their uncertainty dominates over other sources of uncertainty. The uncertainty of these parameters is quantified with the help of statistical models, in the case of hydraulic conductivity with help of a Multi-Gaussian geo-statistical model. The different input values produce realizations of piezometric head values which are different, yet possess equal probability. The covariance matrix \( C \) can be calculated on the basis of these different head predictions.

2. It is assumed now that at the time step (\( t=1 \)), measurement data are available online and that an estimation of the uncertainty of the measurement data is available.

3. The measurement data are used to update the model predictions with the following equation:

\[
x^+ = x^0 + K(y - Hx^0)
\]  

(5.8)

with \( x \) an augmented state vector containing piezometric heads and leakage coefficients at the model nodes. Index „+“ stands for an updated vector and index „0“ stands for the actual state predictions. Vector \( y \) contains the measurement data. Matrix \( H \) is a projection of the model values onto the measurement values. Matrix \( K \) stands for the „Kalman Gain“ and contains the optimal weighting of model prediction values versus measurement values in the update. The Kalman gain is calculated with:

\[
K = CH(HCT + R)^{-1}
\]  

(5.9)

Matrix \( C \) contains covariances of the model states and the log-leakage coefficients, and matrix \( R \) the co-variances of measurement data. Equation (5.8) implies the optimal weighting of model state prediction and measurement values at every model node. All the 100 model runs are updated using the equations (5.8) and (5.9).

4. The results of 100 updated piezometric head distributions are used as initial states for the model runs of the next time step.
6 General Control Approach

6.1 Concept of the Feedback Control with Hydraulic Head Difference as Control State

The analysis in section 4 showed the correlation of artificial recharge, hydraulic head difference and electrical conductivity. An elevation of electrical conductivity in well C can be regarded as indicator for inflowing water from the city domain.

In order to prevent polluted city water from flowing into the domain of the horizontal wells, the heads near the basins have to be higher than the heads closer to the city. Three pairs of measurement points, located in the transition zone between the wells and the city (Figure 19), were selected in order to calculate three head differences ($\Delta h_1$, $\Delta h_2$, $\Delta h_3$) which are used as inputs for the control algorithm. They are regarded as representative values for three relevant regions of influence of three well groups (well A & B, well C, and well D). All pairs are located on a straight North-South axis. If head difference $\Delta h$ for each of the pairs is larger than zero, the groundwater flow direction points away from the wells, avoiding the abstraction of city water.

Figure 18: Selection of hydraulic head differences in the Hardhof well field.
The three head differences were chosen due to a second reason: It is important to make sure that the system response is sufficiently sensitive to the available control factors to make the control problem interesting. Sometimes the variables that can be adjusted only have minor effects on system behavior. In our case it is important to analyze whether the artificial recharge rates have a significant impact on the head differences. To evaluate this sensitivity four simulations were performed which made use of constant artificial recharge rates over a time period of 60 days. For every experiment the artificial recharge rates were changed in the three basins (Figure 19).

Figure 19: Sensitivity analysis of the three chosen pairs of head differences.
The first column shows the result with a constant artificial recharge of 10,000 m³/d in all three basins. The second column shows the outcomes of three changes: In the first row, the artificial recharge in basin I was double and all others kept constant at 10,000 m³/d. The simulation result shows a distinctive rise of $\Delta h_1$. The second row shows the slightly elevated $\Delta h_2$ after applying 20,000 m³/d in basin II (with the other two artificial recharge rates kept at 10,000 m³/d). $\Delta h_3$ shows a distinctive shift for an artificial recharge of 20,000 m³/d in basin III. The outcome of the three different changes of artificial recharge shows a unique outcome of head difference rise for all three measurement points with the most important result being the independency of the head difference rises from each other. The connection between artificial recharge and head difference leads to the setup of the feedback control which is based on two parts: As control state we choose the head difference which has to be controlled by the control factor of artificial recharge in basins and infiltration wells. As example, Figures 20, 21, and 22 show the general principle of feedback control loops for the three control states which are controlled by the control factor of artificial recharge in the basins I, II, and III.

![Figure 20: Feedback control loop for basin I.](image1)

![Figure 21: Feedback control loop for basin II.](image2)
The artificial recharge rate $u$ is calculated by the controller, in this case the Fuzzy Logic Controllers $FLC_a$, $FLC_{II}$, and $FLC_{III}$. The controlled system, i.e. the effect of defined artificial recharge in basins I-III which lead to a change of head (and of the head differences $\Delta h_1, \Delta h_2$, $\Delta h_3$) is also influenced by disturbances such as natural recharge, river stage or the abstraction in well C. In order to keep a desired constant value of $\Delta h_1, \Delta h_2$, and $\Delta h_3$ a reference value $\Delta h_{\text{ref}}$ is given to calculate the control error $e$. For 7 control elements (three basins and four infiltration wells) 7 control loops are designed. Here only the control loops of the three basins are shown for the sake of convenience. Figures 23, 24, and 25 each show the feedback control loops for one dual state controller under time-variant conditions with the flow model representing the controlled system which produces the head values. Due to the discretization in time for the calculation of the hydraulic head there are two distinctive time levels for the feedback control:

a) The controllers get as inputs the head differences $\Delta h_1, \Delta h_2$, and $\Delta h_3$ at time $t$ (here $t$ is one day with $t=1,2,3...$) and the rates of change $\Delta h_1(t) - \Delta h_1(t-1)$, $\Delta h_2(t) - \Delta h_2(t-1)$, and $\Delta h_3(t) - \Delta h_3(t-1)$.

b) The controllers calculate the necessary artificial recharge rates $u_I(t+1)^*, u_{II}(t+1)^*, u_{III}(t+1)^*$ which are supposed to influence the hydraulic head $h$ of the next day $(t+1)$. Elsewhere in the text they will be denoted as $u_j(t+1)$.

c) After the model run the hydraulic head of the next day $t+1$ leads to the calculation of the head differences which are used as input for the next control step.

d) The two control states are updated and used as inputs for the next control run.
Figure 23: Feedback control loop for the first pair of control states which are time-variant.

Figure 24: Feedback control loop for the second pair of control states which are time-variant.
6.2 Introduction to Fuzzy Logic Control

Fuzzy Logic Control is based on the theory of Fuzzy Logic (a super-set of Boolean logic) which was introduced by Zadeh (1965). It is the application of Fuzzy Logic to control systems’ design (Nauck et al, 1997). Fuzzy Logic is used to represent imprecision and uncertainty of real world systems and technical processes and uses sets of fuzzy numbers for computation purpose instead of crisp numbers. Uncertainty and imprecision of a real world system cannot be easily modelled. The model parameters of an environmental system such as that of a groundwater aquifer are not certain. The use of a numerical flow model may result in poor predictions if the measurements of new natural events are not integrated in the model. Therefore a full and complete numerical model describing every possible cause-and-effect event is not feasible (Byrne, 2003). Besides the model uncertainty the system response for defined control action is connected with implicit expert knowledge. Here we talk about Fuzzy Logic used for control purpose rather than modelling.

Increased numerical complexity required for conventional modelling techniques thus led to the application of Fuzzy Logic to control systems’ design in the form of Fuzzy Logic controllers (FLC). The algorithm of the FLC transfers human perceptions in the form of implicit expert knowledge into the numerical domain, thus creating suitable system controller design which may incorporate all forms of non-linear behavior between system state and control action.
The Fuzzy Logic approach is also used in the area of control system design where human expert knowledge, rather than precise numerical modelling of a process is used to design and implement the required controller. Human expert knowledge is gained in a heuristic process where empirical information is obtained during process operation. The rule-base reflects the human expert knowledge, expressed as linguistic variables in the form of if...then statements, while the membership functions represent expert interpretation of those same variables (Byrne, 2003). The Fuzzy logic controller’s algorithm consists of a three partite design: First, the input and output variables of the transfer function are fuzzified. The range of values of input and output is divided up in different membership functions which are normed between 0 and 1. The rule base comprises all statements of system states and control action (Byrne, 2003). In the second part, inference and aggregation methods are in use to compute the controller’s output. Here inference and aggregation are terms to describe the calculation process with fuzzy sets. After the inference the de-fuzzification method transforms the fuzzy output value into a crisp value.

6.3 Design of a Fuzzy Logic Controller with Hydraulic Head Difference as Input and Artificial Recharge as Output

Important for the operation of a Fuzzy Logic Controller are linguistic variables (Passino and Yurkovich, 1998) which can be considered as descriptive terms that might be used by a decision maker or an expert to describe the system’s response on specific control factors. Furthermore, linguistic variables apply also to the possible actions which are required to control the system. For the controller which is later used for the first case study (section 7), the linguistic variables are based on the hydraulic head difference, $\Delta h(t)$ and the rate-of-change of the head difference $c_i$ which can be calculated with the flow model. The controlled quantity is the artificial recharge rate in a basin or infiltration well.

$$u_j(t+1) = p_{ij} \times f(\Delta h_i(t), c_i(t))$$

(6.1)

where $u_j$ indicates the infiltration rate of a controller (artificial recharge basin or a group of infiltration wells, $j= 1, 2, \ldots, 7$) that uses the head difference $\Delta h_i(t)$ obtained by the groundwater model as first input, and its time derivative $c_i(t) = \Delta h_i(t) / \Delta t$ as second input. The function gain parameter (FGP) $p_{ij}$ can be scheduled for every controller individually with the help of a genetic search algorithm typically presented by Tang (2001). The
controllers’ functions yield the necessary recharge rate of the $j$th basin or injection well $u_j(t+1)$ for the next time step $t+1$. Figure 26 shows the controller. The term $P$ stands for the proportional input value $\Delta h_i$ and the term $D$ for the derivative input value $c_i$.

\[
\Delta h_i(t + 1) = p_{ij} \ast f(\Delta h_i(t), c_i(t))
\]

Figure 26: Fuzzy Logic PD-controller with input and output variable.

The Fuzzy Logic Controller’s rule base (Zadeh, 1965), (Passino and Yurkovich, 1998) consists of a set of rules in the form of if...then...statements that describe the control action which are necessary and useful on the occurrence of system states which are measured or computed with the model. The statements consist of an antecedent/premise (i.e. system state/ input) and its associated consequent (i.e. the action to be taken in order to achieve adequate system control, in the specific case the artificial recharge). The statements are used in an ‘if condition then conclusion’ form. All statements together form the rule base. Combinations of multiple premises and consequents are possible. The more combinations are used the more precise the rule-base is. In theory, the rule base of a Fuzzy Logic Controller should cover all possible system responses in respect to the applicable control actions. This is to provide a reliable system control. The descriptive use of linguistic variables and the rule statements do not create a fuzzy logic system per se. The linguistic variables and rule statements could be used in any boolean-based system, such as a typical decision support system. What makes the controller ‘fuzzy’, is the use of membership functions (MFs) which are denoted as $\mu$ (Passino and Yurkovich, 1998) in order to quantify to which degree of certainty each rule is true in respect of the system state at any particular time. The membership functions are in general of triangular shape with several membership functions used to partition the domain of the numeric value under consideration. The use of membership functions ensures that certainty is based on the subjective interpretation of an expert rather than upon a probability distribution. Degrees of certainty (i.e. degree of membership of a fuzzy set) range from 0 to 1 in value and hence partial membership is possible. The FLC aggregates the levels of certainty for the entire rule -base to obtain an aggregate fuzzy output set, which is subsequently used to obtain a crisp (i.e. numerically valued), control value. The combination of the rule-base, and associated membership
functions constitute together the controller knowledge base, which in effect represents the embedded expert system knowledge.

a) Fuzzification:

The fuzzification is the transformation of crisp numerical inputs and outputs (i.e. head difference and artificial recharge) into fuzzy values (Passino and Yurkovich, 1998). The premises of each rule, Figure 27, are later evaluated with respect to their degree of membership of the fuzzy sets defined across the range of possible values the input (i.e. hydraulic head difference) may assume. As an example, Figure 28 below shows the normalized membership functions \( \mu \) for the two inputs (hydraulic head difference and rate of change of head difference) as generated using the Matlab fuzzy logic function.

b) Inference:

After the fuzzification of input and output variables the inference is performed which itself consists of the two parts of rule matching and the computation of conclusions based on implication.

(i) Rule Matching

In order to match a rule in the rule base, the control algorithm evaluates the possible applicability of each of the rules with respect to the input (e.g. head difference). In general two logic operators are used to produce a conjunction of at least two premises: the AND conjunction (which is connected with a \( \text{minimum (min)} \) or \( \text{product} \) operator) and the OR conjunction (\( \text{max} \) operator). Figure 27 shows all rules with an AND conjunction. As we use two premises within each rule (we have two input variables), the certainty as to what degree the rule as a whole applies to the two inputs have been evaluated. To perform this certainty evaluation, the control algorithm uses the \( \text{min} \) operator to the fuzzy input values. This process is also called rule activation.

(ii) Implied Conclusions

Each consequent of the 7 rules (Figure 27) is a fuzzy set of the membership function (Figure 28) which is truncated (Byrne 2003) in accordance with the degree of certainty the conjunction of premises of the rules apply to the input value between 0 and 1. The whole degree of certainty is computed with the activated/ matched rules of the current inputs. For all rules that are activated an implication operator is applied to the consequent fuzzy set
(fuzzy output variable) in order to truncate this fuzzy set relative to its degree of certainty. As the minimum operator \((\text{min})\) is used to evaluate the degree of certainty in our example (Figure 28) for all activated rules, the consequent fuzzy set is truncated by this amount accordingly.

1. If \((\Delta h \text{ is } \text{"negative"}) \text{ and } ((\Delta h/\Delta t) \text{ is } \text{"negative"})\) then (infiltration is \text{"large"})
2. If \((\Delta h \text{ is } \text{"negative"}) \text{ and } ((\Delta h/\Delta t) \text{ is } \text{"zero"})\) then (infiltration is \text{"less large"})
3. If \((\Delta h \text{ is } \text{"zero"}) \text{ and } ((\Delta h/\Delta t) \text{ is } \text{"negative"})\) then (infiltration is \text{"less large"})
4. If \((\Delta h \text{ is } \text{"zero"}) \text{ and } ((\Delta h/\Delta t) \text{ is } \text{"zero"})\) then (infiltration is \text{"middle"})
5. If \((\Delta h \text{ is } \text{"positive"}) \text{ and } ((\Delta h/\Delta t) \text{ is } \text{"zero"})\) then (infiltration is \text{"less small"})
6. If \((\Delta h \text{ is } \text{"zero"}) \text{ and } ((\Delta h/\Delta t) \text{ is } \text{"positive"})\) then (infiltration is \text{"less small"})
7. If \((\Delta h \text{ is } \text{"positive"}) \text{ and } ((\Delta h/\Delta t) \text{ is } \text{"positive"})\) then (infiltration is \text{"small"})

Figure 27: Fuzzy Logic PD-controller’s rule base. Seven conjunctive.

c) Defuzzifyfication

The output process of the Fuzzy Logic Controller’s algorithm consists of the aggregation of the implied fuzzy sets of the output variable which are the results of the inference part to produce fuzzy output. The transformation of the fuzzy output to a crisp output is called defuzzifyfication. The most used method (Byrne 2003) to transform the fuzzy output is the the computation of center-of-gravity (COG). The computation method of the center-of-gravity for the aggregated fuzzy output is defined as:

$$u_{\text{AR}_\text{Crisp}} = \frac{\sum_i \mu(x_i) * x_i}{\sum_i \mu(x_i)} \quad (6.2)$$

\(u_{\text{AR}_\text{Crisp}}\) denotes the crisp output (i.e. the artificial recharge), \(\mu(x_i)\) is the membership function value (between 0 and 1) of the \(i\text{th}\) input value \(x\) (e.g. head difference). To use this method, two constraints have to be considered:

The truncated output membership function cannot span an infinite area, which is the theoretical case for the membership functions of the inputs (Passino and Yurkovich, 1998). For every possible system state or input, an implied conclusion (aggregated fuzzy output) must exist, otherwise the denominator of the COG equation (Eq. 6.2) could be a zero-value thus producing an infinite crisp output (Passino and Yurkovich, 1998).
Figure 28 shows the complete inference and aggregation scheme, which includes the aggregated output fuzzy set upon which the center-of-gravity method is used to calculate a crisp value. As an example, Figure 29 shows the time signal of head difference and change of head difference which are used as inputs (day 9) for the computation of the artificial recharge, Figure 28. The head difference at this day is 0.08 m and its derivative is 0.03 m. The red line defines the match/activation of the two inputs with 7 membership functions each. The activation is according to the defined rule base shown in Figure 27, with the rules Nr. 4, 5, 6, and 7 being valid. This yields the inference of the four membership functions (equivalent numbers) of the two inputs. When using the minimum operator (product operator) four output membership functions are activated: Nr. 4, Nr.5, Nr.6 and Nr.7. After all the fuzzy sets are then aggregated. Finally the four aggregated membership function values lead to the fuzzy output. The crisp output of the fuzzy output is calculated with the COG equation (Eqn. 6.2) which is 3,340 m$^3$ in this example.

**Inference and Aggregation (day 9)**

![Scheme of Inference and Aggregation](image)

Figure 28: Scheme of Inference and Aggregation. Yellow signifies the truncated fuzzy sets of the two inputs. Blue signifies the truncated fuzzy sets of the output.
Figure 29 shows the time dependent input and output of the FLC in open loop conditions.

The described FLC function yields the transfer function curve for all possible inputs, Fig. 30. When all possible input values are used to calculate the respective function value, all function values can be plotted and produce a 2D-surface in 3 dimensions.

Figure 30: Transfer function curve (control surface) of S8-10 for all possible values of the two input variables. The maximum possible output (artificial recharge) in the example is 10,000 m³.
6.4 Hierarchical Control Concept

The main idea of hierarchical concepts is to divide up the control tasks (decomposition) among control units (or controllers) for the management of a system.

There are two basic principles of decomposition (Brdys and Tatjewski, 2005): functional decomposition and spatial decomposition. In the first case a set of functionally different partial control objectives are assigned to different layers. In the case of the well field control we wish to minimize the artificial recharge and keep the head difference positive.

