Modeling of Water Transport and Treatment at WRK III

Maart 2001

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WRK

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Modeling of Water Transport and Treatment of the WRK III

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Preface

I would like to take this opportunity to thank the WRK III for giving the opportunity to the University and me to do research at their facility in Andijk. During this period I should mention in particular Eng. Nico Koelman, who has given much patience and guidance to obtain all the necessary information. Also I like to thank Dr. Babuška for explaining the advantages and the applications of fuzzy logic without which much more time must be spend processing the data. My special thanks go to Prof.ir. J.C. van Dijk and ir. Rietveld who has given me guidance to bring this study to a conclusion and resulting in this report. Last but not least I would like to thank my parents and my family for their relentless support during my entire study.
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Samenvatting

Inleiding
WRK III zuivert IJsselmeer water tot een halffabrikaat (coagulatie, sedimentatie, filtratie en gedeeltelijk actievekooffiltratie) en transporteert dit water naar PWN, voor infiltratie in de duinen, en naar Hoogovens. Bij het transport en zuivering van het water wordt steeds meer gebruik gemaakt van on-line monitoring en automatische sturing. In dit project is gekeken of met behulp van de beschikbare gegevens het transportsysteem en de zuivering geoptimaliseerd kan worden.

Transport
Het transportsysteem bestaat uit een aantal inlaatpompen, filtraatkelders, filtraatpompen en kelders bij Hoogovens. Het debiert naar PWN is gedurende langere periodes constant, maar het debiert naar Hoogovens fluctueert aanzienlijk en dit is ook merkbaar bij het inlaatdebiert. Het debiert naar Hoogovens en het inlaatdebiert kunnen afgevlakt worden door gebruik te maken van de filtraatkelders en de kelders bij Hoogovens. De huidige sturing is echter opgericht het niveau in de kelders constant te houden. Dit betekent dat van afvlakking geen sprake is. Met behulp van een gesimuleerde PI regelaar is gekeken of er debietsafvlakking bewerkstelligd kan worden als de kelderpeilen wel gevarieerd zouden worden. Het blijkt dat dit mogelijk is. Hiermee wordt echter maar een geringe energiebesparing behaald (<2%). Voor het zuiveringsproces kan het echter wel voordeilig zijn. Een constanter debiet door de zuivering betekent minder uitspoeling uit de sedimentatieunits en minder doorslag door de filters. Het effect hiervan is niet gekwantificeerd.

Sturing van filterterugspoelingen
Het terugspoelen van de filters gebeurt als een maximale filterweerstand (van 1,8 m) optreedt. Hoe lang de filterloopstijl is, is afhankelijk van het te zuiveren debiet, de temperatuur, de troebelheid van het ruwe water en de hoeveelheid toegevoegde chemicaliën. De loopstijl van een filter kan variëren van 40 tot 100 uur. In het totaal zijn er bij WRK III 18 filters in gebruik. Een spoeling duurt niet langer dan 1 uur, dus in theorie heeft er nooit meer dan 1 filter buiten gebruik te zijn (afgezien van de filters in groot onderhoud). In de praktijk gebeurt het echter regelmatig dat meerdere filters tegelijk de maximale weerstand bereiken en gespoeld moeten worden. Dit betekent dat (tijdelijk) de andere filters overbelast worden met gevolgen voor de effluent waterkwaliteit. Om dit te voorkomen is een model ontwikkeld die de filterloopstijl voorspelt. Op basis van dit model kan het tijdstip van spoelen van de verschillende filters worden bepaald.
The model is gebaseerd op Fuzzy Logic en maakt gebruik van historische gegevens met betrekking tot weerstandsbouw, filtratiesnelheid, troebelheid, ijzer- en wispodosering en temperatuur. Het model is geïnitiëerd door gebruikmakend van Bootstrapmethodes. Als het model grote afwijkingen ten opzichte van de werkelijkheid laat zien, treden er mechanismen in werking die daarop bijtijds corrigeren.
### List of Abbreviations

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<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>FTU</td>
<td>Fouling Turbidity Unit</td>
</tr>
<tr>
<td>IBL</td>
<td>Informatie BedrijfsLeiding</td>
</tr>
<tr>
<td>PHD</td>
<td>Proces History Data</td>
</tr>
<tr>
<td>PWN</td>
<td>Provinciaal waterleidingbedrijf Noord Holland</td>
</tr>
<tr>
<td>PI</td>
<td>Proportional integrator</td>
</tr>
<tr>
<td>VAF</td>
<td>Variance Accounted For</td>
</tr>
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<td>WRK</td>
<td>Watertransportmaatschappij Rijn-kennermerland</td>
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1 Introduction

The WRK stands for WaterTransportmaatschappij Rijn-Kennermerland. Its core business is the transport and treatment of water. The WRK has two treatment plants in the Netherlands. The first treatment plant is in Nieuwegein. This plant is called the WRK I and II. The second treatment plant is in Andijk. This treatment plant is called the WRK III. The receivers of the water from the WRK III are Hoogovens and PWN. Hoogovens’ core business is manufacturing high quality steel. It needs the water for various purposes such as for cooling agent. PWN business is converting the water into drinking water.

The report is divided into mainly two sections. These are the transport modelling and the quality modelling. The transport modelling describes using the reservoirs as buffers a more stable flow than the present flow can be achieved. A more stable flow will save pumping energy and will have a positive effect on the treatment process. A transport control model is designed to simulate the transport. The control system task is to keep the water level in the reservoirs constant. By allowing the water level to fluctuate, the flow rate to the reservoirs can flow more stable than before. Simulations are done on data from the past to see how much energy could have been saved in that period. The quality modelling describes how the filtration runtime can be predicted. The prediction is done by a fuzzy logic, which predicts the head loss gradient. The model uses past data for its regression. The accuracy of the prediction is then analysed. The prediction of the runtimes is important because it will then be capable of predicting how the runtimes change when the parameters change. Another reason to predict the runtimes is to foresee problems in the back washing more than two filters, as then a filter has to stay on stand by. This is useful when the treatment process is automated. The structure of the report is shown as follow:

Chapter 2 gives the general description the transport and treatment process of the WRK III.

Chapter 3 models the transport system. First the history of the transport flow are shown which give more insight in how the WRK III worked in the past. It also shows the water levels in the Hoogovens reservoirs and the filtrate reservoirs. Next, the description of the situation is laid out and the object of modelling the transport system is explained. This shows how potentially the reservoirs could be used as buffers. Finally, the modelling of the transport process and results of simulations are shown. Charts will show simulated flow regime and water levels in the reservoirs so that improvements of the transport system can be made.

Chapter 4 models the treatment process with the help of fuzzy logic. In the chapter, the different treatment processes at the WRK III are shown. Next, the situation and objective of modelling are described. A model is made that simulates the filtration process, which can predict the filtration runtimes. Finally simulations and results are shown. The model can be used to predict the filtration runtimes.

Discussion of the results can be found in chapter 5. Conclusions are made on how the results of the transport model can be interpreted and recommendations are done on how to use the buffer capacity of the reservoirs. For the treatment model, conclusions are made on how the model predicts the filtration runtimes. Recommendations are then made on how to use the model and how to improve the model.
2 General description

2.1 Transport

At WRK III, water is transported from the IJsselmeer at Andijk to its water users Hoogovens and PWN. The water is pumped up at two places. (See the transport schema in figure 2.1.) The first place is at the entrance of the treatment plant. Four inlet pumps elevate the water 5 meters so that the water can flow through the water treatment installation under gravity. These pumps each have the maximum capacity of about 5000 m$^3$/hour at a discharge head of 5 meters. The water ends up in the filtrate reservoirs. The second place where the water is pumped up is after the filtrate reservoirs. Four filtrate pumps withdraw water from the filtrate reservoirs. Each of these pump has a maximum capacity of about 5000m$^3$/h. The water is transported through two 60 km pipelines with a static head of about 5 meters to Hoogovens and 8 meters to PWN. Two filtrate pumps are used to transport the water to Hoogovens and the other two filtrate pumps are used to transport the water to PWN. However, different combinations are possible in order to perform maintenance of the pumps. All pumps are able to supply a variable flow efficiently.