On the other hand a spatial decomposition can be regarded as useful if the process or the controlled system comprises subparts which have a clear spatial distribution but are all of the same functional kind (recharge basins and wells).

Most hierarchical control concepts can be described as multilayer-multilevel-concepts because the management of many technical systems requires the local control of technical subparts and the fulfilment of at least two objectives.

The hierarchical control concept was not used so far for a well field management in combination with a groundwater model. In the field of water resources management the hierarchical control concept has been mainly used for the optimal control and management of large water supply networks which require a high computation time for the optimization of chlorination, or reduced pumping energy (Duzinkiewicz et al., 2005). Historically the algorithms were developed in accordance with the implementation of parallel computing in the 1970’s (Findeisen et al., 1980). With the technical advancement and the explosion of computational capacity and speed, the concepts were less and less used. However, since the late 90’s a renaissance can be observed: There are two types of applications responsible for their wider use: First, hierarchical concepts are mainly used for real-time control of industrial robots, devices in the automotive industry, biomedical technology or alarm systems where high speed is necessary to operate many parts of a technical system. The second technical application that requires a hierarchical approach is the use of more and more sophisticated and extended models to simulate or predict the behaviour of environmental systems which have to be managed for the purpose of resource exploitation. For the real-time control of the Hardhof well field we consider the hierarchical approach as useful. Figure 31 shows the concept of the hierarchical control approach. The first layer consists of 7 controllers which control the head differences. They are coupled together by superordinated goal criteria in the second layer which requires the infiltration to be minimised and the compliance with a
given reference value. The FLC functions gain parameters are adjusted via a Simple Genetic Algorithm (SGA) which is described in the next subsection.

![Goal criteria](image)

**Goal criteria**

Reference value: $\Delta h_{ref} = +0.05\, m$

Sigma infiltrations $\rightarrow \text{min!}$

Implies adjustment of controller parameters

![Figure 31: Hierarchical concept of control using head differences as control states for multiple Fuzzy Logic controllers.](image)

6.5 Simple Genetic Algorithms (SGA) for the Gain Scheduling of FLCs

In order to avoid the requirement to test every possible combination of gain parameters of the Fuzzy Logic controllers, a formal search method is necessary to adjust gain parameters (Byrne, 2003). Genetic Algorithms (GA) are among the suitable algorithms for such an adjustment. Genetic Algorithms are search heuristics that imitate the driving mechanism of natural selection (Goldberg, 1989). Introduced by Schwefel (1973) they use the concept of “survival of the fittest” to determine the optimal sample value or optimal point in a search space. Although the use of GAs does not guarantee to find the true global optimum in a defined search space, Genetic Algorithms are known to find suitable solutions for an acceptable calculation time (Byrne, 2003). Using the concept of selection, crossover and mutation, GAs are oriented on identifying a global optimum (or global optima) within a problem domain-space and are hence deterministic. However, the processes of cross over and mutation are stochastic elements of the overall search heuristic. A successive performance testing of potential solutions which form a population in regard to an objective
function value leads to the convergence to optimal solutions. The fitter an individual (i.e., one solution) is the higher will be its probability of being selected for reproduction. An individual can be either a single decision variable or a set of several chromosomes if the genetic algorithm is used for a multi objective optimization. Following pseudo-code shows the main steps of the GA which was used for the control algorithm for the evaluation of potential solutions for FLC function parameters (after Byrne, 2003):

Start SGA procedure:
\( is = 0; \) //"is" iteration step

initialise \( P(is) \) // establish initial population of strings \( P \)
evaluate \( P(is) \) // apply objective function to each string in \( P(is) \)
fitness \( P(is) \) // determine fitness of each string with respect to whole population
while termination condition not met do:
begin
\( is = is + 1; \) // increment generation

select \( P'(is+1) \) from \( P(is) \) // form a new population of fittest members from \( P(is) \)

pair off and mate \( P'(is +1) \) // mate individuals in \( P'(is +1) \) to produce offspring
evaluate offspring \( P'(is +1) \) // apply objective function to offspring of \( P'(is +1) \)

fitness offspring \( P'(is +1) \) // determine fitness of \( P'(is +1) \) offspring

update \( P(is +1) \) // establish \( P(is +1) \) population from fittest of \( P'(is +1) \)
end

end of procedure

6.6 Closed Loop System

In order to test the control concept for later implementation, the closed loop system requires a model which represents the dynamics of the system. The existing flow model is necessary to check the stability of the control concept. The implications of control and model runs are shown in Figure 32. With offline optimization it is possible to adjust the controllers’ parameters, yet it requires model runs. Without a model closed loop simulations
are not possible and therefore the stability cannot be assessed. By implication optimization is then not possible. This corresponds with the control concept which is shown in Figure 31 for the offline-mode. In this mode simulations are used to test the controllers’ performance for long time periods (i.e. with data of 600 days).

<table>
<thead>
<tr>
<th>Control Offline-mode</th>
<th>Model</th>
<th>Without Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Test of control simulation.</td>
<td>Combination not possible!</td>
</tr>
<tr>
<td></td>
<td>Offline-Optimization of controllers’ parameters.</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control Online-mode</th>
<th>Model</th>
<th>Without Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Offline-Optimization of controllers’ parameters.</td>
<td>Possible on the basis of measurements alone.</td>
</tr>
<tr>
<td></td>
<td>Optimal management.</td>
<td>No optimization possible.</td>
</tr>
</tbody>
</table>

*Figure 32: Possible combination of model and control mode and their implications.*

The introduced hierarchical control concept is used for the first case study in section 7. The requirement $\Delta h_i = \Delta h_{ref} (i=1,2,3)$ for all three $\Delta h$ is imposed in the control strategy. $\Delta h_{ref}$ is a user specified reference value for the head difference. The desirable state (i.e., $\Delta h_i = \Delta h_{ref}$) is achieved by optimizing recharge rates in infiltration basins and wells. The calculation of optimal artificial recharge rates by separate controllers and the optimization of the control parameters for each time step can be regarded as a multilevel, hierarchical control approach which is related to the concepts introduced by Duzinkiewicz et al. (2005), Brdys et al. (2008) and Park et al. (2007). It consists of the following steps:

1. For the time step $t (t=1,2,3,...)$ the hydraulic head differences $\Delta h_i(t) (i=1,2,3)$ in the wells are calculated with the groundwater flow model (all boundary conditions, forcings and pumping rates are denoted as BC in Fig. 33). All three are inputs for the control of the artificial recharge (in basins, infiltration wells). These head differences and their time derivatives $c_i(t) = \Delta h_i(t) / \Delta t$ are inputs for the FLCs as well.
Step 2a. All recharge rates for the basins and groups of infiltration wells for the next time step \( t+1 \) are calculated by the non-linear FLC transfer functions, Equation 6.3:

\[
\begin{align*}
    u_1(t+1) &= p_{1i} \ast f_{1i}^-(\Delta h_i(t), c_1(t)) ,
    u_\Pi(t+1) &= p_{\Pi u} \ast f_{\Pi u}^-(\Delta h_2(t), c_2(t)) ,
    u_{III}(t+1) &= p_{III u} \ast f_{III u}^-(\Delta h_3(t), c_3(t)) ,
    u_{S1-6}(t+1) &= p_{S1-6 u} \ast f_{S1-6 u}^-(\Delta h_4(t), c_4(t)) ,
    u_{S7}(t+1) &= p_{S7 u} \ast f_{S7 u}^-(\Delta h_5(t), c_5(t)) ,
    u_{S8-10}(t+1) &= p_{S8-10 u} \ast f_{S8-10 u}^-(\Delta h_6(t), c_6(t)) ,
    u_{S11-12}(t+1) &= p_{S11-12 u} \ast f_{S11-12 u}^-(\Delta h_7(t), c_7(t)) ,
\end{align*}
\] (6.3)

Step 2b. The calculated (preliminary) recharge rates \( u_j(t+1), j=1,2,3...7 \) are used for the model run of the next time step \( t+1 \) which yields the percentages of city water \( \Delta h_i(t+1) \) in the wells.

Step 2c. The head differences \( \Delta h_i(t+1) \) are used together with \( u_j(t+1) \) to calculate the objective function value:

\[
J = w_1 \sum_{j=1}^{m} u_j(t+1) + w_2 \sum_{i=1}^{n} (\Delta h_i(t+1) - \Delta h_{ref})^2 \rightarrow \text{min!}
\] (6.4)

where \( m \) is equal to 7 (i.e., four groups of infiltration wells and the three basins), \( n \) equal to 4 and \( w_1 \) and \( w_2 \) are weighting factors. The simple genetic algorithm sets the function gain parameters \( p_{uj} \) randomly between 0 and 1, and selects the population of parameters with the best fitness per iteration step \( is \). This stochastic search is performed for a predefined number of iterations or using a termination criterion with a small fitness function value (i.e. \( J<\varepsilon \), e.g. \( \varepsilon=1 \)). Each of the optimization iterations requires one model run to calculate a new \( \Delta h_i(t+1) \). The optimization needs in general between 5 to 10 iteration steps to converge, with up to 10 seconds CPU-time per iteration step including the model run with the calculation of \( \Delta h_i(t+1) \). Each of the optimization iterations requires one model run. The optimization needs between 5 to 10 iteration steps to converge, with up to 55 seconds CPU-time per iteration. The simulations were performed on a Fujitsu Siemens Celsius W350, Intel Core 2 Duo E6400.

Step 3. The optimized amounts of artificial recharge \( u_j^*(t+1) \) are used as input for the next model run which yields the head distribution \( h(t+1) \).
Figure 33: Scheme of offline model run and optimisation with the $\Delta h$-criterion. Abbreviations are: Boundary condition (BC), genetic algorithm (GA), iteration step ($is$), head ($h$), function gain parameter ($p$), recharge rate ($u$).
The management of well fields in densely settled areas or coastal areas often faces the challenge of polluted groundwater or brackish water flowing into the protection zones of well catchments (Mantoglou et al., 2004). Dynamic boundary conditions like rivers, precipitation, run-off, evaporation and lateral inflow have an impact on the groundwater flow and its transport mechanisms. The main strategy for the management of well fields of drinking water production up to today is relying on the static concept of well protection zones, taking uncertainty into account (Stauffer et al., 2005).

So far, successful applications of optimal real-time control concepts for environmental and/or resources exploitation systems can be found in the field oil reservoir management (Saputelli et al., 2006) and surface water supply networks and reservoir systems (Becker and Yeh, 1974). Roko Andricevic was one of the first to do simulations with a finite elements groundwater model and real-time control algorithms (Andricevic, 1990). However, his approach was not tested with a real-world system. In optimal groundwater well field management, groundwater models were used to test objective functions that match abstraction demands or quality demands under compliance with constraints and dynamic boundary conditions (Bayer et al., 2009). Many of these applications supply pumping schedules or spatial well placements in off-line mode (Siegfried and Kinzelbach, 2006).

Model runs are combined with optimisation techniques to determine the optimal schedules or optimal well placements under the assumption that all future conditions stay either constant or follow some pre-defined scenario (Siegfried & Kinzelbach, 2006 and Bayer et al., 2009). Recent publications show real-time control concepts for water resources systems, one of them using a model predictive control approach with simulation applied for the management of soil salinity (Park and Harmon, 2009) and another on the dynamic management of optimal pumping schemes (Chul and Chang, 2009) using artificial neural network techniques. However, none of the cited approaches meets the requirements of a real-time control concept for an optimal management of a groundwater well field.

The proposed real-time control concept uses three parts: First, the variably saturated subsurface groundwater model, including aquifer-river interactions, natural recharge and lateral inflow which is used to simulate groundwater heads and velocities (Doppler et al., 2007). The calculated head values of every time step are used as inputs for the control
algorithm which provides as output optimal well operation for the next time step. These two parts can be used to simulate the real-time approach in offline mode. Real-time measurement data can be used to update the model which leads to the possible use in online-mode (Hendricks Franssen et al., 2011).

Based on the groundwater flow model calculation of head values (and for on-line applications the Ensemble Kalman Filter as well) the necessary optimal recharge rates for infiltration basins and injection wells are calculated in order to create the desired hydraulic barrier. For the application in online-mode, real-time measurement data of heads and river levels are used to update the real-time model. Real-time control methods need a sample time that is shorter than the reaction time of the system or the system model. In our case, the time interval of one day is sufficient and is also used as time step for model runs.

### 7.2 The Hierarchical Control using the Δh-Criterion for Offline Tests

In order to test the control concept offline, several numerical experiments were carried out in order to allow a comparison with historical management. The daily drinking water demand is given and therefore the daily historical water abstraction rates have been used as model input. The most important question was whether the artificial recharge rate could be reduced or had to be increased instead to meet the Δh-criterion. Historical data of the period between the 1st of January 2004 and the 23rd of August 2005 (daily values for river stage, lateral inflow, natural recharge, and pumping), were used to simulate offline the optimal control of artificial recharge. Simulation scenario I optimized the artificial recharge such that all three head differences were positive on all days. Simulation scenario II optimized the spatial distribution of recharge, under the additional constraint that the total amount of applied artificial recharge was the same as the one applied historically. Simulation scenario III consisted of an additional number of model runs in order to calculate a Pareto front solution. In these calculations, the amount of required is minimized for a given reference Δh_ref. The result forms a functional relationship between the amount of artificial recharge and Δh_i, for a broad spectrum of Δh_i values. For scenario I, it is found that positive head differences during the complete simulation period of 600 days can only be achieved by an increased amount of artificial recharge when compared with the historical artificial recharge in the basins and infiltration wells. See Table 2. The implication of the increased artificial recharge is an increase of the groundwater level of about 0.5 m, which does not have any negative side effects.
Table 2: Comparison of historical management and optimal management using the $\Delta h$-criterion for simulation scenario I and II (with $\Delta h_{\text{ref}}=0.01\text{m}$) over 600 days. The factor $r$ is the ratio of the avg. artificial recharge and the avg. abstraction.

<table>
<thead>
<tr>
<th></th>
<th>Measurement</th>
<th>Simulation I</th>
<th>Simulation II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall recharge for 600 days in $\text{m}^3$</td>
<td>16,500,000</td>
<td>22,000,000</td>
<td>16,500,000</td>
</tr>
<tr>
<td>Overall abstraction for 600 days in $\text{m}^3$</td>
<td>13,000,000</td>
<td>13,000,000</td>
<td>13,000,000</td>
</tr>
<tr>
<td>$\text{Percentage of days when } \Delta h_1 \text{ negative}$</td>
<td>84</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>$\text{Percentage of days when } \Delta h_2 \text{ negative}$</td>
<td>100</td>
<td>0</td>
<td>15</td>
</tr>
<tr>
<td>$\text{Percentage of days when } \Delta h_3 \text{ negative}$</td>
<td>100</td>
<td>0</td>
<td>40</td>
</tr>
</tbody>
</table>

Historical head differences both obtained by measurement and re-calculated with the flow model were negative on almost all days of the considered simulation period (i.e. 100% of the days $\Delta h_2$ and $\Delta h_3$ were negative, whereas $\Delta h_1$ was negative 84% of the days). Modelled and calculated head differences differ, yet this difference does not matter as the analysis focuses on the comparison of the modelled heads for the historical management with the modelled heads for the optimized management. With the hierarchical control approach described in section 6, better results were produced. However, the overall artificial recharge is 1.7 times higher than the overall abstraction, in order to achieve permanently positive head differences (i.e., 0% of the days with negative $\Delta h$). In simulation scenario II the amount of artificially recharged water is fixed (the optimal search algorithm was enhanced by a constraint of a maximum daily artificial recharge rate of 29,000 $\text{m}^3$ not to be exceeded by the sum of the artificial recharge calculated by the controllers), while the spatial distribution of this recharge is optimized over the different basins and infiltration wells. In this case a still better operation scheme of basins and infiltration wells can be achieved as compared to the historical operation. The spatial distribution of artificial recharge of the real-time control simulation (scenario II) is quite different from the historical one, see Table 3.
Table 3: Comparison of historical mean artificial recharge and optimized artificial recharge in basins and infiltration wells according to simulation scenario II.

<table>
<thead>
<tr>
<th>Basin Nr. or Group of infiltration wells</th>
<th>Historical mean artificial recharge (m³ day⁻¹)</th>
<th>Optimal mean artificial recharge (m³ day⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S 1-6</td>
<td>4,400</td>
<td>500</td>
</tr>
<tr>
<td>S 7</td>
<td>1,000</td>
<td>1,000</td>
</tr>
<tr>
<td>III</td>
<td>8,400</td>
<td>6,000</td>
</tr>
<tr>
<td>S 8-10</td>
<td>3,100</td>
<td>6,000</td>
</tr>
<tr>
<td>II</td>
<td>4,200</td>
<td>7,000</td>
</tr>
<tr>
<td>S11-12</td>
<td>2,000</td>
<td>1,000</td>
</tr>
<tr>
<td>I</td>
<td>4,400</td>
<td>6,000</td>
</tr>
</tbody>
</table>

On average, $\Delta h$ is positive although the same average artificial recharge rate was applied as in the past (Table 2). The average artificial recharge rate of about 27,500 m³ per day yielded a $\Delta h$, averaged over the three observation pairs, of -0.046 m in history (Figure 34). While the historical management comprised about 16% of artificial recharge in S1-6 and 26% in S8-10 and basin II, the focus of the optimized artificial recharge shifts upstream with almost 50% artificial recharge being now recharged in S8-10 and basin II. In simulation scenario III (Figure 34), the management was optimized for different given reference values of $\Delta h_{ref}$, and a comparison was made to the historical (simulated) management.

![Figure 34: Pareto front of optimal control simulations including simulation scenarios I and II. Plotted are the minimized amounts of artificial recharge as function of the average head difference, calculated over three pairs of piezometric heads. In the figure also the measured average head difference for the historical management and the simulated average head difference for the historical management are indicated.]
The results of simulation scenarios I and II are part of the Pareto optimal set of solutions together with the results of scenario III. The values are trade-offs between the two criteria: Achieving positive head values and minimizing the amount of artificial recharge. Acceptable values regarding the control criterion (i.e. its desirable state $\Delta h = \Delta h_{ref}$) are average values of $\Delta h$ to the right of the zero line (Figure 34, dashed line).