The water to PWN ends up in the PWN Dunes. The water to Hoogovens first ends up in the Hoogovens reservoirs. Hoogovens taps water from these reservoirs. Its WRK III's task to make sure that it supplies enough water to the Hoogovens reservoirs so that they do not dry up. This is ensured by a feedback control system.

![Transport scheme](image)

Figure 2.1 Transport scheme

The WRK III has the capacity to transport 109 million cubic meters of water per year. In 1999 the total was about 60 million cubic meters.

2.2 Quality

The raw water that enters the treatment process is from the IJsselmeer. The turbidity measured at the inlet of the treatment process ranges from 2 to 11 FTU. The combined process of coagulation, flocculation and tilted plate sedimentation reduces the turbidity to 0.3 till 0.7 FTU. It is then further reduced by filtration to 0.11 till 0.07 FTU. The water turbidity is thus reduced by a factor of about 100.
The general treatment process can be seen in figure 2.2. The water destined for PWN is further treated by activated coal filtration in order to reduce the concentrations of organic micro pollutants.

![Diagram of treatment process]

Figure 2.2 Treatment process

The control of the quality of the treated water is done by the “chef van de wacht”, or operator. He has two main tasks concerning the treatment process. These are the coagulation process by iron and wispro dosage and the control of the backwash program for the rapid sand filtration.

2.3 Available data

Many data of the treatment process are available and have been saved in computer databases. There are two databases of the WRK III transport and treatment process. The PHD, Process History Data, is a database of recordings of the many sensors that monitors the process. It records continually. Examples of the parameters in the PHD are water temperature, air temperature, room temperature, flow rates, the iron dosage, status of valves and the water levels in the reservoirs. In the IBL, Informatie BedrijfsLeiding, on the other hand is a database of recordings of analysis of the laboratory. The analysis are from samples taken from the treatment process. These analysis are mainlay done once a day. This usually happens in the morning and only during workdays. (Not in the weekends and holidays. Examples are concentrations of algae, iron residue, turbidity, sulphate concentration, chloride concentration and various organisms such as water fleas. There are parameters that are recorded in both databases, for example the turbidity. It appeared that at some periods the turbidity recorded in the PHD database didn’t match the turbidity recorded in the IBL. The PHD recordings of these periods are useless as the turbidity sensors became dirty by the turbid water and as a consequence gave wrong readings. Therefore caution should be taken when using data from these PHD.

In total, per day about 3000 parameters are measured by sensors or in the laboratory. This wealth of information can be used to investigate many things such as the effectiveness of the treatment process.
3 Transport Modelling

3.1 Introduction flow rate control

3.1.1 Flow rate control
The transport system formulated in a water balance equation. The inlet flow into the reservoir must equal the outlet flow plus the increase in the water volume in the reservoir.

The water level in the reservoirs are kept as constant as possible. A feedback control system continually measures the water level and adjusts the flow rate of the pumps accordingly. The following will illustrate the system. Assume that the transport system to Hoogovens is in equilibrium, there is no increase in the volume of water in the reservoir. Then Hoogovens increases the amount of water extracted from the Hoogovens reservoirs. This will initially lower the water level in the Hoogovens reservoirs. A sensor detects this and sends a signal to the filtrate pumps to increase the flow. This will return the water level to its original level. The water level in the filtrate reservoirs will decrease because of the increase of the filtrate flow rate. As before, a signal will be sent to the inlet pumps to increase its flow rate and correct the water level in the filtrate reservoirs. Vice versa happens when Hoogovens decreases its extraction from the Hoogovens reservoirs.

The scheme of the flow control can be seen in figure 3.1.

![Flow control scheme](image)

Figure 3.1 Flow control scheme

The flow to PWN is controlled differently than to Hoogovens. PWN doesn’t have reservoirs where it stores its water temporarily but the water flows directly into the dunes. The flow is therefore constant during these long periods. To increase the flow rate to PWN, PWN has to make a phone call to the WRK III to ask for the increase.

The filtrate reservoirs consist of three equal sized reservoirs that hold water. However, one of the reservoirs performs as activated coal filtration units. Therefore the reservoir has a limited use for other purposes and is therefore ignored in the transport modelling. The following list gives the dimensions and limitations of the remaining two filtrate reservoirs.

- total area = 2*1447 m² = 2894 m²
- maximum water level = 4m
- minimum water level = 0.5 m

The water level is presently held at 2 m.
There are two Hoogovens reservoirs which are connected. The dimensions and limits of the Hoogovens reservoir are as follows:

- total area = 1271 m$^2$ +1509 m$^2$ = 2780 m$^2$
- maximum water level = 3.8 m
- minimum water level = 0.5 m

The water level is held at 3.6 meters.

The maximum water level is determined by the reservoir’s weir. The minimum water level is the level where the pumps can still safely function without the risk of pumping air.

3.1.2 History

The following charts will show how much the water levels and the flow rates have varied in the past. These give an idea which types of fluctuations can be encountered in the future.

The inlet flow chart can be seen in figure 3.2. The total inlet flow varies between a minimum of 4000 m$^3$/h and a maximum of 11000 m$^3$/h. Three clearly different kinds of flow rate fluctuations can be observed in the inlet flow rate.

The first kind can be described as the pulse fluctuation. In the period around 9/4/99 and after 20/7/99 a sudden flow increase from about 6500 m$^3$/h to about 10000 m$^3$/h can be seen. The reason for this large increase is because the WRK I and II were in maintenance done and WRK III had to deliver water to their customers on top of its own regular production. These fluctuations are predictable as long as there are good communications between the two treatment plants.

The second kind of fluctuation is of a short wavelength fluctuation. The fluctuation has a wavelength of about 1 hour and the amplitude varying between 1000 and 3000 m$^3$/h. The fluctuations are caused mainly by small fluctuation demanded by Hoogovens and by the control system that keeps adjusting the pump flow rate in order to keep the water level in the filtrate reservoir constant.

The third kind of fluctuation is a long wavelength fluctuation. This fluctuation has a wavelength at least higher than 80 days. For example, one wave can be seen between the period 30-12-98 to 20-3-99. These are caused by the variation of the demand of the two customers during the period.

![Figure 3.2 Inlet pump flow](image)

Figure 3.3 shows the variation of the water level in the filtrate reservoirs. The water level varies around the 2 meter level. The lowest level reached in that period is 1.50 meters and the highest level reached is 2.50 meters. There is also period between 8-2-99 and 10-3-99
where the water level gradually increased. Here the control system failed to hold the water level stable at 2 meters.

Figure 3.3 Filtrate reservoir water level

Figure 3.4 shows the total filtrate flow rate. The total filtrate flow rate is very similar to the total inlet flow rate except that it is lower. The difference between the inlet flow and the filtrate flow is about 500 m3/h. The reason for this difference is because part of the treated water is used by the treatment plant as backwash water. Backwash water uses water from the filtrate reservoirs and ends back in the IJsselmeer.

Figure 3.4 Filtrate flow

The total filtrate flow can be divided into two main flow rates according to its destinations.

The filtrate flow to PWN can be seen in figure 3.4. The flow rate has no short wavelength fluctuations, because storage occurs within the receiving dunes.
The short wavelength fluctuations are clearly caused by the filtrate flow to Hoogovens.

The difference in the fluctuations can be seen more clearly when comparing the two flows closely in figure 3.5. Figure 3.5 shows how in the 3 day period of the filtrate flow to PWN and Hoogovens.

Figure 3.5 Comparison of the filtrate flows to PWN and Hoogovens

Figure 3.6 shows the water level of the Hoogovens reservoirs. The water level fluctuates between 3.5 meters and 3.8 meters. There are a few very low water levels recorded, but these are recording are errors. It can be seen that Hoogovens is quite strict at maintaining the water level at 3.6 meters as the water level doesn’t deviate a lot from this.

Figure 3.6 Hoogovens reservoir water level

The prediction of the long and short wavelength fluctuations is not a subject of this study.
3.2 Transport control analysis

3.2.1 Situation
The water levels in both reservoirs are held constant. This means that the inlet pumps and the filtrate pumps have to change their flow rates when the water levels change. The main reason that Hoogovens want these water levels constant is to use the water reservoirs as safeguards against the WRK III failure of supplying water. If the WRK III is not able to supply water for whatever reason, Hoogovens can still withdraw water from these reservoirs for about 3 hours. The question is how much risk exists for Hoogovens to need such a facility. The WRK has other ways of supplying water to Hoogovens. One way is by WRK I and II supplying the water. Another way is to use its diesel pumps if the filtrate pumps fail.

The reservoirs can be used as buffers to stabilise the flow rate. This has two advantages. The pumps can operate more constantly which saves energy and implicates less maintenance of the pumps. A second advantage is that the treatment process becomes more efficient.

To use the Hoogovens reservoirs as buffers would require permission from Hoogovens. The filtrate reservoirs on the other hand can potentially always be used as buffers, because the reservoirs are owned by the WRK. This is possible as long as the supply of water to its customers is guaranteed.

The filtrate flow to PWN are already quite stable and to stabilise the flow rate even more would not be possible. Therefore, in this rapport no attention will be paid on how the filtrate flow to PWN can be dampened.

3.2.2 Objective
The objective is to model the transport system to Hoogovens. The model is a design of a controller of the transport system. This model will then be used to discover how energy can be saved by adopting a more stable flow rate when the reservoirs are used as buffers. The simulations would also show how much the flow rates could be dampened which would improve the treatment process.

3.2.3 Theory[1,2]
The energy usage of the pumps depends on mainly three factors. These are the efficiency of the pumps, the static head and the dynamic head. The filtrate pumps have to use most of its energy to transport the water through the 60 km pipeline, the dynamic head. The inlet pumps on the other hand have most of its energy used to elevate the water 5 meters, the static head.

The energy usage is proportional to the flow rate by the power three. This means that high flow rates should be avoided. The filtrate flow to Hoogovens has two main magnitudes. (See figure 3.5). The first flow rate is at about 2500 m³/h. The fluctuations varies around ±350 m³/h. This means that the variation is ±14 % of the magnitude of the flow rate. The second flow rate is at about 4000 m³/h. The variation is then at about ±450 m³/h which is ±11 % of the magnitude of the flow rate. The average fluctuation for the whole period is about 12 % of the magnitude of the flow rate.

The energy usage by the filtrate flow rate when constant can be described by the following simplified formula:

\[ P = \rho \cdot g \cdot Q \cdot k \cdot Q^2 / \eta \]

Where:
P = Power
\( k = \) constant describing the energy usage by elevation and by transport through the pipelines
\( \eta = \) efficiency constant
\( \rho = \) water density
\( g = \) gravity acceleration
\( Q = \) pumping flow rate

Now assume that the fluctuating flow rate has a flow rate that is 50% of the time at 1.12 \( Q \) and 50% of the time at 0.88 \( Q \). The energy usage of a fluctuating flow rate can then be described as follows:

\[
P_1 = \rho g (1.12Q)^2 \frac{k}{\eta}
\]

\[
P_2 = \rho g (0.88Q)^2 \frac{k}{\eta}
\]

\( P_1 \) is the power during half of the time.
\( P_2 \) is the power during the other half of the time.
Comparing the power of a fluctuating flow rate and a stable flow rate, the following equation is reached.

\[
\frac{P_1 + P_2}{2} = 1.04 \times P
\]

Therefore, the expected maximum power savings for the filtrate pumps are 4%. However, this calculation is very crude as the fluctuation is oversimplified. In addition, the formula doesn’t take the throttle valve into account. The filtrate pumps are not capable to operate lower than 500 revolutions. This means that the throttle valve, which is at the Hoogovens reservoirs, has to increase the dynamic head so that the filtrate pumps can deliver water at a lower rate than 3200 m³/h.

There already exist a model of the energy usage by the filtrate pumps made by Lucieer. This model contains more detail of the energy usage and it is calibrated to the actual filtrate pumps. The model can be seen in appendix I.

The possible energy savings by the inlet pumps are based on the efficiency of the pumps at different flow rates. Therefore, the energy saving depends on the manufacturer’s Q-h curve. The Q-h curve of the inlet pumps can be seen in appendix I. The pumps are variable pumps which means that the ratio of the energy usage to flow rate is more or less constant. The expected energy savings by having a stable flow rate should be much lower than the energy savings reached by the filtrate flow.

To illustrate the different energy usage of the filtrate pumps and the inlet pumps, the following values are shown:

<table>
<thead>
<tr>
<th>Type of pumps</th>
<th>Flow rate 4000 m³/h</th>
<th>Flow rate 4500 m³/h</th>
<th>Flow rate change [%]</th>
<th>Energy expenditure change [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>One filtrate pumps</td>
<td>225 kWh</td>
<td>281 kWh</td>
<td>12.5</td>
<td>25</td>
</tr>
<tr>
<td>One inlet pumps</td>
<td>120</td>
<td>140</td>
<td>12.5</td>
<td>16</td>
</tr>
</tbody>
</table>
With an inlet flow to the reservoir that is less fluctuating than the outlet flow, then the water level of the reservoir would fluctuate according to the water balance. However, if the inlet flow were to be constant, then the water level will reach its limits and the system would fail. In order not to let the water level to fluctuate too much, the inlet flow is allowed to fluctuate. This inlet flow regime is called the desired flow to the reservoir. Two types of desired flows are simulated.

![Figure 3.7 Slow inlet fluctuation](image)

The slow inlet fluctuation regime is to let the inlet fluctuate less steeply than the outlet flow. As can be seen in figure 3.7 the inlet flow has a lower peak than the filtrate flow.

![Figure 3.8 Early response slow inlet fluctuation](image)

The early response slow inlet fluctuation regime is where the inlet flow already increases or decreases before the outlet flow but less steeply. This is a feed forward control. This control is only possible when the future fluctuations of the outlet flow is known. As can be seen in Figure 3.8, the peak flow is lower than the outlet flow. The water level fluctuates less than as in the slow inlet fluctuation. (see figure 3.7). This shows that the main advantage of the early response inlet flow rate gives a low fluctuation of the water level.
3.3 Modelling

3.3.1 Transport control model by PI regulator \[^{[3,4,5]}\]

The transport system has to respond to the fluctuations of the flow rate to Hoogovens. The easiest way to dampen the flow rate of the pumps is to adjust the control system that controls the pumps' flow rate. This is achieved by lowering the magnitude of the responds to the fluctuations.

The control system is of a feedback control type. The controlled variable, or output, must be held as close as possible to a usually constant desired value, or input, despite any disturbances. The system has an input, \( c \) and an output, \( r \). The output of the system is the water level. This is continually measured and the feedback will compare this with the input. The input is the desired water level, also called the setpoint. The difference between the input and the output is called the error: \( e = r - c \). The feedback loop causes the system to take corrective action if the output deviates from the input. The corrective action is to increase or decrease the inlet flow rate to the reservoirs. The main task of the controller system is to amplify the error signal so as to respond to the error.

The outlet flow fluctuates. This causes the water level to fluctuate and the control system constantly has to adjust to lower the error. The desired inlet flow is a flow that does not have the short wave fluctuations. The inlet flow tries to follow the long wave fluctuations of the outlet flow. This is achieved by having the inlet flow as the average outlet flow of the past 20 hours. If the water level is unequal to the set point water level then the inlet flow is adjusted by the corrective action. A variation on this is that the desired inlet flow is the average flow rate of the future 20 hours.

The controller to be used will be a PI controller, which stands for proportional Integrator. The PI controller provides a proportional and integral control. The PI controller used for the simulation of the transport system can be seen in figure 3.9.

![Figure 3.9 PI controller of the water level](image)

The blocks are explained below:

- **Inlet flow**: desired inlet flow which is either the average flow rate of the last 20 hours or the average flow rate of the last 20 hours.  
- **Increase inlet flow**: the inlet flow is corrected by the feedback system. This has a non-zero value when the water level is lower or higher than the boundaries.  
- **Integrator**: This is the integral part of the control system. It simultaneously calculates the volume of the reservoirs. This equation is a water balance equation which can be formulated in a first order equation:
The water level is then calculated from the water volume in the reservoirs. This is then compared to the setpoint. The difference between the water level and the setpoint water level is calculated.