7.3 Results of Field Tests (Online Application)

The control-concept was also implemented online at the control center of the waterworks together with the model and the EnKF, Figure 35. The EnKF updated the model predictions with the 87 measured head data each day. The updated model output, the head distribution, is used to calculate the head differences $\Delta h_1$, $\Delta h_2$ and $\Delta h_3$ which are inputs for the controllers to determine the artificial recharge rates for the next day. With several iterations of the flow model optimal values for the controllers’ parameters can be determined. During the night, the control center’s dispatchers use the proposed values of artificial recharge and switch pumps on or off for the supply of basins and infiltration wells.

Figure 35: Control Center of the Hardhof water works (WVZ, 2010).

The next day the procedure of updating the model and adapting artificial recharge amounts is repeated. Figure 36 shows the control system’s architecture. The dispatchers have access to the application server as web clients. The application server loads data from the Data Warehouse (DWH) which stores real-time data of head, electrical conductivity and temperature of 87 piezometers, see section 3. Additionally meteorological data are supplied
by Meteo Swiss. The two modules which are important for the management, i.e. the EnKF and the Real-Time Control call the groundwater flow model via an interface (SPLIB) in order to calculate the optimal artificial recharge for the next day. This value is then used by the dispatchers to adapt the settings in the process control system, which is connected to the vertical wells and the pumps of the network, to supply basins and infiltration wells accordingly.

![System architecture](image)

**Figure 36: System architecture. (TK Consult, 2010).**

The first test period of the real-time control system started in March 2009 and ended in the beginning of May 2009, a second test was performed in late June 2009 until the end of July 2009. The sporadic use of the control module was due to construction work going on which inhibited the use of all basins and infiltration wells. Measurement data are presented to show the system’s performance. The measured value of the EC at the piezometer 3407 (which is one of the measurement points for the calculation of $\Delta h_2$) is of interest regarding the performance of the real-time control in online mode. Horizontal well C is the most likely one to abstract water with high EC originating from the city area. In this particular case, we would expect a negative correlation between $\Delta h$ and EC at the measurement points. In order to avoid “city water” a positive head difference should generate a decreasing value of EC. Head data and measured EC were analysed for the time period over which the online optimal control strategy was applied between the 1st of March 2009 and the 5th of May 2009.
using $\Delta h_{\text{ref}} = 0.05 \text{m}$. Only during this period a full operation schedule was possible. After the 5\textsuperscript{th} of May, construction work made the online-application impossible. When the signal of $\Delta h_2$ converged to $\Delta h_{\text{ref}}$ (still with some oscillations) and became positive in March 2009, the signal of the electrical conductivity $\sigma_{3407}$ decreased over time. After the control went offline, the head difference became negative in June 2009 and the electrical conductivity $\sigma_{3407}$ rose again after a delay time (Figure 37).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure37.png}
\caption{Signal of $\Delta h_2$ during the time period between February 15\textsuperscript{th} and June 30\textsuperscript{th}, 2009. The signal shows the head difference $\Delta h_2$ between the measurement points 3224 and 3407. The head difference $\Delta h_2$ complying with the reference value $\Delta h_{\text{ref}}$ is plotted on the left scale against time. The electrical conductivity $\sigma_{3407}$ in piezometer 3407 is drawn against time, with the scale provided by the axis on the right.}
\end{figure}

We use the discrete cross-correlation function:

$$R(\Delta h_2, \sigma_{3407}, T) = \frac{\sum_k \left[ (\Delta h_2(k) - \mu_{\Delta h_2})(\sigma_{3407}(k-T) - \mu_{\sigma_{3407}}) \right]}{\sqrt{\sum_k (\Delta h_2(k) - \mu_{\Delta h_2})^2} \sqrt{\sum_k (\sigma_{3407}(k-T) - \mu_{\sigma_{3407}})^2}}$$

(7.1)

in order to calculate the correlation coefficients between the two signals $\Delta h_2(k)$ and $\sigma_{3407}(k)$ as a function of time. $T$ is the time delay, $k$ the discrete time index (in days) of the two signal values and $l$ the total number days. A negative and high correlation coefficient $R(\Delta h_2, \sigma_{3407})$ between the two signals was found with a minimum of -0.75 for a time delay $T$ of 20 days, Figure 38. This shows the influence of the controlled positive head difference on a decreasing EC.
An additional analysis can be done for measurements of electrical conductivity in well C which are available for another period for which the optimal control strategy was applied in online-mode (20\textsuperscript{th} of June 2009 through 29\textsuperscript{th} of July 2009, Figure 39). Only during this time period a full operation schedule was possible again ($\Delta h_{\text{ref}}=0.05$ m) due to construction work south of the basins before and after this period. The signal of $\Delta h_2$ did not fully converge to $\Delta h_{\text{ref}}$, yet it became eventually positive in July 2009. The electrical conductivity $\sigma_{\text{wellC}}$ fell from 300 $\mu$S/cm to a minimum of 262 $\mu$S/cm. After the control went offline, the head difference became negative after July 16\textsuperscript{th}.

The decreased electrical conductivity during the control period was achieved with an increased artificial recharge in basin II and in the group of infiltration wells S8-10. The signals of this particular time period can be interpreted again as a proof for the assumption of the correlation between artificial recharge, head difference and electrical conductivity in the wells which was presented in section 4.2.
Figure 39: Effects of real-time management in the time period of June 10th and July 29th, 2009.

The calculated cross correlations functions (Figure 40 and Figure 41) of artificial recharge and electrical conductivity, and head difference and electrical conductivity yield high and negative correlations with minima of ca. -0.68 and -0.69 respectively. It can be concluded that an appropriate artificial recharge (i.e. a recharge with a ratio of recharge/abstraction of at least 1.7) leads to positive head differences and also to a decreased electrical conductivity which is an indicator of less city water arriving in the well. A computed time lag of 4 days (cross correlation artificial recharge/electrical conductivity) and a time lag of 7 days (cross correlation head difference/electrical conductivity) correspond with the typical travel time between basin and well.
The cross correlation was performed with data of electrical conductivity of an abstraction well. Contrary to the typical time lags (i.e. 5 days) of this specific cross correlation the time lag of the maximum value of the cross correlation in Figure 38 is 21 days. This discrepancy could be explained with the fact that the quality of observations of transport mechanisms and mixing effects within a borehole (small diameter) is worse than the observation in abstraction wells. Abstraction wells receive water from the surrounding parts in the aquifer which leads to a more precise estimation of travel times: The accuracy of data from the piezometer is limited.
7.4 Discussion of $\Delta h$-Criterion

The proposed real-time control method possesses the important advantage of a low CPU-time requirement to calculate the optimal allocation of artificial recharge. However, the three dimensional groundwater flow model is associated with uncertainty and does not represent well small-scale heterogeneities and connected structures. Therefore, in spite of a positive head difference in the model, it cannot be excluded that city water could reach the pumping wells. On the other hand, small negative head differences do not automatically imply that city water reaches the wells. As an alternative for assessing the quality of a well management scheme, path lines of the instantaneous flow field can be calculated using particle backtracking from the pumping wells. The path lines indicate from where the pumped water originates. The percentage of city water that is pumped at a given well is calculated as the percentage of path lines weighted with the corresponding flux that originate from the city domain.

This method is presented in section 8 in more detail. For each and every model time step and the instantaneous calculated groundwater flow velocities are assumed constant while 5,400 virtual particles are tracked backward over 200 days. The starting positions of 1,350 virtual particles are placed symmetrically on the surface of a cuboid with dimensions 2 m x 30 m x 30 m containing the well in its center. In order to check whether the back tracking yields the correct flux over the surface of the control volume, the volume flow rates of all particles in x- direction, in y- direction, and in z-direction (depending on the face on which they start) are calculated and summed up and balanced with the abstraction rates of the four horizontal wells. After calculation of the flux of every individual particle over the surface of the respective control volume, the next step is to calculate the percentage of city water. The term “city water” (CW) is used for the flux along path lines, which cross the defined boundary South of the infiltration basins and infiltration wells (Figure 42).

As an example, Figure 42 shows the path lines (red) for the model simulation step of April 30 in the year 2004 with historical pumping rates and recharge rates. The path lines in yellow show the situation under optimal control conditions. The calculated city water percentage is 20 % in well C and almost 12 % in well D on this day.
Figure 42: Path lines produced by particle back tracking with boundary conditions of April 30th, 2004. The computation uses the historical artificial recharge in the basins and wells. The dashed line indicates the boundary of the contaminated city area which is located south of the line. The yellow lines indicate the path lines obtained with real-time control, and the red lines the path lines obtained for the historic management.

Figure 43 shows time series of the percentages of city water that reach the pumping wells C and D (for January 2004- August 2005). These percentages are shown for the historical management and the simulation scenarios I and II with optimization according to the $\Delta h$-criterion. Real-time control with the $\Delta h$-criterion yields better results than the historical management: in simulation scenario I city water is completely avoided, and in simulation scenario II the percentages of city water in both wells C and D are in general clearly lower than for the historical management.
Figure 43: City water (CW) percentages for the period January 2004- August 2005 in the horizontal wells C and D. The CW is calculated for three scenarios: Historical management and optimization with real-time control according to simulation scenarios I and II.
8 The Path Line Method as Control Criterion

8.1 State-of-the-Art Approaches

This section introduces a control approach which uses path line analysis of particles as control criterion for the real-time management of the Hardhof well field under conditions of temporally variable forcings (natural recharge rates, river stages, boundary conditions and groundwater management). In the previous section the real-time control of the Hardhof well field aimed at reducing the inflow of potentially contaminated water from the city centre to the well field by using hydraulic head differences (between the area of the well field and an area closer to the contamination sources) as control criterion ($\Delta h$-criterion). Although the results of offline-simulations and online-application in the field were satisfactory, the focus on particle paths directly addresses the problem of contaminated water that could reach the drinking water wells. The criterion on the basis of particle paths, hereinafter referred to as %s-criterion, can also address the 3D particle paths, whereas the $\Delta h$-criterion is in essence a two dimensional measure. Water from polluted areas could still be attracted from deeper layers in the aquifer. This was the main motivation to proceed with control simulations on the basis of the %s-criterion in this study.

The method of path lines is used in many instances for groundwater resources management, for example for the estimation of capture zones of operating and planned wells (e.g. Bayer et al., 2004; Mulligan et al., 2007), and for the estimation of contaminant travel times (e.g. Shafer, 1987; Zheng et al., 1988). The EU-funded W-SAHaRA- Project (Stochastic Analysis of Well Head Protection and Risk Assessment) analyzed delineation methods for capture zones (e.g. Stauffer et al., 2005; van Leeuwen et al., 2000). If it is assumed that contaminants do not undergo chemical reactions nor decay and do not disperse or diffuse, the contaminant transport problem is reduced to one of delineating the flow pattern (O’Neill, 1990). Contaminant spreading by dispersion and diffusion could be accounted for by randomly dispersing the contaminant “particles” as they move through the aquifer (e.g. Prickett et al., 1981), which is not considered in our study. Several publications (e.g. Katsafirakis et al., 2009; Varljen and Shafer, 1993) show the coupling of particle path line models with optimization methodologies to comply with management tasks, such as optimisation of pumping schedules for well fields threatened by contaminated aquifer parts, or optimization of remediation processes (Bayer et al., 2004). Path line analysis has also been used for the management of artificial recharge for a better protection of groundwater resources from salt water intrusion in coastal aquifers (Shammas, 2008). Another recent study (Tiwary et al.,
2005) deals with path line modelling (using MODPATH) for the assessment of ion migration from a mine into the groundwater in order to judge the degradation of groundwater quality. The effect of sewage water or other contaminants on groundwater resources in urban areas has also been analyzed with the use of path lines (e.g. Pokrajac, 1999; Subha Rao and Gurunadha Rao, 1999). However, none of the cited studies used the path line method for an optimal real-time management or real-time control of a well field. An important difference with the mentioned studies is that the management is optimized again for each time step. The path line analysis is used in our approach to calculate percentages of path lines which originate from the potentially contaminated part of the aquifer. The percentages are then used as control input for the optimal control of the well field (%s-criterion). The results of the optimal control using the percentage criterion are compared to results of control with the Δh-criterion.

Section 8.2 supplies a definition of the term “city water” and an overview on the calculation method of the particle path lines. Additional to that it introduces the definition for calculating the percentage of city water with the path line method. Section 8.3 gives a general introduction to the control methods using the %s-criteria for the real-time management of the well field. Results of offline-simulations and the outcome of the online-application in the control center of the Hardhof water works will be presented and discussed in subsection 8.4. Subsection 8.5 draws some conclusions on the presented approach and its implications.

8.2 Particle Tracking and Path Line Analysis

Path lines of the instantaneous flow field can be calculated by backtracking particles from the abstraction wells. The path lines indicate from where the pumped water originates. In this study we were especially interested in particles that come from the city domain (“city water”), because this is the area that is potentially contaminated. The percentage of city water that is pumped at a well is given by the percentage of path lines originating from the city domain weighted with the flux associated with them. Particle back tracking from the pumping wells was done for the complete simulation period from January 1st 2004 until August 23rd 2005. For every model time step all boundary conditions, forcings and calculated groundwater flow velocities are kept constant assuming quasi-steady state conditions while 5,400 virtual particles (1,350 particles for each of the four horizontal wells) are tracked backward for 200 days. In reality the flow field was not constant over 200 days. But if at no
instant a flow field is allowed which would eventually lead to inflow of city water then no city water is expected to arrive at the wells. Moreover, the needed computer storage for performing full transient transport simulations was prohibitive for this application. The starting positions of 1,350 virtual particles are placed symmetrically on all sides of the surface of a cuboid with dimensions $2 \, m \times 30 \, m \times 30 \, m$ containing the well at its center. The velocity vectors of the instantaneous flow field are used to calculate the positions of the particles at time $t - \Delta t$. The particle positions are calculated with the explicit Euler approach with negative velocity vectors, using the inverted velocity vector field for the back tracking:

$$x(t - \Delta t) = x(t) - v_x(t) \Delta t$$ \hspace{1cm} (8.1a)

$$y(t - \Delta t) = y(t) - v_y(t) \Delta t$$ \hspace{1cm} (8.1b)

$$z(t - \Delta t) = z(t) - v_z(t) \Delta t$$ \hspace{1cm} (8.1c)

where $x$, $y$ and $z$ are the spatial coordinates, $v_x$, $v_y$ and $v_z$ the groundwater pore velocities in the $x$-, $y$- and $z$-direction and $\Delta t$ is the time step. The time step is set such that the Courant criterion is fulfilled (e.g. Bear, 1979).

In order to check whether the path lines indicate reasonably well the correct flux over the surface of the control volume, the volume flow rates of all particles in $x$- direction, in $y$-direction, and in $z$-direction (depending on the face on which they start) are calculated and summed up and balanced with the abstraction rates of the four wells: $Q_{abstrA}$, $Q_{abstrB}$, $Q_{abstrC}$ and $Q_{abstrD}$. The deviation between the calculated flux over the control volume’s surface and the abstraction rate is 2% on average. The calculation of the abstraction rate $Q_{abstr}$ for any of the wells is illustrated in Eqs. 8.2 and 8.3.

$$|Q_x| = \sum_{i=1}^{n} |q_{x_i}| = \sum_{i=1}^{n} \left( |v_{x_i}| \ast a_{x_i} \right)$$ \hspace{1cm} (8.2a)

$$|Q_y| = \sum_{i=1}^{n} |q_{y_i}| = \sum_{i=1}^{n} \left( |v_{y_i}| \ast a_{y_i} \right)$$ \hspace{1cm} (8.2b)

$$|Q_z| = \sum_{i=1}^{n} |q_{z_i}| = \sum_{i=1}^{n} \left( |v_{z_i}| \ast a_{z_i} \right)$$ \hspace{1cm} (8.2c)

$$Q_{abstr} = Q_x + Q_y + Q_z$$ \hspace{1cm} (8.3)

where $Q_x$, $Q_y$, and $Q_z$ are the volume flow rates $Q$ in $x$, $y$ and $z$. The number of particles placed at each side of the cuboid is 225. Thus $n$ equals 450. Figure 44 shows path lines of January 20th, 2004 in three dimensions.
Figure 44: Path lines of tracked particles from the four horizontal wells to basins and infiltration wells in the Swiss coordinate grid, well A (green), well B (magenta), well C (red), and well D (blue). Indicated are also basins I-III.

After calculation of the weighted flux over the surface of the control volume, the next step is to calculate the percentage of city water. The term “city water” is used for the path line analysis and the counting of path lines (weighted with their fluxes) which cross a defined boundary south of the infiltration basins and infiltration wells (see Figure 45). Here, we would like to emphasize again that city water could transport contaminants from the Herdern waste disposal site to the wells (Figure 13).
Figure 45: Contour map of mean values of electrical conductivity (EC) in the Hardhof area. The EC isoline of 400 \( \mu \text{S/cm} \) South of basin II and III is chosen to define the boundary (black dashed line) between city water (CW) and non-city water. After Jäckli (1992).

8.3 The Definition of City Water Percentage (%s)

Based on the previously mentioned study by Kaiser (2001) in sub-section 4.1 which shows a specific spatial distribution of electrical conductivity (EC) with elevated values between 500 \( \mu \text{S/cm} \) and 700 \( \mu \text{S/cm} \) in the city domain and low values between 200 and 270 \( \mu \text{S/cm} \) for the river Limmat, and the outcome of the study of Jäckli (1992) of high EC values in the area of the Herdern waste disposal site (up to 1500 \( \mu \text{S/cm} \)) we designed a boundary for the definition of the area of “city water”. The boundary (Figure 45) between the city water and the non-city water is defined by the EC-contour line of 400 \( \mu \text{S/cm} \). This boundary is used together with the path line method: If particles are attracted from south of the boundary (see Figure 46), it is suggested that city water and therefore potentially contaminated water can reach the wells.
Figure 46: Example of modelled path lines with historical management, 4\textsuperscript{th} of May, 2004. The composed boundary between city water and non-city water is drawn in orange. $K_1$ and $K_2$ show the x- y- coordinates of the Swiss grid for the calculation of the composed boundary. Defined individual areas of effect for basins and infiltration wells are simplified as a red line with marks.

The boundary is set at the Swiss grid coordinates: $y=249730 \text{ m} = \text{const}$ for all x-values smaller than 680250 m. For x-values larger than 680250 m, the linear function $y= m*x + b$ (with $m = -0.378$, $b=506863$) is defined as boundary, see Figure 46. Virtual particles that originate south of this boundary are considered to be city water. As an example, Figure 46 shows the path lines for the model simulation step of day 124 in the year 2004 with historical pumping and recharge rates. The horizontal wells C and D abstract water. The calculated city water percentage is 23\% in well C.
8.4 The Use of the %s-Criterion for Hierarchical Control

Fuzzy Logic Control using the %s-criterion as control state:

The rule bases (or universes of discourse) of the FLC transfer functions were defined a priori on the basis of expert knowledge which consists of information provided by the control staff about historical artificial recharge and the maximum recharge capacity of the recharge basins and infiltration wells. The rule base’s form, Table 4, for the transfer function of basin II is:

Table 4: Implemented rule base.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Linguistic</th>
<th>Fuzzy range of input [%]</th>
<th>Conclusion</th>
<th>Linguistic</th>
<th>Fuzzy range of output [m³]</th>
</tr>
</thead>
<tbody>
<tr>
<td>If %s_{II} &lt; very high &gt;</td>
<td>%s_{II} &gt; 20</td>
<td>Then u_{II}</td>
<td>&lt; very high &gt;</td>
<td>25,000 &lt; u_{II} &lt; 30,000</td>
<td></td>
</tr>
<tr>
<td>If %s_{II} &lt; high &gt;</td>
<td>15 &lt; %s_{II} &lt; 25</td>
<td>Then u_{II}</td>
<td>&lt; high &gt;</td>
<td>22,000 &lt; u_{II} &lt; 27,000</td>
<td></td>
</tr>
<tr>
<td>If %s_{II} &lt; less high &gt;</td>
<td>10 &lt; %s_{II} &lt; 20</td>
<td>Then u_{II}</td>
<td>&lt; less high &gt;</td>
<td>20,000 &lt; u_{II} &lt; 25,000</td>
<td></td>
</tr>
<tr>
<td>If %s_{II} &lt; middle &gt;</td>
<td>8 &lt; %s_{II} &lt; 15</td>
<td>Then u_{II}</td>
<td>&lt; middle &gt;</td>
<td>17,000 &lt; u_{II} &lt; 22,000</td>
<td></td>
</tr>
<tr>
<td>If %s_{II} &lt; low &gt;</td>
<td>5 &lt; %s_{II} &lt; 10</td>
<td>Then u_{II}</td>
<td>&lt; low &gt;</td>
<td>13,000 &lt; u_{II} &lt; 18,000</td>
<td></td>
</tr>
<tr>
<td>If %s_{II} &lt; very low &gt;</td>
<td>3 &lt; %s_{II} &lt; 8</td>
<td>Then u_{II}</td>
<td>&lt; very low &gt;</td>
<td>9,000 &lt; u_{II} &lt; 14,000</td>
<td></td>
</tr>
<tr>
<td>If %s_{II} &lt; zero &gt;</td>
<td>0 &lt; %s_{II} &lt; 5</td>
<td>Then u_{II}</td>
<td>&lt; zero &gt;</td>
<td>5,000 &lt; u_{II} &lt; 10,000</td>
<td></td>
</tr>
</tbody>
</table>

The membership functions \( \mu \) of input and output variables are programmed in C and use a C-code (see Internet link Nr.1 in Appendix) according to methods presented by (Passino and Yurkovich, 1998). In the presented case the rule base uses 7 rules.

Hierarchical Control with %s-criterion:

The real-time control method works on the basis of particle backtracking from the pumping wells. The area contains seven artificial recharge elements (basins or (group of infiltration well(s) (Fig. 47)) and the percentage of city water %s_{i} is calculated for every horizontal well. For the calculation of the controllers’ inputs the relative fluxes in path lines that originate from the city domain and are pumped by the horizontal wells are evaluated. These relative fluxes in path lines can be regarded as percentages %s_{i} of city water in well \( i \) (\( i = 1 \) to 4) that pass the hydraulic barrier which is imposed by the artificial recharge (Fig. 47) of the control elements (i.e., basins or infiltration wells).
Figure 47: Scheme of optimal hierarchical control with $D_s$-criterion. Fuzzy Logic controllers $\text{FLC}_{S1-6}$, $\text{FLC}_{S7}$, $\text{FLC}_{S8-10}$, and $\text{FLC}_{S11-12}$ calculate the individual artificial recharge (AR) for the infiltration wells and controllers $\text{FLC}_I$, $\text{FLC}_{II}$, $\text{FLC}_{III}$ for the artificial recharge of the three basins.

If these relative fluxes in path lines pass also the defined individual area of influence of each basin and infiltration well (Fig. 47) they can be regarded as fractions of city water $%s_f \ (f=I, \ II, \ III, \ S1-6 \ S7, \ S8-10, \ S11-12)$. Following balance is valid (mass balance is accounted):

$$\sum_{i=1}^{4} (\%s_i) = \%s_I + \%s_{II} + \%s_{III} + \%s_{S1-6} + \%s_{S7} + \%s_{S8-10} + \%s_{S11-12}.$$  \hspace{1cm} (8.4)

The requirement $\%s_i = \%s_{ref} \ (i=1, \ 2, \ 3, \ 4)$ is imposed in the goal criteria of the control strategy. $\%s_{ref}$ is a user specified reference value for the percentage of path lines and is set to zero for the optimal control. It is expected that ($\%s_i = \%s_{ref} = 0\%$) is achieved by optimizing artificial recharge rates. For this study the historical water abstraction rates have been used as model inputs. The artificial recharge rate $u$ is calculated with the nonlinear fuzzy logic transfer function:

$$u_j(t+1) = p_{u_j} \ f(\%s_j(t), z_i(t)) \hspace{1cm} (8.5)$$

where $u_j$ indicates the controller (artificial recharge basin or a group of infiltration wells, $j=1, \ 2, \ .., \ 7$) that uses the seven fractions of city water percentages $\%s_j(t)$ as first input, obtained by the particle tracking and its time derivative $z_i(t) = \Delta\%s_j(t) / \Delta t$ as second input.
The function parameter $p_{w}$ can be scheduled for every controller individually with a genetic search algorithm (Tang et al., 2001). (C-code see Internet link Nr.2 in Appendix). The controllers’ functions yield the necessary recharge rate of the $j$th basin or injection well $u_j(t+1)$ for the next time step $t+1$. The calculation of optimal artificial recharge rates by separate controllers and the optimization of the control parameters for each time step can be regarded as a multilevel, hierarchical control approach which is related to the concepts introduced by Br dys et al. (2008). It was also used in the previous section. The scheme of the algorithm (Figure 48) consists of the following steps:

**Step 1.** For the time step $t$ ($t=1,2,3,...$) the percentages of city water $%s_f(t)$ in the wells are calculated with the groundwater flow model (all boundary conditions, forcings and pumping rates are denoted as BC in figure 48) and the path line method. The calculated fractions of city water $%s_f(t)$ ($f=I, II, S7, S8-10, S11-12$) are input for

---

**Figure 48: Scheme of offline model run and optimisation with the %s-criterion. Abbreviations are: Boundary condition (BC), genetic algorithm (GA), iteration step (is), head (h), function gain parameter ($p$), recharge rate ($u$), velocity ($v$).**
the control of the artificial recharge (in basins, infiltration wells). These fractions and their time derivatives \( z_i(t) = \Delta \% s_i(t)/\Delta t \) are inputs for the FLCs as well.

**Step 2a.** All recharge rates for the basins and groups of infiltration wells for the next time step \( t+1 \) are calculated by the non-linear FLC transfer functions which were described in chapter 3.1 and are all according to Equation 8.6:

\[
    u_j(t+1) = p_{\text{in}} \ast \hat{f}_{u_{\text{in}}}(\% s_i(t), z_i(t)),
    \]

\[
    u_{\text{III}}(t+1) = p_{\text{uq}} \ast \hat{f}_{u_{\text{uq}}}(\% s_{\text{III}}(t), z_{\text{III}}(t)),
    \]

\[
    u_{S1-6}(t+1) = p_{\text{uq}} \ast \hat{f}_{u_{\text{S1-6}}}(\% s_{S1-6}(t), z_{S1-6}(t))
    \]

\[
    u_{S7}(t+1) = p_{\text{uq}} \ast \hat{f}_{u_{\text{S7}}}(\% s_{S7}(t), z_{S7}(t))
    \]

\[
    u_{S8-10}(t+1) = p_{\text{uq}} \ast \hat{f}_{u_{\text{S8-10}}}(\% s_{S8-10}(t), z_{S8-10}(t)),
    \]

and

\[
    u_{S11-12}(t+1) = p_{\text{uq}} \ast \hat{f}_{u_{\text{S11-12}}}(\% s_{S11-12}(t), z_{S11-12}(t)).
    \] (8.6)

**Step 2b.** The calculated (preliminary) recharge rates \( u_j(t+1) \) are used for the model run of the next time step \( t+1 \) which yields the percentages of city water \( \% s_i(t+1) \) in the wells.

**Step 2c.** The city water percentages in the wells \( \% s_i(t+1) \) are used together with \( u_j(t+1) \) to calculate the objective function value:

\[
    J = w_1 \sum_{1}^{m} u_j(t+1) + w_2 \sum_{1}^{n} (\% s_i(t+1) - \% s_{\text{ref}})^2 \rightarrow \min!
    \] (8.7)

where \( m \) is equal to 7 (i.e., four groups of infiltration wells and the three basins), \( n \) equal to 4 (i.e. four horizontal wells) and \( w_1 \) and \( w_2 \) are weighting factors. A simple genetic algorithm sets the function gain parameters randomly between 0 and 1, and selects the population of parameters with the best fitness per iteration step. This stochastic search is performed for a predefined number of iterations or using a termination criterion with a small fitness function value (i.e. \( J < \varepsilon \), e.g. \( \varepsilon = 0.01 \)). Each of the optimization iterations requires one model run to calculate a new \( \% s_i(t+1) \). The optimization needs between 5 to 10 iteration steps to converge, with
up to 150 seconds CPU-time per iteration step including the model run with the
calculation of $\%s_{(t+1)}$.

Step 3: The optimized amounts of artificial recharge $\mu_j(t+1)$ are used as input for the next
model run which yields the state vector of piezometric heads (or head distribution)
h$_{(t+1)}$.

8.5 Simulation Experiments (Scenario I, II, and III)

In order to calculate the possible re-distribution and optimal amount of artificial recharge to
achieve 0 % city water (i.e. $\%s$ =0%) in the four horizontal wells with the path line method,
three simulation experiments were performed. The data of all boundary conditions and
forcings were implemented as 5 days-average for the simulations. The first simulation
experiment (scenario I) was designed to optimize the spatial distribution of artificial
recharge under the condition of a given average total artificial recharge rate of 28,000
m$^3$/day using the $\%s$-criterion. In this case, the optimized spatial distribution of artificial
recharge is compared with the historical distribution. The result should be a reduced $\%s$ in
the horizontal wells compared to the percentage of city water achieved with the historical
management. The second simulation experiment (scenario II) aims at an optimal control of
the recharge facilities to achieve a 0 % value of $\%s$ in all wells. In this case, the total amount
of artificial recharge is not fixed. Therefore, one expects an elevated artificial recharge rate
compared with the historical one to get a zero inflow from the city to the wells. The third
simulation experiment (scenario III) uses the optimal control algorithm based on the $\Delta h$
criterion to define optimal rates of artificial recharge and calculates afterwards $\%s$ in the
four wells. The results of scenario III are compared with results for scenario I to assess the
quality of the $\%s$-control concept. The quality of the optimal control concept is also
evaluated by calculating the ratio of the average artificial recharge rate and the average
abstraction rate:

$$r = \frac{\sum_{j=1}^{m} \mu_j}{\sum_{i} A_j}$$

(8.8)

where $A_k$ is the pumping rate for any of the four horizontal wells ($l=4$). Historical
management produced a ratio of $r=1.3$. The simulation results will show whether the
historical ratio can be maintained or should be increased.
8.6 Offline-Simulations using the %s-Criterion for Optimal Control

This subsection presents the comparison of simulated historical management results and the findings of optimal control simulation scenarios I and II. Figures 45 and 46 show the signals for the city water percentage (%) for the situation with the historical management and the optimal %s-control approach with simulation scenarios I and II. In the historical management case well C received on average 12% city water (Figure 49), whereas well D received 6% city water (Figure 50).

![Graph comparing historical and simulation scenarios](image_url)

**Figure 49:** Time signal of city water percentage in well C. Comparison of historical city water percentage obtained by optimal control with %s-criterion. The red signal is achieved with the historical management and the blue one with simulation scenario I (optimal control according %s-criterion), the green one with simulation scenario II.
In periods of intensive abstraction (between 12,000 and 18,000 m$^3$/day and per well) the amount of city water is above 20% in well C which also coincides with measured peak values of electrical conductivity above 310 $\mu$S/cm. In case of optimal control with simulation scenario I the mean value for the same period decreases to 5% in well C and 2% in well D. In case of simulation scenario II, for both wells a zero-percentage was achieved. The %s of the wells A and B were in all cases (historical management, simulation scenario I and II) 0% or close to 0%. In simulation scenarios I and II the reduced %s in the two wells C and D are achieved by an optimal and new distributions of artificial recharge which differs from the artificial recharge distributions of the historical management. Table 5 shows the distribution scheme for the simulation scenarios I and II. Compared to the spatial distribution of the historical artificial recharge, the focus of recharge defined by optimized control is now in basin II and in the infiltration wells S8-10. Historically basin I was supplied with a mean artificial recharge value of 6,000 m$^3$/day, or ca. 22% of the total daily mean recharge of 27,500 m$^3$/day. With the optimal control of the %s-criterion, the artificial recharge in basin I was decreased to less than 10% of the total optimized supply.

<table>
<thead>
<tr>
<th></th>
<th>Historical</th>
<th>Simulation I</th>
<th>Simulation II</th>
</tr>
</thead>
<tbody>
<tr>
<td>S 1-6 [m³/d]</td>
<td>4,320</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>S 7 [m³/d]</td>
<td>1,060</td>
<td>1,000</td>
<td>1,000</td>
</tr>
<tr>
<td>Basin III [m³/d]</td>
<td>8,400</td>
<td>9,700</td>
<td>10,700</td>
</tr>
<tr>
<td>S 8-10 [m³/d]</td>
<td>3,180</td>
<td>5,500</td>
<td>7,500</td>
</tr>
<tr>
<td>Basin II [m³/d]</td>
<td>4,250</td>
<td>9,800</td>
<td>10,600</td>
</tr>
<tr>
<td>S 11-12 [m³/d]</td>
<td>2,120</td>
<td>1,200</td>
<td>2,150</td>
</tr>
<tr>
<td>Basin I [m³/d]</td>
<td>4,440</td>
<td>1,500</td>
<td>1,450</td>
</tr>
<tr>
<td>Abstraction</td>
<td>-22,000</td>
<td>-22,000</td>
<td>-22,000</td>
</tr>
<tr>
<td>Horizontal wells</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A-D [m³/d]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage A [%]</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Percentage B [%]</td>
<td>0</td>
<td>0.05</td>
<td>0</td>
</tr>
<tr>
<td>Percentage C [%]</td>
<td>11</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>Percentage D [%]</td>
<td>6</td>
<td>2</td>
<td>0</td>
</tr>
</tbody>
</table>

In scenario I the historical recharge/abstraction ratio $r$ of 1.3 is fixed, and the optimized artificial recharge distribution produces a lower CW-percentage. To achieve a zero-percentage (simulation scenario II) with the %s-criterion, an average artificial recharge of 33,400 m³/day is the minimum necessary rate which leads to $r \approx 1.52$ for artificial recharge/abstraction. Figure 51 shows the particle path line situation of May 4th, 2004 (as an example of uncontrolled, historical conditions) and the path line situation according to optimal control (simulation scenario II).
In the previous study to define the city water percentage in the horizontal wells (Kaiser, 2001) the city water percentages were determined with a tracer study which was based on measurements of electrical conductivity, chlorate and Freon. Data of two days was collected: The first collection was done in April 2000 and the second one in March 2001. Tables 6 and 7 show the results of city water percentage according to Kaiser (2001).

**Table 6:** Comparison of city water percentages in wells C and D. Simulation time period: April 9th-17th, 2000.

<table>
<thead>
<tr>
<th></th>
<th>Tracer study</th>
<th>Simulation with %s-criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well C [%]</td>
<td>25</td>
<td>29.9</td>
</tr>
<tr>
<td>Well D [%]</td>
<td>50</td>
<td>36.7</td>
</tr>
</tbody>
</table>

**Table 7:** Comparison of city water percentages in wells C and D. Simulation time period: March 5th-13th, 2001.

<table>
<thead>
<tr>
<th></th>
<th>Tracer study</th>
<th>Simulation with %s-criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well C [%]</td>
<td>20</td>
<td>14.5</td>
</tr>
<tr>
<td>Well D [%]</td>
<td>19</td>
<td>11.0</td>
</tr>
</tbody>
</table>

In order to evaluate whether our model reproduces well the historically measured percentages of city water we performed model simulations with historical data of pumping rates and artificial recharge for April, 2000 and March, 2001. The simulation results (Table 6 and 7) can be compared with the results of the tracer study of both time periods. Due to the
fact that the data of the tracer study was taken on one single day the accuracy of the results is limited. Although the model yields smaller city water percentages compared to those of the tracer study, both pairs of results display a reasonable good consistency regarding the ratio of the city water percentages in the two wells.