- Output: water level of the reservoirs
- Feedback: the arrow pointing down from the water level difference block is the feedback of the system.
- Difference relay threshold: This gives the deadzone. The water level can fluctuate freely between two limits where the control system doesn't change the inlet system.
- Amplifier: this is the magnitude of the response of the error. The higher the magnitude, the stronger the response. The lower the response, the better the flow rate is dampened and the more energy is saved. However, the water level should never cross the outer limits of the water levels in the allowed in the reservoirs.

3.3.2 Model parameters

With the PI controller in mind, the parameters of the model are listed below. These parameters are named so as to understand clearly which function the parameter should be placed in the model.

Controlled parameters
These parameters have to be kept in check. They have to be kept in their limits or otherwise the system fails.

- The water level of the Hoogovens reservoir
- The water level of the filtrate reservoir

Regulated parameters
These parameters are controlled by the feedback system.

- Pumping flow rate of the inlet and filtrate pumps

Disturbance parameter
These parameters are induced onto the transport system. The system has to react to this parameter in order to achieve the controlled parameter

- Demand of the Hoogovens flow rate, which is also the filtrate flow

Constant parameters
These are the parameters that do not change during the simulation

- The inlet pumps and the filtrate pumps characteristics: Q-h curve
- Dimensions of the pipelines and the reservoirs
- The limits of the water level allowed in the reservoirs

PI Control variables
There are two control variables of the PI controller described in chapter 3.3.1 which have to be tweaked until the best results is achieved. These are as follow:

- Amplifier K: This amplifies the error and gives the magnitude of the response to a certain error. The response becomes stronger when the error is larger or when the amplifier K is set larger.
- Deadzone: This is the space in which the water level can fluctuate freely. When the Deadzone's limits are crossed, then the feedback system changes the flow rate.
3.4 Simulink model

The transport system is first divided into two sub-models. The simulink model can be seen in figure 3.10. The first sub-model simulates the control of the water level in the Hoogovens reservoir. The input data is the flow to Hoogovens from the Hoogovens reservoirs. This is the outlet flow of the Hoogovens reservoirs. The sub-model decides the inlet flow to the Hoogovens reservoirs based on the average outlet flow of the Hoogovens reservoirs and the control variables of the water level control. The water level variables are the amplifier and the dead zone, and are shown in the figure just under the sub-model. The simulated inlet flow of the Hoogovens reservoir is the new input data of the second sub-model and is called the filtrate flow. The energy consumed by one filtrate pump is calculated based on the filtrate flow. The second sub-model simulates the control of the water level in the filtrate reservoirs. The sub-model decides the inlet flow of the filtrate reservoir based on the filtrate flow and the water level control variables of the filtrate reservoirs. The energy consumption by one inlet pump is calculated based on the inlet flow to the filtrate reservoirs. It is assumed that the pump only delivers water to the filtrate reservoir. The output data are recorded in Simulink monitors and can be seen on the right hand side of figure 3.10. These are the flow rates, the water levels and the calculated energy savings compared to the present energy consumption.

Figure 3.10 Simulink control transport system
The following assumptions were made:
- One filtrate pump and one inlet pump is operational.
- The inlet pump does not supply water for back washing, but only to the filtrate reservoirs.
- The inlet pump only supplies water that is meant for Hoogovens.
- The energy consumption of the filtrate pumps is based on the transport model of Lucieer.
- The water level fluctuation caused by the flow to PWN is considered to be constant because the flow to PWN is most of the time stable.

The Hoogovens sub-model is shown in figure 3.11. The water level controller of the Hoogovens sub-model is the same as the filtrate sub-model, except that the reservoirs have different volumes. The sub-model is a PI regulator and is described in chapter 3.3.1.

![Diagram of Hoogovens water level control subsystem](image)

Figure 3.11 Hoogovens water level control subsystem

The inputs are the flow rate to the Hoogovens reservoirs and the water level of the reservoirs. From this, the flow rate to Hoogovens is calculated by a water balance equation. This value is then fed into the water level controller where it is the outlet flow of the reservoirs. The controller decides what the inlet flow of the reservoir is.
3.5 Simulations and results

The input is the flow rate to Hoogovens of the first half of the year in 1999, (180 days). The simulated data are then compared to the measured data. The total energy consumption by the one filtrate pump was in that period about 1,000,000 kWh. The total energy consumption of the one inlet pump was in that period about 450,000 kWh.

Different simulations are performed. The first simulation is where the desired inlet flow rate is the average of the past 24 hours. The second simulation is where the desired inlet flow rate of the reservoirs are the average of the future 24 hours. These flow regimes are to follow the long wave fluctuations and not to follow the short wave fluctuations. Simulations are also performed with different control parameters, amplifier K and the deadzone. The charts shown in this chapter are the ones that have their control parameters adjusted until the most satisfactory results were reached. The most satisfying result is when the energy savings are the largest.

- Simulation 1: Feedback control using two reservoirs
  Figure 3.12 shows the measured and the simulated flow rates to Hoogovens. The figure shows clearly that the filtrate flow is dampened considerably when using the Hoogovens reservoirs as buffers. The filtrate flow does not follow the short wave fluctuations of the flow to Hoogovens. Figure 3.13 shows that the simulated water level fluctuates much more than the measured water level because of the more stable flow rate.

![Figure 3.12 Simulation 1, filtrate flow](image1)

![Figure 3.13 Simulation 1, Hoogovens water level](image2)
Many simulations were done with different values of the dead zone and the amplifier K. Table 3.1 shows the simulation without a deadzone and with the fluctuation allowed by Hoogovens. Hoogovens currently allows the water level to fluctuate between 3.2 and 3.8 meters. Therefore the simulated energy savings is 4470 kWh.

Table 3.1

<table>
<thead>
<tr>
<th>Set point water m</th>
<th>Lowest water level [m]</th>
<th>Highest water level [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dead zone 3.61-3.59 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amplifier K</td>
<td>Energy savings [kWh]</td>
<td>Energy savings [kWh]</td>
</tr>
<tr>
<td>4</td>
<td>6200</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>5200</td>
<td>3.14</td>
</tr>
<tr>
<td>6</td>
<td>4470</td>
<td>3.21</td>
</tr>
<tr>
<td>7</td>
<td>3950</td>
<td>3.27</td>
</tr>
</tbody>
</table>

Table 2 shows simulations without a dead zone and using the whole filtrate reservoir as buffer. The lowest limit allowed is 0.5 meters. The simulated energy saving is 18400 kWh, 1.84% of the total energy used.

Table 3.2

<table>
<thead>
<tr>
<th>Set point water m</th>
<th>Lowest water level [m]</th>
<th>Highest water level [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dead zone 2.2-2.4 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amplifier K</td>
<td>Energy savings [kWh]</td>
<td>Energy savings [kWh]</td>
</tr>
<tr>
<td>0.5</td>
<td>21700</td>
<td>0.1</td>
</tr>
<tr>
<td>0.8</td>
<td>18400</td>
<td>0.56</td>
</tr>
<tr>
<td>2</td>
<td>12300</td>
<td>1.16</td>
</tr>
<tr>
<td>3</td>
<td>10400</td>
<td>1.47</td>
</tr>
<tr>
<td>4</td>
<td>9000</td>
<td>1.64</td>
</tr>
</tbody>
</table>

Table 3 shows simulations with the use of the dead zone. By using a dead zone, the result is that the simulated energy saving is 16000 kWh, 1.6% of the total energy used) as the lowest water level allowed is 0.5 meters. In this case the buffer capacity of the reservoir is not optimally used, as there is still a lot of room for the water level to rise upwards. If, for example the set point water level was chosen higher, then the buffer capacity was better used.