8.7 Offline-Simulations with Δh-Criterion (Scenario III)

Real-time control based on the Δh-criterion was introduced in the previous section. Figure 52 and 53 summarize the main results.

Figure 52: Comparison of city water percentage calculated with %s- and Δh-criterion for well C. Time period from January 1st to 2004- August 23rd, 2005.

Figure 53: Comparison of city water percentage calculated with %s- and Δh-criterion for well D. Time period from January 1st, 2004 to August 23rd, 2005.

Control according to the Δh-criterion and the %s-criterion scenarios show that either control criterion results in lower percentage of %s in the wells C and D, even if the historical average artificial recharge of about 28,000 m³/day was prescribed as a constraint for these control simulations. However, for both wells the average %s value for control using the Δh-criterion is higher than that obtained with the %s-criterion. Control with the Δh-criterion results on
average in 7% of city water in well C (5% for %s-criterion, and 12% for historical management) and 4% of city water in well D (2% for %s-criterion, 6% for historical management). The percentage city water for control according to the \( \Delta h \)-criterion is on average closer to the results of the %s-criterion than to the historical management, yet the results for control with the %s-criterion are clearly preferable. In section 7, \( r \approx 1.7 \) was necessary for control according to the \( \Delta h \)-criterion aiming at permanent positive head differences. The optimal control scheme of simulation scenario II (achieved with the %s-criterion) was used to calculate the three head differences for the time period of January 1\textsuperscript{st}, 2004 - August 31\textsuperscript{st}, 2005: On average, the head differences are: \( \Delta h_1 = -0.02 \text{m} \), \( \Delta h_2 = 0.02 \text{m} \), \( \Delta h_3 = 0 \text{m} \). The negative value of \( \Delta h_1 \) is due to less artificial recharge in basin I and infiltration wells S11-12.

### 8.8 Online-Application

The real-time control module was designed and used to simulate an optimized management with the two different control criteria. The online application was tested for the \( \Delta h \)-criterion in the time period of March-June 2009, chapter 7, and for the %s-criterion in the time period from April 11\textsuperscript{th}, 2010 until May 31\textsuperscript{st}, 2010 and also the period from 26\textsuperscript{th} of July until 11\textsuperscript{th} of October 2010. Due to the implementation of a new process control system in the control center real-time control was not possible for the period between May 31\textsuperscript{st}, 2010 and July 26\textsuperscript{th}, 2010. The path line method was implemented together with the control algorithm at the control center of the Hardhof groundwater works, where the pumps of the four horizontal wells are operated during night shifts. Figure 54 illustrates the operating schedule.
Figure 54: Scheme of the online implementation of the optimal control algorithm together with the real-time model.

For real-time applications, the groundwater flow model is updated with help of EnKF. At noon the EnKF assimilates 87 measured piezometric head data and uses model calculations for 100 stochastic realizations to calculate the mean hydraulic head distribution and its variance (day 1). After the data assimilation, the calculated groundwater velocity vectors \( \mathbf{v} \) for day 1 are used as input for the path line method. The city water percentages \( \%s \) at each of the four horizontal wells for Day 1 are calculated and the controller hierarchy uses the calculated percentages as input values and optimizes the artificial recharge rates for the next day (Day 2). EC measurement data were taken in the horizontal wells to analyse the impact of the optimally distributed recharge rates fulfilling the \( \%s \)-criterion. Figure 55 shows the measured EC in the four horizontal wells.
Figure 55: Measured electrical conductivity in wells A, B, C and D. Time period April 1st and September 30th, 2010. The optimal management started on the 11th of April 2010.

At the beginning of the period the average EC values were 285 μS/cm in the wells A and B, 310 μS/cm in well C, and 316 μS/cm in well D. After eventually applying the optimized recharge and infiltration rates from the 11th of April onwards (requiring %s=0), the EC–values decreased mainly in the wells C and D. The decrease was due to a higher recharge in basin II and in the infiltration wells S8-10. The EC decreased from an average 310 μS/cm to 283 μS/cm in well C and from an average 315 μS/cm to an average 291 μS/cm in well D. The reduction of electrical conductivity in well A was not achieved by artificial recharge but by reduced abstraction rates. The electrical conductivity in well B was almost constant at an average value of 285 μS/cm. Due to the implementation of a new process control system and construction works in the basins, online-control was only possible from April 11th until May 31st (period I) and later from 27th of July until 30th of September 2010. Both periods displayed a decreasing electrical conductivity in well C in reaction to the on-line control. Analogous to the result for well C, the signal of electrical conductivity in well D displays the same pattern in time.

Figures 56 shows a screenshot of the operational decisions (Betrieb) and control states and factors on September 10th, 2010. Figure 57 shows the path line situation of the same day. The calculated %s in the four wells are at a low level, except the %s_C. However, the artificial
recharge in the infiltration wells and basins which is produced by the current operation (Betrieb) are not according to the overall recharge calculated by the optimal control. This leads to a $\%_{sc}$ of 5%. Still, the measured conductivity in well A, B, and D is below 300 $\mu$S/cm.

Figure 56: Screenshot of the management sheet of recharge basins and infiltration wells.
8.9 Discussion and Conclusions

The %s-criterion is a surrogate control criterion: For each day the path lines are calculated with the instantaneous flow field, assuming that all conditions stay constant. However, if the %s-criterion is optimally controlled (i.e. %s=0) for each day of the time period between 1st of January 2004 and 23rd of August 2005, the criterion can be regarded as conservative and robust because its requirement regarding optimality (i.e. %s>0) does not allow inflow of city water. The limitations of the %s-criterion lie within the maximum travel time for the calculation of the path lines. We chose a maximum of 200 days as abort criterion for the calculation of the path lines which has no implications on the quality of the results (more than 99.5% of the particles reached the defined control planes in x-, y- and z-direction or the defined boundaries of the river or the city domain).
In comparison to the path line method, a transport model for the transient simulation of electrical conductivity in the groundwater would be better suited to estimate EC values in the horizontal wells. However, this is far from trivial as the EC of the groundwater is modified during its transport below the city. The space-time distribution of the processes and sources that result in the EC-increase of the city water are largely unknown and therefore it is difficult to simulate these processes in a reliable manner. A dense network of on-line sensors that measure EC could alleviate this problem, and these measurement data could be assimilated by a transport model to update the spatial distribution of EC in time.

So far, the online application in the field showed that the %s-criterion for the control leads to reduced (measured) EC-values of the pumped drinking water, indicating a reduced inflow of city water. The CPU-time per optimization iteration is ca. 2.5 minutes yielding 12.5 minutes for 5 iterations. The simulations were performed on a Fujitsu Siemens Celsius W350, Intel Core 2 Duo E6400. This is the main reason to limit the number of particles to 1,350. The number of particles could be increased to 2,000 or even 3,000 in order to produce better results in terms of resolution. The introduced %s-concept could be used for different classes of problems, mainly for all groundwater model calculations using the finite element approach. Well sites without artificial recharge basins, yet threatened by all kinds of contamination in the soil or groundwater could rely on this concept in order to adapt the necessary abstraction rates in real-time.

Tracer studies similar to the cited one (Kaiser, 2001) are expensive and time consuming for control labs of water works and will not be performed on a routine basis. Furthermore the results are only valid for the time of sampling and the specific sampling location. Contrary to that, the real-time model produces a daily control criterion (%s) for the well field management with regard to the whole affected area.

In this section we have presented the two control criteria for the real-time management of the Hardhof groundwater works. One criterion ($\Delta h$) is based on the head differences for three pairs of observation points in the transition zone between the city and the well field. The other criterion (%s) is based on the calculation of percentages of city water pumped by wells using the path line method. Both criteria were tested with a three dimensional groundwater flow model which was used to simulate groundwater flow for the period January 2004 to August 2005. Both methods were not only tested in off-line mode with a deterministic model approach, but also in on-line mode (for two periods: Spring 2010 and summer 2010), making use of real-time model updating with the Ensemble Kalman Filter.
The simulations produce an average city water content of 11% in well C and an average CW content of 6% in well D. The simulation results with real-time optimal control focusing on the minimization of the inflow of city water showed a different distribution of artificial recharge compared with the historical AR distribution. The artificial recharge is also lower than for real-time control according to the $\Delta h$-criterion. The $\Delta h$-criterion yields an average artificial recharge/abstraction ratio of 1.7, whereas the %s-criterion yields an average ratio of 1.52. The historically applied ratio was 1.3, leading to a too large inflow of potentially contaminated water from the city area. In general, the control simulation with the %s-criterion gives better results than the control simulations with the $\Delta h$-criterion and shows that with real-time control the management of the waterworks is improved compared to traditional management, reducing the risk of attracting contaminated water, even without increasing the artificial recharge.

The comparison of calculated and measured (tracer study) city water percentages in the horizontal wells shows that the model and path line method yields reasonable good estimates results of city water percentages in the wells. Therefore we regard the real-time control approach using real-time data as a better method for the management of the water works than the former approach which mainly relied on well monitoring and sporadic tracer studies to operate wells and artificial recharge facilities.
9 Alternative Control Approach I: Multi Objective Optimization

9.1 Multi Objective Optimization for Groundwater Well Field Management—Advantages and Drawbacks

A state-of-the-art approach to manage a groundwater well field is a combination of flow model and a pure optimization approach, typically multi objective to adjust control variables (e.g. pumping rates or remediation well placement). At least two objectives are of interest in well management in order to regard it as multi objective: It may require a minimum energy use and a maximum supply with drinking water. Many case studies in water resources management involve multi objective optimization approaches with stochastic search algorithms (such as Evolutionary Algorithms) and coupled groundwater models. Typical case studies involve optimal pumping strategies for limited groundwater resources (Siegfried and Kinzelbach, 2006), or the optimal placement of wells to decrease potential for pollution encroachment (Bayer et al., 2005). Remediation processes can be optimized as well with scenarios involving the optimal placement of pumping wells and injection wells and the in situ operation (e.g. Wang and Zheng, 1998).

The main disadvantage of multi objective optimization (MOO) which uses evolutionary search algorithms is the calculation time to yield a satisfactory fitness of the selected solutions which aim at the global optimum. An important strategy to reduce the computation time is achieved by sophisticated software or hardware architectures. According to Coello (2006) one of the main research fields of MOO is the introduction of auxiliary algorithms to shorten the search for the fitness.

However, in the end it is aimed at parallelization of calculation processes. Li and He (2007) analyzed the performance of multi objective optimization approaches which use evolutionary algorithms (EMO). The combination of Evolutionary Algorithms (EA) and real-world MOPs (Multi Objective Problems) is often impractical due to the real-time constraints of the problems which limits the possibility of the EA to deliver the optimal solution. They suggest a method which is called evolvable hardware (EHW) to speed up the evolutionary search to find the solution for the real-world MOPs.

In groundwater resources management, the parallelization of search algorithms with a master-worker model could be a strategy to satisfy computational requirements which are demanding, especially for real scenarios (Siegfried et al., 2009).
All of these approaches share the fact that optimization is performed offline, due to large computation times which are caused by a high number of generations to let the objective function converge, if non-derivative search algorithms are used. Yet, most of the MOO strategies use the stochastic genetic algorithm approach. However, an important question for real-time control tasks is the run-time. The faster a control algorithm produces a control factor to influence the system, the better the performance can be regarded. With the trend of establishing large flow models, the need to integrate real-time data of boundary conditions (natural recharge, river stages, temperature etc.) and the consideration of uncertainty of this data, the question arises whether the common known state-of-the-art approaches (either improving the calculation speed by hardware/software parallelization or offline-simulations) can still cope with the requirement of real-time reaction in online-mode.

If optimization is performed for problems with heat or solute transport in well fields, the question of calculation time is even more serious. Regarding real-time control of well fields, a real-world system was not involved for field tests so far. Therefore we regard the hierarchical concept as sophisticated and robust approach to meet the requirements of online real-time control.

In order to show the performance of these two approaches, we compare the strict optimization approach which is tested with a widely used and analyzed approach (Non-dominated search, NSGA-II) which was introduced by Deb et al. (2002). In this case, the Limmat aquifer flow model is used to calculate optimal artificial recharge rates (optimal=minimum) that comply with boundary conditions and constraints. The case study was performed in order to analyze this typical approach and to compare it with the hierarchical control approach which we propose as an alternative algorithm to avoid calculation time and achieve a similar optimal solution.

Subsection 9.2 will provide simulation results with optimally distributed artificial recharge in a steady state condition to show the need to adjust recharge rates over time due to impact of changing forcings and boundary conditions: In general, the system requires a time-variant management of the artificial recharge. The subsection 9.3 shows the performance of the hierarchical control approach regarding the $\Delta h$-criterion. In this subsection the performances of feedback control without parameter optimization and with parameter optimization are compared in the subsections 9.4 and 9.5 the setup of the multi objective optimization approach which uses an evolutionary algorithm is shortly introduced. The main simulation results of this strict optimization algorithm which is coupled together with the
flow model are compared with the outcome of the hierarchical approach. A conclusion is drawn in subsection 9.6.

### 9.2 Case Study with Steady State Optimal Artificial Recharge

The main task of optimal real-time control is to secure an improved management when we consider the historical management to be the reference of comparison. Historical management led to an increased percentage of city water mainly in wells C and D. Using the $\Delta h$-criterion for the simulation of the historical and the optimized management, the outcome of the steady state optimal management can be evaluated.

The basic question whether real-time control (or time-variant control) is superior to conventionally optimized, yet steady state management can be answered with the simulation of artificial recharge which is applied constantly over time under changing boundary conditions or for selected time periods with flood conditions of the river or low river stages, heavy pumping or normal conditions. In this case the artificial recharge rate was chosen according the average recharge distribution which was yielded by the simulation scenario II (see chapter 7).

Figure 58 shows the three head differences with an optimal steady state artificial recharge scheme. The following average and optimal recharge rate were chosen:

- Basin I: 6,000 m$^3$/d; basin II: 10,000 m$^3$/d; basin III: 10,000 m$^3$/d; S1-6: 500 m$^3$/d; S7: 1,000 m$^3$/d; S8-10: 6,000 m$^3$/d; S11-12: 2,000 m$^3$/d. High abstraction rates in May 2004 lead to negative head differences which increases the risk to attract city water. A real-time control scheme would aim at an adaptive distribution of the artificial recharge in time. Therefore real-time control must be regarded as necessary in this specific case.
9.3 Performance Difference of Feedback Control and Hierarchical Approach

Figures 59 and 60 show the simulation results. The signal of the three head differences obtained by feedback control without parameter optimization, with the artificial recharge scheme being adjusted in real-time is clearly better than the one achieved with steady state optimal artificial recharge. The drawdown in May 2004 and at days in August and November can be avoided due to larger recharge rates. However, the recharge/abstraction ratio is ca. 1.8. The optimization yields permanent positive head differences with a slightly reduced artificial recharge in the chosen time period. Oscillations of the feedback control are reduced. The hierarchical control approach delivers the most preferable of all three approaches. It avoids the oscillating effects of the pure optimization, because it uses the fuzzy logic control output as favourable working point.
9.4 Setup of the Multi Objective Optimization Approach (MOO) using the Flow Model

In order to perform a straightforward optimization, two objectives were chosen, the first one being the total artificial recharge in the basins and the infiltration wells:

a) Total infiltration of basins and wells: \( m=7 \)

\[
I_{\text{inf,ge}r} = w_j \sum_{i}^{m} u_i(t+1) \rightarrow \min!
\]  \hspace{1cm} (9.1)

b) The second objective is the sum of the three head differences:

\[
I_{\Delta h} = w_2 \sum_{i}^{3} \left( \Delta h_i - \Delta h_{\text{ref}} \right) \rightarrow \min!
\]  \hspace{1cm} (9.2)

In the first case we wish the artificial recharge to be minimal and the second the head difference to be close to a reference value. Two kinds of constraints are chosen: First, the
maximal capacity of artificial recharge and infiltration rate per day for the three basins and
12 infiltration wells:

\[ 5,000 m^3 \leq u_{\text{BI-III}} \leq 30,000 m^3 / d, \quad 500 m^3 \leq u_{\text{SI-12}} \leq 3,000 m^3 \]  \hspace{1cm} (9.3)

The constraints for the appropriate head differences are defined as:

\[ 0 m < \Delta h_1 \leq 0.05 m, \quad 0 m < \Delta h_2 \leq 0.05 m, \quad 0 m < \Delta h_3 \leq 0.05 m \]  \hspace{1cm} (9.4)

To calculate the optimal artificial recharge rates following C-code was used: The evolutionary algorithm NSGA-II (see Internet link Nr. 3 in Appendix) for multi objective optimization with constraints which was introduced by Deb et al. (2002). Figure 61 shows the calculation scheme of the MOO approach and the flow model. The scheme is analogous to the introduced hierarchical scheme. Instead of the parameter optimization of fuzzy logic controllers used by the hierarchical approach, the control variables to yield the optimal solution, i.e. the artificial recharge rates \( u \) are directly adjusted. The iteration step number is corresponds with the number of generations of the evolutionary algorithm which was selected between 10 and 50 (with at least 20-30 generations producing a reasonable good result for the head differences).

---

**Figure 61: Concept of the Multi Objective Optimization using the NSGAII-algorithm.**
9.5 Simulation Results of the MOO Approach and Comparison with Hierarchical Control

The time signal of the three head differences for one year (1\textsuperscript{st} of Jan. 2004 - 31\textsuperscript{st} of Dec. 2004) obtained with the NSGAII algorithm (Figure 62) displays good results, yet larger oscillations from day to day can be observed if the result of the hierarchical control approach (Figure 60) is used as reference.

The head differences are all three positive (or at least almost zero) for an average AR/abstraction-ratio of 1.68. CPU-time: $\sim 4'10"$ for 20 generations and $\sim 6'25"$ for 30 generations (Fujitsu Siemens Celsius W350). Good results were obtained with ca. 30 generations (Figure 62). An increased number of generations (e.g. 50 or 100 generations) produced only slightly better results.