Table 3.3

<table>
<thead>
<tr>
<th>Set point water m</th>
<th>Lowest water level [m]</th>
<th>Highest water level [m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dead zone 0.75-3.8 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amplifier K</td>
<td>Energy savings [kWh]</td>
<td>Energy savings [kWh]</td>
</tr>
<tr>
<td>1</td>
<td>17000</td>
<td>0.42</td>
</tr>
<tr>
<td>1.1</td>
<td>16000</td>
<td>0.53</td>
</tr>
<tr>
<td>1.5</td>
<td>14000</td>
<td>0.889</td>
</tr>
<tr>
<td>2</td>
<td>12300</td>
<td>1.16</td>
</tr>
</tbody>
</table>
Figure 3.14 shows the simulated flow rate of the inlet and outlet of the filtrate reservoirs. The fluctuations of the inlet flow are nearly the same to that of the filtrate flow. As can be seen, the dampening of the inlet flow is much less than the dampening of the filtrate flow. This is because the filtrate flow rate has most of its fluctuation dampened already and so further dampening by the filtrate reservoirs gives only marginal improvement of the stability. Figure 3.15 shows the fluctuation of the measured and the simulated water level. It shows that the simulated water level fluctuates as much as the measured one except that it has periods where it stays relatively stable.

Figure 3.14 Simulation 1, inlet flow

Figure 3.15 Simulation 1, filtrate water level

The energy savings after simulations with different amplifier K and different deadzones came to a value of 50 kWh.
Simulation 2: feed back control using only the filtrate reservoir

The second simulation of the inlet flow rate is using only the filtrate reservoirs as buffers. Figure 3.16 shows how the simulated inlet flow rate does not follow the short wave fluctuations of the filtrate flow. The water level in the filtrate reservoirs fluctuates much more than the measured water level. (see fig 3.17). The inlet flow fluctuations is dampened using only the filtrate reservoirs as buffers.

![Figure 3.16 Simulation 2, inlet flow](image)

The energy savings came to 60 kWh.
- Simulation 3: Feed forward control

Finally the last simulation was done by having the desired inlet flow of the filtrate reservoirs as the average flow rate of the future 24 hours. Again, as seen in chart 3.18 the flow rate is dampened. Figure 3.19 shows that the water level fluctuating.

Figure 3.18 Simulation 3, filtrate flow

Figure 3.19 Simulation 3, Hoogovens water level

The energy savings of this simulation came to 22800 kWh.
The size of the buffer capacity of the Hoogovens reservoirs is about 10500 m³. There are plans to add two other 10500 m³ reservoirs, which could triple the buffer capacity. Simulations are carried out on the transport model with the desired inlet flow being the average flow rate of the future 24 hours as these give the best energy savings results. Table 3.4 shows the energy saving.

<table>
<thead>
<tr>
<th>Set point 2.1 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dead zone 0.75-3.8 m</td>
</tr>
<tr>
<td>Size</td>
</tr>
<tr>
<td>0.3333</td>
</tr>
<tr>
<td>0.5</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
</tbody>
</table>

Doubling the Hoogovens reservoirs improves the overall energy savings by 7.5%. Figure 3.20 shows how the improvement of the energy savings by doubling the Hoogovens buffer capacity will not have a large increase in energy savings.

Figure 3.20 Hoogovens reservoir size vs. energy savings
3.5 Conclusion and discussion

The maximum energy savings were found to be 22800 kWh when the feed forward control was used. The saving is 2.28% of the total energy usage of that period. This is 1.7% lower than the estimated savings calculated in chapter 3.3. The discrepancy lies in the calculations were based on fluctuations with an average of 12%. In actual fact, the fluctuations were on average lower than 12%. Another reason is that the estimate did not take into account of the throttle valve that dissipates energy in order for the pumps to supply at lower flow rates. Savings of 22800 kWh means a saving of about 2850 guilders (12.5 ct/kWh) for half a year. The feed back control gives an energy savings of 18400 kWh. This is a 20% lower saving than the feed forward savings.

The simulations made and shown in table 3.4 gives the improvement of the energy savings if the reservoirs were made larger. The doubling the buffer capacity gave further savings of 7%. Doubling the buffer capacity of the reservoirs is very expensive (about a million guilders) and with only an extra savings of 7%, about 200 guilders per half year, it becomes apparent that the reservoirs should not only be made to save energy. The simulated cost saving are quite low, lower than 6000 guilders per year. The possible savings could become much larger in the future if the WRK III has to operate at full capacity, delivering 109 million cubic meters per year instead of only 60 million cubic meters in 1999. For example, if the flow to Hoogovens were to be at an average of 4500 m³/h, then according to the theory in chapter 3.2.3 is the savings about 4%. This will give a yearly saving of nearly 20000 guilders, (12.5 ct/kWh). With the fluctuating electricity costs that increase, the cost savings could even be greater. However, to build an extra reservoir to exclusively be used as a buffer, the costs saving by a more constant flow would not cover the investment of building the reservoir. A reservoir can costs more than a million guilders. The cost of implementing the model is only to reconfigure the transport feedback control system.

The model dampened the amplitude of the fluctuations by about 80% to 90% and the small wave fluctuations are gone. The second simulation using only the WRK III filtrate reservoirs will also dampen the fluctuation. This means that the WRK III doesn’t need the Hoogovens reservoirs. The much more stable flow would be advantageous to the treatment process, as the treatment process does not have to deal with the flow fluctuations.

It is recommended that the usage of the buffer capacity should implemented as the treatment process will surely benefit from the less fluctuating flow rate. If the water levels are not allowed to be as minimal as 0.5 meters, then an alternative could be done to combine the buffers capacity of the Hoogovens and the filtrate reservoirs with a stricter minimum water level.
4 Treatment process model

4.1 Introduction treatment process \cite{6}

4.1.1 Coagulation and flocculation \cite{7}

At the WRK III the coagulation and flocculation forms flocs out of the turbidity. The tilted plate sedimentation and the rapid sand filtration will later remove these flocs. The coagulate at the WRK III is iron salt, Fe(III)SO4.

The operator sets the iron dosage to certain amount so that the required turbidity can be reached. The dosage of the iron sulphate varies between 15 and 35 g/m³. The concentration of coagulant in water is kept constant by a regulating system during variations in the flow.

The operator changes the setting of the regulating system when necessary.

The paddle flocculators ensure the mixing. The revolutions of the stirring units change only with temperature so that the flocculation energy remains the same. The operator never changes this set up. Table 4.1 shows the dimensions of the flocculators.

<table>
<thead>
<tr>
<th>Table 4.1 Paddle flocculator dimension</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotation velocity of the paddles</td>
<td>0 – 12 revolutions per min</td>
</tr>
<tr>
<td>Diameter</td>
<td>1,8 meter</td>
</tr>
<tr>
<td>Number of coagulation streets</td>
<td>6</td>
</tr>
<tr>
<td>Number of stirring units per street</td>
<td>12</td>
</tr>
<tr>
<td>Flocculation energy</td>
<td>10-50 s⁻¹</td>
</tr>
<tr>
<td>Stay time of the water</td>
<td>4*8 min</td>
</tr>
<tr>
<td>Dimensions:</td>
<td></td>
</tr>
<tr>
<td>Length</td>
<td>11,6 m</td>
</tr>
<tr>
<td>Breadth</td>
<td>11,6 m</td>
</tr>
<tr>
<td>Height</td>
<td>6,3 m</td>
</tr>
</tbody>
</table>

Figure 4.1 shows the cross section of the paddle flocculation. The water enters from the top left in canal I and leaves at the bottom right. The first paddles that the water reaches have a high rotation velocity. The next paddles have decreasing rotation velocities.

Figure 4.1 Cross section of the Paddle flocculator
To enhance the strength and weight of the flocs, wispro is also dosed. However, wispro has a negative effect on later treatments processes such as the filtration because it is difficult to remove from the filters during back washing. The dosage of wispro ranges between 0.3 g/m³ and 0.7 g/m³ or not.

4.1.2 Tilted plate sedimentation \(^7\)

The tilted plate sedimentation removes the flocs by sedimentation of the flocs. The tilted plates are of the up flow type. The flocs slide down the plates to the sludge collector. The created sludge will finally be dehydrated and dumped onto a landfill. A cross-section of the tilted plate sedimentation tank can be seen in figure 4.2.

Water enters the tilted plate sedimentation tanks from the paddle flocculation. The water will flow out to the sand filter series.