![Figure 62: Time signal of head differences obtained with NSGAII for 365 days.](image)

As example for the convergence performance of the objective function values Figure 63 and 64 show the objective function values (equation 9.2) of each iteration of the NSGAII (in this specific case for 30 generations). The original values are multiplied with the factor 100.
Figure 63: Objective function values ($I$) of head differences for day 120 (NSGAII).

Figure 64: Objective function values ($I$) of head differences for day 121 (NSGAII).

The hierarchical control uses the simple genetic algorithm which was shortly introduced in section 6. The number of iterations was fixed for the comparison study.

**Number of iterations**: Maximum generation size 5-10 (fixed).

**Head differences** are all three positive for average AR/abstraction $=1.7$ CPU –time: $\sim 1'52''$ for 10 generations.

For the time period January 1$^{st}$ 2004 and December 31$^{st}$, 2004 the convergence rates (percentage of cases of objective function value’s convergence) are 80% for the hierarchical control and 91% for the strict optimization approach.

As an example the simulation results for January 17$^{th}$, 2004 are shown in Figure 65. The convergence of the objective function value at this specific day is faster for the hierarchical control approach.
9.6 Discussion and Conclusion

The comparison of both management approaches leads to following conclusions: The hierarchical approach is faster compared with the conventional optimization approach which leads to the conclusion that the hierarchical approach should be preferred for real-time control.

In time periods of less dynamic boundary conditions the strict optimization displays a good performance. With high abstraction rates in the wells (May 2004) the hierarchical control approach shows a better performance and it is also faster than the conventional MOO approach.

In terms of convergence of the objective function value, the multi objective optimization approach is preferable to the hierarchical one. However, the MOO approach leads to increased oscillation effects of the head differences over time whereas the hierarchical control “flattens” the time signal.

Regarding run time, the hierarchical control needs less CPU time compared with the one which is necessary for the strict optimization (MOO). As \(\Delta h\) is a mere constraint used by the strict optimization the approach is more prone to oscillating effects over time which are avoided by the hierarchical approach where \(\Delta h\) is the control state to be influenced by the feedback controller in order to get close to a constant reference value. In order to avoid oscillating effects, an optimization approach could aim at the calculation of an optimal, yet constant recharge scheme. This study was performed as well and showed that a constant artificial recharge with an optimal spatial distribution for the chosen time period is the least desirable.
An additional case study could use the %s-criterion for simulations with the multi objective optimization approach. In this case the run-time will be a limiting factor again because the number of generations is coupled with the number of model runs and this specific case will lead to calculation times of hours for one time step. In this case, real-time control is hardly possible.

10 Alternative Control Approach II: Expert Systems

10.1 Introduction

In this section a case study is presented which was performed in a Master project study (Marti, 2010) that I had supervised. The goal of the study was to find out whether a simple and fast approach, an expert system for the well field management might produce similar results as the one used for the well field operation right now. For this purpose a very simple expert system was designed and tested. The subsections present in short the main parts of the method for the development of the expert system as well as the main results of the simulative management of the artificial recharge. As control criterion for the management the %s-criterion was used. A discussion of the results shows the strengths and weaknesses of the expert system approach compared with the historical management and the hierarchical control system.

10.2 Definition of Expert Systems

Expert systems are knowledge based systems which incorporate information of trained dispatchers, technicians or engineers (hence: expert) who control a certain process and possess implicit knowledge of this process. Knowledge based systems reflect the management by representing the expert’s implicit knowledge in linguistic terms (If...then...relationships). After a phase of training, the expert system is adapted and it can be used to control a process. However, many expert systems are used with a human decision maker still supervising the operation. This is due to the special nature of knowledge based systems: For the expert system’s training phase offline-data input is needed. If the range of the training data does also not include extreme, yet sporadically occurring events, the
trained expert system will later not produce the proper management suggestion when used for operation in such a situation.

a) Decision support systems:
Complex systems usually require a broad knowledge for their management. Operators of complex systems more and more rely on digitalized expertise to support decision making processes, so called decision support systems. Decision support systems help a decision maker to process raw data, to use personal knowledge of other experts, the retrieval of useful information. A well designed decision support system expedites decision making, increases organizational control, and helps to automate the management process (Sprague and Carlson, 1982). One special form of a decision support system is an expert system.

b) Expert Systems (general approach):
Expert systems are built on human rule based reasoning (Jackson, 1999) or if ... then ... relationships, for example: “If many path lines cross the boundary, then city water may enter the well field”. Such relationships are relatively easy to comprehend and to program and they can be used independently from each other. An additional example: “If many path lines cross the boundary then city water may enter the well field if artificial recharge is low”. The knowledge base (or rule base) of the expert system consists of many if ... then ... relationships which are combined in a tree structure. The path through the tree is not predetermined but depends on the outcome of each if ... then ... relationship. In essence, an expert system consists of a set of rules that are produced by inductive reasoning and form up a generalized set of conclusions from a collection of specific observations (Holland et al, 1989).

10.3 Design of the Expert System for the Simulation of the Well Field Management

The design of the expert system and the simulation of the well field management were performed in three phases. The phases are presented in Figure 66 below:
Phase I comprises the creation of a knowledge base which is necessary to build up the expert system’s algorithm which is used later in Phase II. The knowledge base uses data sets of one year (1st of January-31st of December, 2004) for the analysis of selected days where remarkable events occur.

Phase II: In a first step the performance is tested and iteratively refined on the basis of path line situations of 28 selected days in the year 2004. In a second step - when the performance for the 28 path line situations was satisfactory - the expert system was tested for all days of the time period of January 1st - December 31st 2004 by computing the percentage of city water in each horizontal well.

As soon as the city water content was acceptable, the expert system was validated in Phase III.

**Phase I: Creating the Knowledge base**

In order to develop the expert system a knowledge base has to be established. Since the development of the expert system is based on the flow model and the path line method introduced in section 8, only model input and output data are relevant for this study. The designer has to understand the nature of the model input and output data and how they are correlated. The following data were analyzed:

- Abstraction rates in all four horizontal wells,
- artificial recharge in the recharge basins I, II, and III
- infiltration in the infiltration wells S1-6, S7, S8-10, S11-12
- Stage of river Limmat
- computations of the lateral inflow to the model as well as the natural recharge at the surface
- measurements of hydraulic head in several piezometers in the well field
- computations of the %s in the horizontal wells

All listed data serve as input for the flow model. The percentages of city water in each horizontal well are the result of the model runs using the particle back tracking approach, introduced in section 8. For this work only the river stage at Hardturmssteg was relevant since it is close to the river bank where the infiltration into wells A and B takes place. All data were available in the form of daily mean values from January 1\textsuperscript{st} to December 31\textsuperscript{st} 2004. For the validation phase data from January 1\textsuperscript{st} to January 31\textsuperscript{st}, 2005 were available. All data were calculated with a 5 days-average. Therefore, the value of day \(i\) is the average over the last 4 values and the value at day \(i\). In addition to the averaging over 5 days, the city water percentages were weighted with the abstraction rates in the respective wells as introduced in section 8.

**Time series:**

A first look at the data shows the annual variation and leads to a qualitative estimation of relationships between the different data sets. The time series of the data were plotted in Figure 67 and analysed for the later design of the knowledge base of the expert system.

![Time series of data](image)

Figure 67: Time series of data of concerning well C which are used for the design of the expert system, (Marti, 2010).
Based on the time series, 28 days of the year 2004 were selected for phase II, the development of the expert system. The criteria for justification, Table 8, were "Normal operation" where no changes of the important variables were noted, and "High" or "Low" situations where one or several variables were at a peak or low stage compared to the remaining data of the year 2004.

Table 8: Selected days of time period from January 1st to December 31st, 2004.

<table>
<thead>
<tr>
<th>Day Nr.</th>
<th>Justification</th>
<th>Day Nr.</th>
<th>Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>34</td>
<td>Change of artificial recharge distribution</td>
<td>144</td>
<td>Low abstraction in well C</td>
</tr>
<tr>
<td>41</td>
<td>Normal operation</td>
<td>157</td>
<td>Flood peak (river stage high)</td>
</tr>
<tr>
<td>44</td>
<td>EC in well C low</td>
<td>163</td>
<td>Low abstraction in well C</td>
</tr>
<tr>
<td>65</td>
<td>Normal operation</td>
<td>169</td>
<td>EC in well C low</td>
</tr>
<tr>
<td>68</td>
<td>Normal operation</td>
<td>198</td>
<td>High %s in well C</td>
</tr>
<tr>
<td>71</td>
<td>EC in well C low</td>
<td>206</td>
<td>Low %s in well C</td>
</tr>
<tr>
<td>93</td>
<td>Normal operation</td>
<td>210</td>
<td>EC in well C high</td>
</tr>
<tr>
<td>108</td>
<td>Normal operation</td>
<td>211</td>
<td>High %s in well C</td>
</tr>
<tr>
<td>115</td>
<td>High artificial recharge in basin II</td>
<td>232</td>
<td>Normal operation</td>
</tr>
<tr>
<td>117</td>
<td>High abstraction in well C</td>
<td>258</td>
<td>Normal operation</td>
</tr>
<tr>
<td>122</td>
<td>High %s in well C</td>
<td>265</td>
<td>Low river stage</td>
</tr>
<tr>
<td>124</td>
<td>High infiltration in S8-10</td>
<td>271</td>
<td>High river stage</td>
</tr>
<tr>
<td>127</td>
<td>High %s in well B</td>
<td>278</td>
<td>Low %s in well C</td>
</tr>
<tr>
<td>137</td>
<td>Zero %s in well C</td>
<td>310</td>
<td>Normal operation</td>
</tr>
</tbody>
</table>

Phase II - Development of expert system and training

For the development of the expert system, the information gathered during Phase I was transferred into a rule base consisting of if . . . then . . . relationships. For the expert system three levels of if . . . then . . . relationships were chosen, each level looking at one of three selected variables influencing the water quality in well C. The variables were selected based on the data analysis in phase I. They comprise the abstraction rate in well C, the city water percentage in well C and the water level. The variables are classified as 0 for "no measurement", low, medium, high, and extreme for "extremely high" (Marti, 2010). To each of these classes a number is attributed and multiplied with the weight assigned to the relevance of each variable yielding a value for the if ... then ... relationship. The values for each level are summed up and classified into low, medium, high, and extremely high. To each of these four classes recharge scheme is attributed. The recharge scheme consists of fractions of the total abstraction rate in all four abstraction wells. S 1 to 6 in well group 1, S7 in well group 2, S8 -10 in well group 3, and S11-12 in well group 4. The tree structure of
Figure 68 was implemented in a Java script (Marti, 2010). The expert system was coupled via a bash script with the flow model and the path line module for the performance testing. The following two subsections describe the learning phase of the expert system. It is iteratively refined until it provides a recharge scheme that reduces the inflow of city water to zero.

**Figure 68**: The conceptual structure of the expert system. An example for a path through *the if ... then ... relationships* is depicted with black arrows, Marti (2010).

### Part 2 - Testing path line situations

After implementation of the described algorithm in Java it was tested by comparing path line situations of the 28 selected days of the year 2004 (Marti, 2010). The following routine was used: The path lines of day $i$ were computed after a time-varying model run from day 1 to day $i$ in which the infiltration scheme computed with the expert system was fed into the groundwater model starting from day $i = 4$. At day $i$ the flow field was frozen and the particles were tracked backwards. If there were path lines crossing the boundary between city domain and well domain (Figure 42), the rule base of the expert system did not capture the relationships between the variables influencing the water quality of the Hardhof sufficiently well and the knowledge base had to be improved. In this case the designer of the expert system has to improve the knowledge base by adjusting the relationships between the input variables, and test again. If no particles cross the boundary anymore the expert the next testing step is initiated.

### Part 3 - Testing percentage of city water

As soon as the path line situations of all 28 selected days in 2004 are satisfactory, the expert system is used for simulations with data of the whole year. In this part of the design process the percentage of city water in the four wells is calculated for every day using the recharge
scheme proposed by the expert system as input for the next day. Based on the comparison with the historical percentage, it has to be decided whether the infiltration scheme proposed by the expert system was acceptable or not. In case too much city water was still found in the wells the knowledge base again had to be improved. If the amount of city water calculated with the expert system decision was lower than the city water percentage with the historical infiltration scheme, the expert system counted as validated. The rule base of the expert system was then able to suggest an infiltration scheme for each day of 2004 yielding an improved water quality compared to the historical scheme. Based on the data analysis the following variables were found to be relevant for the %s in well C on day $i$: Abstraction rate in well C on day $i$, stage of the river Limmat on day $i = 14$ and the %s in well C on day $i = i - 1$. The weights of the three levels of the expert system are:
- 0.5 for the abstraction rate in well C on day $i$
- 0.2 for the stage of the river Limmat on day $i = 14$
- 0.8 for the percentage of city water on day $i = i - 1$

The classification into 0, low, medium, high, and extreme is shown in Table 9 below. The infiltration scheme for the four classes “low”, “medium”, “high”, and “extreme” is given in Table 10. The total amount of abstraction is first multiplied with a factor to make sure the hydraulic barrier is sufficiently high and then distributed between the recharge basins I, II, and III and between the infiltration well groups 1, 2, 3, and 4. Within the groups each well gets the same amount of water.

**Table 9: Classes for three factors: Abstraction, river stage and percentage city water.**

<table>
<thead>
<tr>
<th>Class</th>
<th>Abstraction [m$^3$/d]</th>
<th>River stage [m a.s.l.]</th>
<th>Percentage [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>&lt;= 0</td>
<td>&lt;= 395.0</td>
<td>&lt;= 0</td>
</tr>
<tr>
<td>low</td>
<td>0&lt;...&lt; 2,500</td>
<td>=&gt; 398.9</td>
<td>0 &lt; ...&lt; 5</td>
</tr>
<tr>
<td>medium</td>
<td>2,500 &lt;= ... &lt; 6,500</td>
<td>398.4 &lt;= ...&lt; 398.9</td>
<td>5 &lt;= ... &lt; 10</td>
</tr>
<tr>
<td>high</td>
<td>6,500 &lt;= ...&lt; 12,000</td>
<td>398.2 &lt;= ...&lt; 398.4</td>
<td>10 &lt;= ... &lt; 20</td>
</tr>
<tr>
<td>extreme</td>
<td>12,000 &lt;=</td>
<td>395 &lt;= ... &lt; 398.2</td>
<td>20 &lt;=</td>
</tr>
</tbody>
</table>

**Table 10: Definition of ratios for control elements.**

<table>
<thead>
<tr>
<th></th>
<th>low</th>
<th>medium</th>
<th>high</th>
<th>extreme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basins/Wells</td>
<td>2:1</td>
<td>2:1</td>
<td>1:1</td>
<td>1:2</td>
</tr>
<tr>
<td>I/II/III</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Injection well</td>
<td>0:1:3:2</td>
<td>0:1:4:2</td>
<td>0:1:4:2</td>
<td>0:1:4:2</td>
</tr>
<tr>
<td>groups 1:2:3:4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor</td>
<td>1</td>
<td>1</td>
<td>1.3</td>
<td>1.5</td>
</tr>
</tbody>
</table>
Phase III – Validation of the expert system’s performance with new data

The expert system was validated with data from January 1st to January 31st, 2005. In this phase the performance of the expert scheme is tested with data of new situations that were not used during the learning phase (Phase II). For the quasi real-time simulation the bash script is used again. A recharge scheme is calculated by the expert system and used as input for the next day. Again, if the %s in the horizontal well is close to zero, the expert system is robust enough to cope with new data sets. If, on the other hand, the %s are increased with respect to the historical city water percentage, the expert system still possesses the drawback of a limited knowledge base which has to be expanded again.

10.4 Simulation Results and Comparison with Hierarchical Control

The performance of the expert system is evaluated by comparing its simulation results to those of the hierarchical control approach. Table 11 shows the main findings for the example of well C. The %s in the wells A, B, and D were zero. In this particular case the expert system performed worse than the hierarchical control did. In terms of CPU-time the expert system performed much better. Yet the hierarchical control performed better in terms of average %s in well C. The simulations were performed on a Fujitsu Siemens Celsius W350, Intel Core 2 Duo E6400.

Table 11: Comparison of simulation results of expert system and hierarchical control. Time period: January 1st - December 31st 2004.

<table>
<thead>
<tr>
<th></th>
<th>Expert system</th>
<th>Hierarchical control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of avg. recharge/abstraction</td>
<td>1.28</td>
<td>1.45</td>
</tr>
<tr>
<td>Average recharge [m³/d]</td>
<td>25,500</td>
<td>31,000</td>
</tr>
<tr>
<td>City water percentage in well C [%]</td>
<td>0.13</td>
<td>0.008</td>
</tr>
<tr>
<td>Computation time [s]</td>
<td>0.2</td>
<td>600</td>
</tr>
</tbody>
</table>

The simulation results for the artificial recharge for day 124 (May 3rd, 2004) are shown in Table 12. At this specific day the %s in well C reached a peak value due to high abstraction rates around this date. The calculated artificial recharge in the infiltration wells S8-10 exceeds the maximum capacity per infiltration well (8,000 m³).
Table 12: Comparison of simulation results produced by expert system and hierarchical control for May 3rd, 2004 (day 122).