![Figure 4.2 Cross section tilted plate sedimentation](image)

Each tilted plate sedimentation unit has the following dimensions shown in table 4.2.

<table>
<thead>
<tr>
<th>Table 4.2 Tilted plate sedimentation batch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of sedimentation streets</td>
</tr>
<tr>
<td>Tilted plate sedimentation dimensions (l,b,h)</td>
</tr>
<tr>
<td>Number of plates:</td>
</tr>
<tr>
<td>Angle of the plates:</td>
</tr>
<tr>
<td>Energy area:</td>
</tr>
<tr>
<td>Space between the plates (w):</td>
</tr>
</tbody>
</table>

4.1.3 Filtration \(^7\)

The sand filters reduce the turbidity before the water is pumped to the customers. The impurities will clog the sand filters and they have to be back-washed frequently.

The following will show the back washing procedure:

- At a filter head loss of 1.8 meters, the sand filter is put on non-active. Then if the backwashing unit is not occupied, the sand filter gets back-washed. The back washing will clean and unclog the sand filters. The duration of back washing takes about 45 to 60 minutes. The back washing is done in three distinct stages. If the back-washing unit is
occupied, the sand filter is put on stand-by. Here the operator has to monitor and if necessary intervene and make the decision in the back-washing order.

- First stage of back washing is scrubbing by aeration. This will effectively loosen the clogged sand filter. This takes about 5 minutes
- Second stage is the back washing itself. Here back-washing water is forced through the sand filter at about 400 m$^3$/h. this takes about 40 minutes
- The last stage is the after-back-wash. Water flows through the sand filter at a normal pace until the turbidity of the effluent is acceptable (not changing). This usually takes about 15 minutes.

There are in total of 18 sand filters, 6 sand filters in each sand filter batch. The sand filter batches are called the 30-serie, 40-serie and 50-serie batches. Within a batch, the sand filters are of the same type except for sand filter 34, which is experimental sand filter containing granite instead of sand. The 30, 40 and 50-serie sand filters are supposed to be the same, but because of slow maintenance, the layer sheet to keep the grains in place of the 50-serie batch has not yet been replaced. Therefore, the 40-serie filters will be used for this rapport. The dimensions of the sand filters are shown in table 4.3

Table 4.3 Rapid sand filter dimensions

<table>
<thead>
<tr>
<th>Dimension</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>• Sand filter bed</td>
<td>18</td>
</tr>
<tr>
<td>number</td>
<td>39 m²</td>
</tr>
<tr>
<td>Sand density</td>
<td>2640 kg/m³</td>
</tr>
<tr>
<td>Gravel density</td>
<td>4200 kg/m³</td>
</tr>
<tr>
<td>• 50 serie (these will soon be rebuilt as the 40-serie sand filters)</td>
<td></td>
</tr>
<tr>
<td>Gravel bed height</td>
<td>ca 30 cm + 10 cm</td>
</tr>
<tr>
<td>Gravel diameter $(d_{90} - d_{10})$</td>
<td>15-25 mm + 8-11 mm</td>
</tr>
<tr>
<td>Sand bed height</td>
<td>ca 100 cm and above 120 cm</td>
</tr>
<tr>
<td>Sand diameter $(d_{90} - d_{10})$</td>
<td>1,9-2,6 and above 1,2 -1,7 mm</td>
</tr>
<tr>
<td>Flow rate</td>
<td>20 m/h tot 9m/h</td>
</tr>
<tr>
<td>• 40 en 30 serie</td>
<td></td>
</tr>
<tr>
<td>Gravel bed height</td>
<td>ca 30 cm</td>
</tr>
<tr>
<td>Gravel diameter $(d_{90} - d_{10})$</td>
<td>8-11 mm</td>
</tr>
<tr>
<td>Sand bed height</td>
<td>ca 100 cm en above 120 cm</td>
</tr>
<tr>
<td>Sand diameter $(d_{90} - d_{10})$</td>
<td>1,9-2,6 en 1,2 -1,7 mm</td>
</tr>
<tr>
<td>Sand filter rate</td>
<td>20 m/h tot 9m/h</td>
</tr>
<tr>
<td>Extra</td>
<td>Netting between gravel and sand</td>
</tr>
</tbody>
</table>

The back-washing water is kept in two large reservoirs that are housed in the roof of the plant. Each reservoir keeps about 500 m$^3$ of water. Only two filter can be back washed at a time. If three filters have to be back washed, one is forced to be in stand by until one of the other is finished.
An example of a typical filtration can be seen in figure 4.3. The figure shows the head loss vs. time of the 40 serie filters.

![Figure 4.3 Filter head loss vs time](image)

Only three of the six available filters are active. If all six were in operation, the runtimes would be much longer than three days. Runtimes longer than three days gives the risk of developing biological fouling in the filters. The average maximum head loss is 1.8 meters, the average clean bed head loss is 0.2 meters and the runtimes are about two and a half days, 60 hours. The head loss gradient can be calculated from these values. This comes to an average head loss gradient of 0.027 m/hour.

4.1.4 Quality demands

The quality of the treated water has to achieve a certain standard demanded by the customers. There are essentially two types of demands for the quality of the treated WRK III water. These are the contractual demands and guidelines.

The WRK III must ensure that the contractual demand is always met. The following shows the contractual demand from Hoogovens and PWN.

- Turbidity 0.2 FTU Hoogovens
- Turbidity 0.2 FTU PWN

As shown above, a contractual demand is available for the turbidity. The turbidity is an important parameter for Hoogovens because it indicates how many solids are present in the water. These solids can sedimentate in the Hoogovens pipelines and clog these. The turbidity is important for PWN because this prevents the clogging of the dune infiltration. Figure 4.3.1 shows the turbidity after the filtration in 1999. The turbidity after filtration is sufficiently lower than the demanded turbidity.
Figure 4.3.1 Turbidity after filtration

The guidelines for PWN and Hoogovens are shown in table 4.4

<table>
<thead>
<tr>
<th>Hoogovens</th>
<th>PWN</th>
</tr>
</thead>
<tbody>
<tr>
<td>MFI</td>
<td>&lt;5</td>
</tr>
<tr>
<td>Sulphate</td>
<td>&lt;150 mg/l</td>
</tr>
<tr>
<td>Oxygen</td>
<td>&gt;4 mg/l</td>
</tr>
<tr>
<td>Ferro</td>
<td>&lt;0.02 mg/l</td>
</tr>
<tr>
<td>Hydrogen carbonate</td>
<td>&lt;140 mg/l</td>
</tr>
<tr>
<td>AOC</td>
<td>&lt;20 μg/l</td>
</tr>
<tr>
<td>SI-index</td>
<td>&lt;0.2</td>
</tr>
<tr>
<td>Ammonium</td>
<td>&lt;0.5 mg/l</td>
</tr>
<tr>
<td>Nitrate</td>
<td>0.05</td>
</tr>
<tr>
<td>Total phosphate</td>
<td>&lt;0.1 mg/l</td>
</tr>
<tr>
<td>AOX</td>
<td>&lt;25 μg/l</td>
</tr>
<tr>
<td>Total THM</td>
<td>&lt;5</td>
</tr>
</tbody>
</table>

Guidelines are quality objectives for the WRK III to achieve. When the treated water does not meet the quality set by the guidelines, measures are taken to solve this. However, the WRK III does not have to ensure that the guidelines are achieved and so the occasional crossing of the guideline limits are allowed. If the WRK III has to ensure that the quality has to follow the guidelines, then large investments have to be made to facilitate this.

An important guideline for PWN is the MFI. The MFI is only measured at the end of the treatment process. To follow the MFI through the treatment process, the operator follows the turbidity as an indication of the MFI. If the turbidity is high at a certain stage of the treatment process, the operator has to intervene in order to meet the MFI guideline.

The table shows that PWN has more guidelines than Hoogovens. The reason for this is because the water to PWN is for human consumption and strict laws are implemented to ensure that the water is safe. The WRK III sometimes supplies two different types of treated water, water only meant for PWN and water for Hoogovens.
4.1.5 Treatment costs
The chemicals and the backwash operations are the operational cost factors concerning the treatment. The total cost of the chemicals used for the treatment process is nearly 1.5 million Dutch guilders for the year 2000. The different costs of chemicals projected for the year can be seen in the following chart, in figure 4.4.

![Chart showing costs for the year 1999](image)

**Figure 4.4 Total costs of chemicals for the treatment process in 1999**

As can be seen in the chart, the ferrosulfate, calcium hydrate and active coal make the largest costs. These costs amount to 1,334,484 guilders.

Backwash costs are considered an expensive part of the operations at the WRK III. Assume the backwash water costs about 50 cents per m$^3$. The total cost of one backwash is 250 guilders (one backwash uses 500 m$^3$ of water). This means that with a backwash frequency of one backwash per two days and with eighteen sand filters, the total cost comes to about 820 thousand guilders. If the runtimes can be increased by one day, the total costs will be 540 thousand guilders. This gives savings of nearly 300 thousand guilders.

Other expensive costs are the workforce and the yearly write-off for the initial investment, but these are constant costs.
4.2 Treatment process Analysis

4.2.1 Situation

The quality of the treated water has to reach turbidity below 0.2 FTU. This is mainly achieved by monitoring the turbidity before and after each treatment process. When the situation is stable, the plant is run automatically by a combination of a computer control system of Honeywell and a telemetry system. However, when there is a change in the water quality, for example a higher temperature or lower inlet turbidity, the treatment plant does not adapt automatically. The operator has to change the settings in order to treat the water adequately. According to history, the turbidity of the WRK III water sufficiently passes the turbidity demand of 0.2 FTU.

The operator has two main ways in finding information about the plant. This is by online reading of the recordings of the sensors and by the daily morning rapport of the water quality made by the laboratory. The operator uses his experience to decide how to act on the information. Different operators have different reactions to the readings. The operator always has to be present day and night to keep the treatment plant in operation. There are seven different operators; each doing an 8 hour shift and each operator has an own opinion on how to run the plant.

When analysing the costs of running the WRK, the potential savings could be made in the operation costs. If, for example the night shift could be controlled automatically, this would reduce costs. To automate the treatment control, a model is needed on which the automation bases its actions.

The treatment processes of coagulation, flocculation, tilted plate sedimentation and filtration are individually well documented. However, the combined processes are much more difficult to put into a formula. There are many factors influencing the treatment processes, for example flow rates, temperature, algae type, algae concentration, turbidity and type of chemicals in the water. A black box model is much practical to use as it is only based on the data. The WRK III also has a lot of information on the treatment process that can be used for the model. A black box model that could be used is the fuzzy logic model. The fuzzy logic model will mimic the experience of the operators as it is totally based on historical data. The question now arises which part of the treatment process should be modelled. When examining the costs of the treatment process shown in chapter 4.1.7, lowering the dosage of chemicals would not yield a lot of saving, as the total costs of the chemicals are relatively low to start with. The lowering the number of back washing will give more savings in operation costs. A model that can predict the filtration runtimes will be needed. There is not yet any documentation at the WRK III that the operators use to control the filtration runtimes by changing the iron or wisipro dosage. The present method is by experience of the operators. A model that can reliably predict the runtimes will have the following advantages:

- The model can run the filtration process with its back washing procedure without an operator. This could replace the operator's night shift.
- If the predicted runtimes deviate from the measured runtimes, the treatment process should be checked for malfunctions
- The model can predict future problems of more than two filters having to be back washed at the same time. The model can make sure no filter is in stand-by by for example back washing a filter an hour sooner.
- Simulations could be performed to research how the iron and wisipro dosage could be adjusted in order to obtain a longer runtime.
4.2.2 Objective

To design a model that can predict the filtration runtimes. The runtimes are depended on the filtration flow, the temperature and the turbidity of the water that enters the filters. The turbidity of the water depends on the effectiveness of the coagulation, flocculation and tilted plate sedimentation. The model will thus simulate the coagulation, flocculation and tilted plate sedimentation by representing the result of the turbidity by the filtration runtimes. The longer the filtration runtime, the less the water is turbid, (temperature and filtration flow remaining equal.) The model will be done in fuzzy logic. Fuzzy logic will be used because of its independence of using difficult deterministic formulas to describe the treatment process. Research is done on how well the fuzzy logic model can describe the treatment process and how well simulations can be performed.

4.2.3 Linear model and Fuzzy logic theory \(^{\text{[9,10,11,12]}}\)

A linear and fuzzy logic model are compared with each other on their prediction power. The reason a linear model is chosen as comparison is it is a very simple and easy model to obtain from the treatment process. If the linear model predicts better or as good as the fuzzy logic model, then the linear model should be chosen.

Models can be categorised into fundamentally two different ways: a black box model or a white box model. Both models will map the input data onto the output data. The difference between the models is the basis of the mapping function. The mapping function of the black box model is not based on the physics of the process but it is based on the input data and output data. This model requires collecting relevant data from the process in order to design the model. Regression methods are used on the data to acquire a valid model. On the other hand, the white box model is based on the physics of the process. Therefore a white box model can map the input data onto the output data without using the output data as reference. However very few white box models do not have to use some data from the process. These models usually need to be calibrated before the models can predict accurately. These models are then called gray models.

Models can further be categorised in either a global model or a local model. A global model only uses one function to describe the whole process. The function could be a linear or non-linear equation. The same function is used with all the input data. A local model divides the process in parts and each part has its own sub-model. The division of the process can depend on many factors but could also simply divided equally. Each part is described by a particular function that could be linear or non-linear. Thus, the function to use for the model depends on the input data. Example of this is illustrated below:

| Input data | 1 2 3 4 5 6 7 8 |
| Output data | 2 4 6 8 10 18 21 24 |

The function that best describe the above process is a local model. The local model linear functions are:

For input data 1 to 5 the sub-model function is \( y = 2x \)
For input data 6 to 8 the sub-model function is \( y = 3x \)

The linear model is a simple global model and fast to construct. The fuzzy logic model is a local model.

The linear model consists of a linear function that maps the input data onto the output data. This means the equation of the function has the form:

\[ y = a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + \ldots + b \]
Where:
y = output data
a = constants
b = offset
x = input parameter

It might be possible to describe the treatment process linearly. In this rapport, the linear model will be used as a comparison to the fuzzy logic model. If the fuzzy logic model does a worst prediction than a linear model, then the linear model should be used.

A fuzzy logic model can best be described in five steps that were performed by the fuzzy logic model of the Matlab toolbox. The steps are:

The first step is to fuzzify the inputs into sets. These sets are called fuzzy sets. A fuzzy set is a cluster of input data that have the same characteristics. The allocation of the data is done by a fuzzy logic's membership function. A membership function is a curve that defines how each point in the input space is mapped to a membership value between 1 and 0 onto an output set. To illustrate this, temperature data is clustered into a set for high temperature. In the traditional set, a threshold is defined between high and low temperature. For example higher than 10 degrees, the temperature is considered high. A temperature data belongs either in the high temperature set or not in the high temperature set. This is called a crisp set which has a high temperature represented as 1 and low temperature represented as 0. A fuzzy logic set does not have this clear-cut threshold but has a much more vague idea of the threshold. Any temperature data belongs to the high temperature set to a certain extent. So for example, a temperature does not have to have the value of 1 high temperature or 0 not high temperature but could also have the value in between of 1 and 0. The degree at which a data belongs to the set is described in fuzzy logic by the membership function. These functions can be linear or non-linear. Non-linear functions are for example trapezium shaped, gauss shaped, bell shaped, exponential, etc. In this rapport, the gauss shape is used. To illustrate the difference of the crisp set and the fuzzy logic set can be seen in figure 4.5.

![Crisp set vs. fuzzy logic set](image)

Figure 4.5 Crisp set vs. fuzzy logic set

The next step of fuzzy logic is to apply the fuzzy operator. The fuzzy operator is the rules that make a statement how the fuzzy sets belong to an output. A single fuzzy rule has the form “if x... then y” The if-part of the rule is called the antecedent. The then-part of the rule is called the consequent. The operator defines how the antecedent is mapped onto the consequent by logical operations. Example of operations are the AND operation of the OR operations. Fuzzy logic does the AND operation as minimum and the OR operation as maximum. To illustrate an fuzzy operator, let there be two input fuzzy sets, temperature and turbidity and an output set sand filter runtime.