<table>
<thead>
<tr>
<th></th>
<th>Recharge according to expert system [m³] (5 days average)</th>
<th>Recharge according to hierarchical control [m³] (5 days average)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basin I</td>
<td>2,800</td>
<td>14,000</td>
</tr>
<tr>
<td>S 11-12</td>
<td>17,600</td>
<td>4,000</td>
</tr>
<tr>
<td>Basin II</td>
<td>16,900</td>
<td>24,500</td>
</tr>
<tr>
<td>S 8-10</td>
<td>35,400</td>
<td>9,000</td>
</tr>
<tr>
<td>Basin III</td>
<td>11,200</td>
<td>23,400</td>
</tr>
<tr>
<td>S7</td>
<td>8,800</td>
<td>1,500</td>
</tr>
<tr>
<td>S 1-6</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Sum</td>
<td>92,700</td>
<td>76,400</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Given abstraction</th>
<th>Given abstraction</th>
</tr>
</thead>
<tbody>
<tr>
<td>HW A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>HW B</td>
<td>-25,400</td>
<td>-25,400</td>
</tr>
<tr>
<td>HW C</td>
<td>-19,200</td>
<td>-19,200</td>
</tr>
<tr>
<td>HW D</td>
<td>-19,000</td>
<td>-19,000</td>
</tr>
</tbody>
</table>

Figure 69 and 70 show the two different path line situations according to the recharge management of the expert system and the hierarchical control approach using the %s-criterion. The two methods perform well, no path line transgresses the city domain boundary, yet the difference is the high amount of artificial recharge in the infiltration wells, which was not in agreement with the maximum infiltration capacity.

Figure 69: Path line situation on May 3rd, 2004 with expert system's control. Path lines obtained with expert system's management are indicated in red, Marti (2010). The blue circle indicates the path line situation for well C.
The performance of the expert system after the training phase was assessed as well. The calculations with data of the time period 1.1.2005 - 31.1.2005 yielded a slightly elevated %s in well C which was higher than the %s obtained with the historical management. For well D, on the other hand, the situation was dramatically improved. Figure 71 shows the percentages of city water in the four horizontal wells.

Figure 71 shows the percentages of city water in the four horizontal wells. (Marti, 2010).

Figure 70: Path line situation on May 3rd, 2004 with hierarchical control.
The expert system underestimated the necessary artificial recharge when low river stages occur. The data set used for the training phase did not incorporate low river stage and therefore the weight for the input value of river stage is too low. With a low river stage the flow field is in general directed towards the Limmat river causing an elevated %s in well C. A possible improvement could be achieved by increasing the weight of the river stage input leading to increased artificial recharge in basin II for low river stages.

11 Assessment of Parameter Uncertainty in Real-Time Control

11.1 Overview

The feasibility of optimal real-time control for urban drinking water well fields threatened by non-remediated pollution sources in the ground was shown by the successful implementation of the control approach and its daily operation at the Hardhof well site which was described in the sections 7 and 8.

Before the implementation of the control system was performed, the flow model of the Limmat valley aquifer was established to simulate the well field operation in transient state and to test the control algorithm’s performance in offline-mode. The calibrated, deterministic flow model represented reality and showed reasonable good results of simulated groundwater heads in comparison with measured heads. However, the most important model parameters, i.e. hydraulic conductivity $K$ and leakage $L$ (to compute the amount of natural recharge by the river) were fixed. The shapes of the well catchments differ according to the aquifer heterogeneities yet in the deterministic model these heterogeneities are smoothed out. Due to these smoothed conditions the well capture zones are more symmetric than in reality. This affects directly the quality of information of the two kinds of control criteria used so far to compute the management decisions. In order to assess the quality of management decisions in the most important part of the aquifer, i.e. the Hardhof well field, the parameter uncertainty should therefore also be integrated in the offline simulations (Gorelick, 1990), (Gorelick, 1997). The risk to attract city water can directly be evaluated by using the conditioned $K$ and $L$ fields from the Ensemble Kalman
Filter as input to calculate the head differences and the percentages of city water for these different stochastic realizations.

The real-time control of urban drinking water wells can be considered as a novel approach. However successful applications can also be observed among case studies in petroleum reservoir engineering to maximize benefits. The contribution of a real-time control concept for the well field operation under uncertainty of important parameters is highly relevant: With a deterministic model approach the control signal can be reduced to zero (with an appropriate management) whereas the stochastic approach always incorporates the risk, i.e. the probabilistic terms of a signal. Even with successful management a small risk to attract city water still exists. This mirrors reality in a better way than a deterministic model would do. Although the control decision has to be eventually definite for every time step, the probability to receive city water still exists. Two experiments are used to compare the outcome of the deterministic and the stochastic model approach: First, the ensemble of the parameters K and L are used as input for the model simulations with the operational setting of the historical management and the optimal management of the computations with the deterministic model for selected time periods (large abstraction rates, low river stage etc.).

In the second experiment the results (Δh and %s) of each realization are taken as direct input for the control system in order to compute the optimal artificial recharge rate (producing 100 realizations of artificial recharge rates for basins and infiltration wells) for every time step with transient boundary conditions of one year. The realizations are either used to calculate an average value of all realizations for the next time step or they are used to calculate a control decision with the weighted difference between the optimal result of the deterministic model approach and the average value of the realizations.

Historical data of 2004 and 2005 were used to simulate the well field operation with all transient boundary conditions and forcings being un-changed. Two time periods were chosen: around 20th of January (high pumping activity in well C) and around 30th of April (high pumping activity in all four wells).

11.2 Results of Simulations with Realizations for Day 20 (January 20th, 2004)

Data of pumping on the specific day is shown in Table 13, artificial recharge (historical and optimal) in Table 14, and the average city water percentages in the wells in Table 15. The
optimal recharge is according to the management presented in section 8 which uses the %s-criterion.

Table 13: Abstraction at 20th of January.

<table>
<thead>
<tr>
<th></th>
<th>Pumping rate [m$^3$/d]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well A</td>
<td>0</td>
</tr>
<tr>
<td>Well B</td>
<td>-9920</td>
</tr>
<tr>
<td>Well C</td>
<td>-7320</td>
</tr>
<tr>
<td>Well D</td>
<td>-2650</td>
</tr>
</tbody>
</table>

Table 14: Average amounts of artificial recharge at day 20.

<table>
<thead>
<tr>
<th>Basin or Infiltration well</th>
<th>Historical AR [m$^3$/d]</th>
<th>Optimal AR [m$^3$/d]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basin I</td>
<td>4200</td>
<td>2200</td>
</tr>
<tr>
<td>S 11-12</td>
<td>1400</td>
<td>2000</td>
</tr>
<tr>
<td>Basin II</td>
<td>6000</td>
<td>10000</td>
</tr>
<tr>
<td>S 8-10</td>
<td>2100</td>
<td>6000</td>
</tr>
<tr>
<td>Basin III</td>
<td>9300</td>
<td>9000</td>
</tr>
<tr>
<td>S7</td>
<td>700</td>
<td>1000</td>
</tr>
<tr>
<td>S1-6</td>
<td>4200</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 15: Comparison of average (100 realizations) city water percentages in the wells.

<table>
<thead>
<tr>
<th></th>
<th>%s with historical AR [%]</th>
<th>%s with optimal AR [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Well A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Well B</td>
<td>0</td>
<td>3.4</td>
</tr>
<tr>
<td>Well C</td>
<td>7.8</td>
<td>3.2</td>
</tr>
<tr>
<td>Well D</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

The results of the path line situation for the two different management-schemes are shown in Figures 72 and 73. The city water percentage in well C can be reduced, but the city water percentage in well B rises in comparison to the historical situation.
Figure 72: Path line situation for historical management conditions (Jan 20th, 2004). 10 out 100 realizations plotted in 2D-projection.

Figure 73: Path line situation for optimal management conditions (Jan 20th, 2004). 10 out of 100 realizations plotted in 2D-projection.
11.3 Results of Simulations with Realizations for Day 120 (April 30th, 2004)

Data of pumping on the specific day are shown in Table 16, artificial recharge (historical and optimal) in Table 17, and the average city water percentages in the wells in Table 18. Optimal artificial recharge (which is larger than the recharge under historical management) reduces the average city water percentages in all three affected wells B, C, and D. The optimal recharge is according to the management in section 8 and used the %s-criterion.

Table 16: Pumping operation at 20th of January.

<table>
<thead>
<tr>
<th>Well</th>
<th>Pumping rate [m³/d]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>-27420</td>
</tr>
<tr>
<td>C</td>
<td>-19150</td>
</tr>
<tr>
<td>D</td>
<td>-19150</td>
</tr>
</tbody>
</table>

Table 17: Average amounts of artificial recharge at day 120.

<table>
<thead>
<tr>
<th>Basin or Infiltration well</th>
<th>Historical AR [m³/d]</th>
<th>Optimal AR [m³/d]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basin I</td>
<td>7650</td>
<td>25000</td>
</tr>
<tr>
<td>S 11-12</td>
<td>6320</td>
<td>6600</td>
</tr>
<tr>
<td>Basin II</td>
<td>7570</td>
<td>26000</td>
</tr>
<tr>
<td>S 8-10</td>
<td>9480</td>
<td>9900</td>
</tr>
<tr>
<td>Basin III</td>
<td>13500</td>
<td>25000</td>
</tr>
<tr>
<td>S 7</td>
<td>3160</td>
<td>3300</td>
</tr>
<tr>
<td>S1-6</td>
<td>7440</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 18: Comparison of average (100 realizations) city water percentages in the wells.

<table>
<thead>
<tr>
<th>Well</th>
<th>%s with historical AR [%]</th>
<th>%s with optimal AR [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>5.4</td>
<td>0.05</td>
</tr>
<tr>
<td>C</td>
<td>6.8</td>
<td>0.13</td>
</tr>
<tr>
<td>D</td>
<td>0.04</td>
<td>0</td>
</tr>
</tbody>
</table>

Figures 74-79 all show the comparison of pairs of results obtained by the historical and the optimal management conditions. The optimal recharge/pumping ratio of 1.42 is necessary to reduce the risk of city water in the four wells.
Figure 74: City water percentages (%) obtained from 100 realizations by historical management.

Figure 75: City water percentages (%) obtained from 100 realizations by optimal management (%$s$-criterion).
Figure 76: Path line situation for historical management conditions (Jan 20th, 2004). 10 out of 100 realizations plotted.

Figure 77: Path line situation for optimal management conditions (Jan 20th, 2004). 10 out of 100 realizations plotted (s-criterion).
Figure 78: 100 realizations of the three head differences ($\Delta h_1$, $\Delta h_2$, $\Delta h_3$) obtained by historical management. Overall average: -0.094 m.

Figure 79: 100 realizations of the three head differences ($\Delta h_1$, $\Delta h_2$, $\Delta h_3$) obtained by optimal management (%-criterion). Overall average: +0.089 m.

11.4 Second Experiment

Future simulations will focus on the possibility to control the artificial recharge directly under uncertainty of hydraulic conductivity and leakage. The computation of control decisions under uncertainty which is known can be categorized as decision making under risk. This leads to two possible decision makings: The first one can be described as robust control which uses the realization with the highest risk (worst case ensemble member) or it
uses the Brier scoring rule which measures the average squared deviation between the predicted probabilities for the ensembles and their outcomes, so a lower score represents higher accuracy. The experiment presented in this thesis uses the worst case member of the 100 realizations which yields to robust management. The concept of real-time control under uncertainty of K and L was tested in the experiment and uses the 95% percentile as worst member. Figure 80 shows the scheme. 100 ensembles of K and L are used to calculate 100 realizations of groundwater heads \( h_1, \ldots, h_{100} \) at time step \( t \) and the city water percentages (\( \% \)) in the four wells based on the velocity flow fields. After computation of 100 realizations, five values of the \( \% \)-ensembles are selected: The median and the 5%- , the 25%- , the 75%- , and the 95%- percentiles respectively. An optimal control decision (artificial recharge) will then be computed which will be applied for the next time step \( t+1 \). The setup of the simulation uses the data set of the time period 1\textsuperscript{st} of January 2004-31\textsuperscript{st} of August 2005 (sections 7 and 8).

![Figure 80: Experimental setup for real-time control under uncertainty. K- vector of hydraulic conductivity, L- vector of leakage, BC- vector of boundary conditions (including pumping), h- vector of heads, u- artificial recharge.](image)

The simulation results of city water percentage in well C for the time period of 12 days (end of April- beginning of May, 2004 with high pumping rates) are shown in Figure 81. With historical management a 90%- uncertainty bandwidth is produced with a median ranging between 7% and 12% city water. The first trial of real-time management aims at a robust
(and conservative) control and uses the 95%-percentile value as input for the control. The control can be regarded as worst-case-scenario management as it considers the highest percentile as proper input. The optimal management leads to a reduced uncertainty bandwidth with a 95%-percentile smaller than 2%. The strongly reduced risk to receive city water is achieved with a high amount of artificial recharge \((r=1.4; r=\text{recharge/abstraction})\).

If the 75%-percentile or the 50%-percentile (median) is taken as control criterion a less stringent quantification of city water percentage (and less artificial recharge) could be obtained. Future experiments will focus on selected time periods as the simulation of one year would require a CPU-time of ca. 150 days. Besides the presented time period (large abstraction rates in wells B, C, and D) three other time periods will be chosen for simulation: High river stage, low river stage, normal well operation with intermediate river stage.

11.5 Discussion

The simulation results of real-time control of the Hardhof well field under uncertainty of the two model parameters hydraulic conductivity and leakage proved to be feasible. The two
experiments showed the need to consider parameter uncertainty in order to improve the picture of the flow modeling.

The outcome shows that the stochastic real-time management (i.e. distribution of artificial recharge in time and space) is different from the deterministic one. Reality is well approximated by the deterministic model, yet the possible deviations and the associated risk only captured by the stochastic approach.

In future simulations the real-time control under uncertainty of $K$ and $L$ with the $\%s$-criterion will be performed for selected time periods which present typical cases (e.g. low and high river stages; average abstraction). Additional to this experiment, the real-time control under uncertainty of $K$ and $L$ with the $\Delta h$-criterion will be performed for the time period of one year (1st of Jan - 31st of Dec. 2004). The two experiments will use the worst case member approach and also the Brier scoring rule to select the best member as control input.
12 Conclusions and Perspective

12.1 General Conclusions on Real-Time Control

In the preceding chapters the concept of a real-time control system was introduced. We come to the following general conclusions:

- Real-time control for a well field was applied successfully using a hierarchical control concept.
- Real-time control contributes to an optimized well field management and secures the required drinking water quality.
- The methods applied are robust, and can incorporate real-time measurement data.
- Hierarchical control is an appropriate algorithm if it is coupled with a sufficiently fast groundwater flow model (run times in the range of seconds or minutes for the simulation of one day).
- Artificial recharge has to be increased over abstraction (and historical recharge) in order to guarantee a permanent protection of the well field.
- If we assess the control concept regarding variable costs, an increase of artificial recharge by a recharge/abstraction ratio of 1.7 (resulting from the $\Delta h$-criterion) or 1.5 (resulting from the $\%s$-criterion) would lead to an increase of ca. 52,000 CHF and 29,000 CHF per annum respectively. By contrast, the cost of pumping polluted water in the horizontal wells would be higher.
- Real-time control requires a robust and optimal solution within a short time in order to adjust the control factors just-in-time.

At the very beginning of this work it was expected to save energy for the artificial recharge but if the management is aimed at securing the water quality standard, an augmented artificial recharge is necessary. The associated costs are marginal compared to possible costs incurred for remediation of the Herdern site or the cleaning up (involving down times) of the horizontal wells if contaminants have entered the wells. However, an optimal management which aims at energy saving (i.e. minimum of artificial recharge) can still outperform the historical management strategy by adjusting the spatial distribution in basin an infiltration wells.
12.2 Conclusions and Recommendations on Offline-Simulations with the Two Control Criteria

The offline-simulations with the two control criteria showed the need to modify the historical artificial recharge scheme in basins and infiltration wells in order to improve the conditions, i.e. to avoid the inflow of city water. Two criteria were used to simulate the historical management with the established flow model. First, the head differences at three chosen measurement points were used as simple, yet effective control states and as inputs for fuzzy logic controllers which calculated the necessary daily recharge and infiltration rates.

a) Recommendations for the improvement of the $\Delta h$-criterion:
Tests with not only two but many pairs of measurement points to calculate the head gradient or local velocity vectors in $x$- and $y$-direction would be recommendable. A more sophisticated method could use selected velocity vectors of the calculated flow field south of the infiltration wells and basins. If the velocity vector in $x$- and $y$-directions would point away from the wells this could be regarded as a good state, if pointing towards the wells, it would imply an unfavourable condition, i.e. again possible inflow of city water.

b) Recommendations for improvements of the $\%s$-criterion:
Tests with more than 1,350 particles per well for the path line calculation would be useful to achieve a better resolution. Possible sensitivity analyses with 2,000-5,000 particles per well could be performed.

12.3 Conclusions and Recommendations on Online-Applications

The control approach was implemented for the daily management of the well field and the recharge installations. The results of the field measurements showed a beneficial effect under both control criteria. The reduction of electrical conductivity in horizontal wells and at measurement points led to the conclusion that both control methods improved the management regarding the standard of the abstracted drinking water. In order to achieve the requirement of 0% city water an augmentation of artificial recharge over the actual pumping rate was necessary. A new distribution was recommended which went along with the increase in artificial recharge. The historical average ratio of 1.3 could not be maintained
if a permanent state of low EC values is necessary to meet the HACCP standards (i.e. “at any
time”).

Four periods of applied defined control resulted in measurements of decreasing electrical
conductivity in the wells C and D which are proof for the assumption that artificial recharge
has to be increased and also its spatial distribution has to be adapted compared to the
historical one in order to reduce the fraction of city water in these two wells. Two periods in
spring and summer 2009 and two periods in summer and early fall 2010 were presented
which used the $\Delta h$-criterion for control.

After all, the implemented real-time system is possibly the first one of its kind in Europe. Its
remarkable success could have an impact on the state-of-the-art methods used until now:
Methods to protect well fields have relied on the static designation of well head protection
zones, the delineation of well catchments and on chemical analyses of water samples. The
real time control adds the dynamic dimension of time and allows a flexible reaction to alarm
values of flow directions or concentrations in the water. The typical adaptive management
of well fields that has been done in the past, involved time horizons of weeks and months.
With the presented real-time control approach it can now be done within a day.

12.4 Conclusions and Recommendations on Alternative Control Approaches

Two alternative control approaches were compared with the hierarchical control approach.
The widely used strict optimization approach with multiple objectives and an evolutionary
search algorithm (NSGA-II) proved to be slower than the hierarchical approach, yielding
similar results of optimized head differences.

An intuitively designed decision support system or expert system, which represented
approaches of knowledge based systems, is faster in comparison with hierarchical control.
Yet, robustness is the Achilles’ heel. Knowledge based systems produce good results as long
as the current input data is of similar quality and range as the data used for its training, yet
they may fail if completely new data are used as input.

In addition to the presented alternatives, the following group of automatic management
approaches could be recommended as subjects of research: The group would comprise
methods that are classified as agent based approaches or cellular automata approaches.
### 12.5 Perspective: Future Work

Future work should aim at unsolved problems or new aspects of real-time control, mainly regarding optimal real-time control under uncertainty of head predictions, or optimal real-time control with more than one criterion at the same time. The Limmat valley aquifer model has been enhanced by adding setups for modelling heat transport (Engeler et al., 2011) and solute transport processes (Baatz, 2010). A solute transport model could be used to assess the control criterion which uses the path line method (\%s-criterion). It would be useful to check whether high (simulated) electrical conductivity values correlate with high percentages of city water in the horizontal wells. Table 19 shows the possible combinations of simulations with control approaches and models that have been performed so far or could be set up in future. A heat transport model could be used to test the hierarchical concept as well. In this case temperature values in wells and measurement points would be the control criterion. The comparison of hierarchical control with pure optimization methods for the well field management is under trial with the focus being the analysis of the run-times.

#### Table 19: Combinations of simulations with control approaches and models (outlook).

<table>
<thead>
<tr>
<th>Possible combination for simulation</th>
<th>Hierarchical control</th>
<th>Strict optimization</th>
<th>Decision support systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow model</td>
<td>Done</td>
<td>Done</td>
<td>Done</td>
</tr>
<tr>
<td>Heat transport model</td>
<td>Model for real-time application is not established yet.</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
13 References


SPRING Software, delta h Ingenieurgesellschaft mbH. 2010. Witten, Germany.


a) Technical data of wells and artificial recharge installations

**Technical data of vertical wells**

<table>
<thead>
<tr>
<th>Design</th>
<th>Slotted filter pipes: diameter 600 mm, depth : 20 – 24 m (from surface). Wells are supplied with subaqueous pumps</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Delivery rate</strong></td>
<td>At low groundwater level: 20,000 m³/day (in total) At high groundwater level: 30,000 m³/day (in total)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Design</th>
<th>Slotted filter -pipes: diameter 600 mm, depth 16 – 34 m (from surface)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Delivery rate</strong></td>
<td>At low groundwater level: 42,000 m³/day (in total) At high groundwater level: 50,000 m³/day (in total)</td>
</tr>
</tbody>
</table>

**Technical data of recharge basins**

<table>
<thead>
<tr>
<th>Basin I</th>
<th>Filter area (rectangular shape): 3,825 m² length: 85m, width: 45 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basin II</td>
<td>Filter area (rectangular shape): 4,000 m² length: 80m; width 50 m</td>
</tr>
<tr>
<td>Basin III</td>
<td>Filter area (trapezoidal): 3,905 m² 71m x 75m / 355 m</td>
</tr>
<tr>
<td>Vertical design of slow sand filter</td>
<td>1.2 mm fleece mat 7 cm split layer (grain diameter 3-6 mm) 100 cm filter sand (grain diameter 0.2-2/2.4mm)</td>
</tr>
<tr>
<td></td>
<td>ca. 30 cm filter gravel (grain diameter 4-15mm) ca. 80 cm coarse filter gravel (grain diameter 15-30mm)</td>
</tr>
<tr>
<td></td>
<td>Transition to natural brash</td>
</tr>
<tr>
<td><strong>Normal filter velocity</strong></td>
<td>2.5 - 3m/day</td>
</tr>
<tr>
<td><strong>Maximum filter velocity</strong></td>
<td>10m/day</td>
</tr>
<tr>
<td><strong>Water storage level</strong></td>
<td>Maximum: 3 m</td>
</tr>
<tr>
<td><strong>Length of cascade</strong></td>
<td>70 m</td>
</tr>
</tbody>
</table>
**Technical data of infiltration wells:**

<table>
<thead>
<tr>
<th>Design</th>
<th>Slotted filter-pipes: diameter 600 mm, depth: 25 – 30 m (from surface).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infiltration rate per day</td>
<td>3500 m³/day (for each well)</td>
</tr>
</tbody>
</table>

**Technical data of horizontal wells:**

<table>
<thead>
<tr>
<th>Abstraction capacity</th>
<th>Maximum 50,000 m³/day (ca. 600 l/s).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Depth of wells</td>
<td>20-25 m</td>
</tr>
<tr>
<td>Well shaft diameter</td>
<td>4 m</td>
</tr>
</tbody>
</table>
| 12 Horizontal filter pipes on 2 levels, star-shaped design | Internal diameter 300 mm length 300 - 380 m  
Slotted filter (stainless steel)  
Ø 300 mm (horizontal wells A, B und D)  
Ribbed filter (polypropylene) Ø 170 mm (horizontal well C) |
| Subaqueous pumps                           | 3 Pieces. Type: K 302-2a à 193 l/s  
30 m of manometric delivery height |
| Motors                                     | 3 Pieces: 90 kW /400 V  
1450 Revolutions per minute |
| Aeration of well shaft                     | 2 compressors  
à 200 m³ air injection per hour |
| Electrical power supply                    | Transformer station (6 kV/400 V)  
High-voltage switch board  
Low-voltage switch board  
Battery for co-current flow 48 V for control and emergency operation |
b) Technical data of measurement device
c) Source Code

1) Code for PD-FLC-Controller is adapted after:

http://www2.ece.ohio-state.edu/~passino/FCcode.txt

Note: This program has evolved over time and uses programming ideas of Kevin Passino, Andrew Kwong, Scott Brown, Jeff Layne, and Brian Klinehoffer.

```c
int fuzzy1(double bII, double percentageC1, double *noval)  
{

    //******************* variable declarations
    *****************************************

    // Initialize variables
double  eold=0.0;       // Initial condition used to calculate c
    
    // Next, initialize parameters for the fuzzy controller
    int   nume=7;   // Number of input membership functions for the e universe of discourse
    int   numc=7;   // Number of input membership functions for the c universe of discourse
    
    double ge=bII*0.015, gc=bII*0.015, gu=30000;
    // Scaling gains for tuning membership functions for universes of discourse for e, c and u respectively
    // These are tuned to improve the performance of the FLC

    double we=0.5*(1.0/ge);
    // we is half the width of the triangular input membership function bases (note that if you change ge, the base width will correspondingly change so that we always end up with uniformly distributed input membership functions)

    double wc=0.2*(1.0(gc);
    // Similar to we but for the c universe of discourse

    double base=0.5*gu;
    // Base width of output membership functions of the fuzzy controller

    // Place centers of membership functions of the fuzzy controller:
    
    // Centers of input membership functions for the e universe of discourse for of fuzzy controller (a vector of centers)
    double ce[7], //The values will be set in the "ec_centers()" routine

    // Centers of input membership functions for the c universe of discourse for of fuzzy controller (a vector of centers)
    cc[7]; //The values will be set in the "ec_centers()" routine
```
// This next matrix determines the rules of the fuzzy controller.
// The entries are the centers of the output membership functions.
// Notice that it is scaled by gu, the output scaling factor,
// since it is a normalized rule-base.
// Also, there is the parameter gf that is either =0 or =1.
// If gf=0 then the rule-base
// has 49 rules with output membership functions that are triangular
// with base widths base=0.4*gu and centers at zero.

double gf=1;
double fuzzyrules[7][7];
    //The values will be set in the "fc_rules()" routine

int d=1;
    // This sets the number of steps the knowledge-base modifier looks
    // back in time. For this program it must be an integer
    // less than or equal to 10 (but this is easy to make larger)

    // The next four vectors are used to store the information about
    // which rules were on 1 step in the past, 2 steps in the past, ....,
    // 10 steps in the past (so that picking 0<= d <= 10 can be used).

int meme_int[10]={0, 0, 0, 0, 0, 0, 0, 0, 0, 0};
    // sets up the vector to store up to 10 values of e_int

int meme_count[10]={0, 0, 0, 0, 0, 0, 0, 0, 0, 0};
    // sets up the vector to store up to 10 values of e_count

int memc_int[10]={0, 0, 0, 0, 0, 0, 0, 0, 0, 0};
    // sets up the vector to store up to 10 values of c_int

int memc_count[10]={0, 0, 0, 0, 0, 0, 0, 0, 0, 0};
    // sets up the vector to store up to 10 values of c_count

    // Declarations of other variables used in the program
int     i,j,k, l, t;     // used in loop

double  u1;   //controller output

double  e = percentageC1;

        // (error: city water percentage)

int     e_count, c_count, e_int, c_int;

double  mfe[7], mfc[7];

FILE    *myfile;
// Executing the initializing routines:
ec_centers(ce, ge, cc, gc);
    // setting centers of mfs for e & c

fc_rules(fuzzyrules, gu, gf);
    // establish the rule table for the fuzzy controller

    // check the initialization
    // ----- ce & ge ---------------
    printf("ce=[ ");
    for (i=0; i<=6; i++)
        printf("%f  ", ce[i]);
    printf("],  ge=%f \n", ge);

    // ----- cc & gc -------------
    printf("cc=[ ");
    for (i=0; i<=6; i++)
        printf("%f  ", cc[i]);
    printf("],  gc=%f \n", gc);

    // ----- gu, gf, gp ------------
    printf("gu=%f,  gf=%f \n", gu, gf);

    //------- fuzzyrules -----------
    /*printf("fuzzyrules=\n");
    for (i=0; i<=6; i++)
        {
            for (j=0; j<=5; j++)
                printf("%f  , fuzzyrules[%d][%d]", fuzzyrules[i][j]);
        }*/

myfile=fopen("data1.dat","w"); // open a file to store data

for (t=0; t<1; t++)
{
    // First, for the given fuzzy controller inputs we determine
    // the extent at which the error membership functions
    // of the fuzzy controller are on (this is the fuzzification part).
    c_count=0; e_count=0;
    // These are used to count the number of
    // non-zero mf certainties of e and c
// Define controller input e as e1 (piezometric head difference between obs.points)

\[ c = \frac{(e - e_{old})}{2}; \]

// Calculates the change in error input for the fuzzy controller

\[ e_{old} = e; \]

// Saves the past value of e for use in the next time through the loop

// The following if-then structure fills the vector mfe
// with the certainty of each membership function of e for the current input e

if (e <= ce[0]) // Takes care of saturation of the left-most membership function
{
    mfe[0] = 1.0; // i.e., the only one on is the left-most one
    for (i = 1; i <= 6; i++)
    {
        mfe[i] = 0.0;
    }
    e_count = e_count + 1; e_int = 0;
}
else
{
    if (e >= ce[nume - 1]) // Takes care of saturation of the right-most mf
    {
        for (i = 0; i <= 9; i++)
        {
            mfe[i] = 0.0;
        }
        mfe[6] = 1.0; // One mf on, it is the right-most one
        e_count = e_count + 1; e_int = nume - 1;
    }
    else // In this case the input is on the middle part of the universe of discourse for e
    {
        // Next, we are going to cycle through the mfs to find all that are on
        for (i = 0; i <= nume - 1; i++)
        {
            if (e <= ce[i])
            {
                mfe[i] = MAX(0, (1.0 + (e - ce[i])/we));
                // In this case the input is to the left of the center ce(i) and we compute the value of the mf centered at ce(i)
                // for this input e
                if (mfe[i] != 0)
                {
                    // If the certainty is not equal to zero then say that have one mf on by incrementing our count
                    e_count = e_count + 1;
                    e_int = i; // This term holds the index last entry with a non-zero term
                }
            }
        }
    }
}
else
{
    mfe[i]=MAX(0,(1.0+(ce[i]-e)/we) );
    // In this case the input is to the
    // right of the center ce(i)
    if (mfe[i]!=0)
    {
        e_count=e_count+1;
        e_int=i;       // This term holds the index of the
                        // last entry with a non-zero term
    }
}
// end of else
}   // end of for
}       // end of else
}                  // end of else

// Next we will save the number of mfs that are on and the pointer
// e_int as to which rules were on.  This vector of length
// 10 saves the last 10 values of e_count and e_int as time
// progresses (hence, it is a moving window).
for (i=0; i<=8; i++)
{
    meme_count[i+1]=meme_count[i];
    meme_int[i+1]=meme_int[i];
}
meme_count[0]=e_count;
meme_int[0]=e_int;

// The following if-then structure fills the vector mfc with the
// certainty of each membership function of c for the current
// value of c (to understand this part of the code see the above
// similar code for computing mfe)
if (c<=cc[0])       // Takes care of saturation of the left-most
{
    // membership function
    mfc[0]=1.0;       // i.e., the only one on is the left-most one
    for (i=1; i<=10; i++)
        mfc[i]=0.0;
    c_count=c_count+1; c_int=0;
}
else
{
    if (c>=cc[numc-1])       // Takes care of saturation of the right-most mf
    { for (i=0; i<=9; i++)
        mfc[i]=0.0;
        mfc[10]=1.0;       // One mf on, it is the right-most one
        c_count=c_count+1; c_int=numc-1;
    }
    else            // In this case the input is on the middle part of the
    {                // universe of discourse for c
// Next, we are going to cycle through the mfs to 
// find all that are on
for (i=0; i<=numc-1; i++)
{
    if (c<=cc[i])
    {
        mfc[i]=MAX(0, (1.0+(c-cc[i])/wc ));
        // In this case the input is to the 
        // left of the center cc(i) and we compute 
        // the value of the mf centered at cc(i) 
        // for this input c
        if (mfc[i]!=0)
        {
            // If the certainty is not equal to zero then say 
            // that have one mf on by incrementing our count
            c_count=c_count+1;
            c_int=i;        // This term holds the index last entry 
            // with a non-zero term
        }
    }
    else
    {
        mfc[i]=MAX(0,(cc[i]-c)/wc );
        // In this case the input is to the 
        // right of the center cc(i)
        if (mfc[i]!=0)
        {
            c_count=c_count+1;
            c_int=i;       // This term holds the index of the 
                        // last entry with a non-zero term
        }
    }
}

// Next we will save the number of mfs that are on and the pointer 
// c_int as to which rules were on. This vector of length 10
// saves the last 10 values of c_count and c_int as time progresses
// (hence, it is a moving window).
for (i=0; i<=8; i++)
{
    memc_count[i+1]=memc_count[i];
    memc_int[i+1]=memc_int[i];
}
memc_count[0]=c_count;
memc_int[0]=c_int;

// These four loops calculate the crisp output using only the non-zero premise of error,e,
//and change in error, c. The minimum operator is used for the premise and implication.

num=0.0;
den=0.0;

for (k=(e_int-e_count+1); k<=e_int; k++)
{   // Scan over e indices of mfs that are on
    for (l=(c_int-c_count+1); l<=c_int; l++)
    {   // Scan over c indices of mfs that are on
        prem=MIN(mfe[k], mfc[l]);
            // Value of premise membership function
        // The next calculation of num adds up the numerator for the
        // defuzzification formula.
        num=num+fuzzyrules[k][l]*base*(prem-(prem*prem)/2.0);
        den=den+base*(prem-(prem*prem)/2.0);
    }
}

u1=num/den;
if (u1 <= 2000)
{u1 = 2000;}
printf("artificial recharge u1=%10.4f\n", u1); //minimum artificial recharge

printf("pumpmenge u1 übergabe noval=%10.4f, %10.4f\n", u1, noval[1]);

    // Crisp output of fuzzy controller that is the input
    // to the pumping well, inf.basin, or inf.well

    // save data
    fprintf(myfile, "%f\n", u1);

} // This end statement goes with the first "while" statement in the program
fclose(myfile);  // close the data file

// save the rule-base matrix of the fuzzy controller into a disk file
myfile=fopen("fuzrules.dat","w");
for (i=0; i<=6; i++)
{   for (j=0; j<=5; j++)
    {fprintf(myfile,"%f ", fuzzyrules[i][j]);
     fprintf(myfile,"%f\n", fuzzyrules[i][6]);
    }
    fclose(myfile);
} // This ends the fuzzy function fuzzy1
```c
int ec_centers(double *ce, double ge, double *cc, double gc)
{
    int i;
    // Centers of input membership functions for the universe of discourse for FLC
    for (i=0; i<=6; i++)
        ce[i]=(-1.0+0.2*i)*(1.0/ge);
    // Centers of input membership functions for the c universe of discourse for FLC
    for (i=0; i<=6; i++)
        cc[i]=(-1.0+0.2*i)*(1.0/gc);
}

int fc_rules(double fuzzyrules[][7], double gu, double gf)
{
    // The next matrix determines the rules of the fuzzy controller. The entries are the centers of the output membership functions.
    int i,j;
    double temp[7][7]=
    {{0, 0, 0, 0, 0, 0, 0.1},
     {0, 0, 0, 0, 0, 0.1, 0.8},
     {0, 0, 0, 0.1, 0.8, 0.85},
     {0, 0, 0.1, 0.8, 0.85, 0.9},
     {0, 0.1, 0.8, 0.85, 0.9, 0.95},
     {0.1, 0.8, 0.85, 0.9, 0.95, 1},
     {0.1, 0.8, 0.85, 0.9, 0.95, 1, 1}};
    for (i=0;i<=6;i++)
        for (j=0; j<=6; j++)
            fuzzyrules[i][j]=temp[i][j]*gu*gf;
}
```

2) Code for Simple Genetic Algorithm is adapted after:
http://www2.ece.ohio-state.edu/~passino/ICbook/Code/gac.txt

3) Code for Strict Optimization:
http://www.iitk.ac.in/kangal/codes.shtml
Curriculum Vitae

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2006-2010: Ph.D. student at the Institute of Environmental Engineering (IfU), ETH Zurich.

2001-2005: Automation and Control Engineering (Dipl. Ing. /“M. Eng.”) at Technical University of Ilmenau, Germany.


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