A rule could be:

If there is a high temperature AND a low turbidity then the filter runtime is high.
Other rules are for example
- If high temperature or a low turbidity then low filter runtime
- If high temperature AND not high turbidity then medium runtime

The consequent of the rule is a fuzzy output between the numbers 1 and 0. A fuzzy logic model usually has more than one rule.

The third step of the model is applying the implication method. The implication method converts the input fuzzy data set into an output according to the operation. Hence implementing the operation. For example, using the above operator, assume the data is a temperature of 2 degrees and a low turbidity of 0.5 FTU. Then according to the operator, the temperature should be high if a high filtration runtime is desired. The temperature of 2 degrees still belongs to the high temperature (>10 degrees) to a certain degree. Therefore implementing the rules onto the data, an output is generated.

The next step is aggregating all outputs. All the operators generate an output, and based on these outputs, a decision has to be made of the value of the total consequent. This is done cumulative (sum) in the Matlab toolbox.

Finally, the last step is the defuzzification. This is converting the fuzzy set made by the aggregation into a value of the output. The average of the aggregate output gives the value.

An example of the structure of a fuzzy logic model is illustrated in figure 4.6. Four parameter if input data are clustered, each in four clusters. Then the consequent value is produced by the rules. Next the sum is of the four consequences of the rules are taken. Finally the average of the sum calculated and defuzzified which produces the output value.

![Figure 4.6 Fuzzy logic structure](image)

The clusters and the membership functions are found by fuzzy logic regression. The fuzzy logic model is made by Matlab toolbox and uses the fuzzy logic Takagi Sugeno type. The first steps of designing the fuzzy logic model is by finding the parameters that are important to the process. Then data is collected from these parameters. The data is divided into input data and output data. The input data is the collected data from the parameters that effect the process. The output data is the collected data from the parameters that the process
produces. The data that are used for building the model are called the training data. Next, the function of the black box that maps the input data onto the output data must be made.

A function must be calibrated before it can be valid for the black box model. The method of calibrating the function is called regression. Regression is the method of finding the root of the functions. An example of regression is shown below:

**Linear function:**

\[ Y = aX + b \]

Where  
\( a = \text{constant} \)  
\( b = \text{offset} \)  
\( X = \text{input data} \)  
\( Y = \text{output data} \)

\( X \) and \( Y \) are the training data. The root of the functions are the constants \( a \) and \( b \). The regression of the function will give values to the constants \( a \) and \( b \) and hence a linear function.

If the function does not perfectly map all the input data onto all the output data, the regression will then produce a function that maps the input data as close as possible onto the output data. It does this by the least square root error method. For example a process has the input and output value

Input data \( X = [2 \ 4 \ 6] \)  
Output data \( Y = [4 \ 5 \ 7] \)

The linear functions are:

\[ 4 = a*2 + b \]
\[ 5 = a*4 + b \]
\[ 7 = a*6 + b \]

No value of \( a \) and \( b \) can totally satisfy all three equations. An estimate is made by linear regression by the least square root method.

By regression, the constants \( a \) and \( b \) are:

\( a = 0.778 \)  \( b = 0.1778 \)

The linear function after regression is:

\[ Y = 0.778X + 0.1778 \]

The linear function maps \( Y \) as:

\[ Y' = [1.7538 \ 3.2898 \ 4.8458] \]

As can be seen by comparing the measured \( Y \) and the linear function \( Y' \), there is a difference in value. The calculated difference is then the error of creating a linear function of the process. The accuracy of mapping the input data onto the output data depends on three factors. These factors are the errors in measuring the data, the errors in collecting invalid data
and errors caused by using the wrong functions for regressions. The accuracy in measuring the data depends on:

- Accuracy of the instruments.
  This depends on the instruments that measure the value of the parameter. All Instruments measure the data with certain boundaries to their accuracy. Instruments that give wrong readings because they malfunction can cause an error.
- Human error
  The reading by humans of the data off the instruments can be inaccurate. When the instruments automatically register the data onto into the computer database, human median error could lie with the calibration of the instruments onto the source.
  The errors are called the noise of the data. The noise of the data must be deleted from the training data, but are left in because it is unknown whether the data are noise data or valid data. The noise of the data gives a negative influence for the regression. In order to even out the noise there needs to be a large amount of correct data in the training data set.
  Processes can change during time and data that is collected are only valid during a certain time frame. If a model is made to predict a particular data, the data that is collected a long time ago might not be useful for the regression of the function. The ways to solve this problem can be done by defining the data that were collected long ago less important in the regression. Examples are:

- The further the data is collected in the past, the less data of it is included in the training data.
- Points of significance can be attributed to the data, the closer the data is to the data to be predicted the more significance points it gets. These significance points can then be used in the regression.

4.3 model structure

4.3.1 Direct prediction of the runtimes

The direct prediction model hinges on the concept of totally ignoring the different treatment processes. The black box model is created of the total process. It predicts the filter head loss in one step. The input parameters are:

- Iron dosage
- Wispro dosage

These two parameters are the parameters that are controlled by the operator. The operator increases or decreases the dosage to control the quality of the water.

- Water temperature
  Water temperature influences the treatment process because at different temperatures the viscosity of the water changes. This is importan factor for coagulation, flocculation sedimentation and filtration.
- Rapid sand filtration flow rate
  The filtration flow rate effects the runtime because it effects the head loss. A higher flow rate causes a higher head loss, which means the maximum head loss of 1.8 meter is reached quicker.
- Inlet turbidity
  This is a measure of the initial quality of the water and the treatment process tries to decrease this.

The output parameter is

- The filter head loss gradient of the sand filter

An illustration of the direct prediction model is shown in figure 4.7
4.3.2 Two step prediction of the runtimes

The two step model divides the treatment process into two sub-models. The first sub-model consists of the chemical dosage, the flocculation and the tilted plate sedimentation. The first sub-model predicts how much turbidity and iron concentration are left after the tilted plate sedimentation. Its input parameters are:

- Inlet turbidity
- Inlet flow rate
- Water temperature
- Iron dosage
- Wispro dosage

The output parameters are:
- Turbidity after tilted plate sedimentation
- Iron concentration after tilted plate sedimentation

The second sub-model consists of the rapid sand filtration part of the treatment process. This sub-model uses the predictions of the first sub-model to predict the filter head loss of the sand filters. The turbidity and the iron concentrations in the water are the most important parameters in clogging the sand filters. Its input parameters are:

- Turbidity after tilted plate sedimentation
- Iron concentration after tilted plate sedimentation

These two concentration indicate quality of the influent water to the filters. In general, the worst the quality, the earlier the filters get clogged.
- Water temperature
- Sand filter flow
- Sand filter runtime

The output parameter is
- The filter head loss of the sand filter

The second sub-model is actually a rapid sand filtration model. There already exist many rapid sand filtration models, either black box models or white box models.
An illustration of the two step model is shown in figure 4.8.

4.3.3 Structure comparison

The two step model uses the data that is available after the tilted plate sedimentation. The advantage of using this model is that it recognises that the treatment process is a two-phase process. The model simulates this two-phase process by having two steps for the prediction. However the disadvantage is that it needs data after the tilted plate sedimentation which is not measured continually. Data from the laboratory must be used. These data are too few to be used effectively for regression.

The one step model is more suited as it is based on data present in the PHD database. This gives the model many more data to use, for example measurements taken every 10 minutes. The model is also much simpler as it does the prediction directly. The one step model is further elaborated in this report.

4.4 Fuzzy logic Modelling

4.4.1 model parameters

The following parameters can be distinguished:

Controlled parameters
The controlled parameters are the parameters that are controlled by the model.
- Filtration runtimes

Regulated parameters
These are the parameters that the operator can change during the purification process.
- Wispro dosage
- Iron dosage
- Sand filter backwash management

Disturbance parameters
These are the parameters that are imposed on the purification process and are difficult to predict. The purification process will always have to react to these parameters.
- Inlet turbidity
- Water temperature
- Inlet flow

Constant parameters
These parameters will not change during the purification process. Therefore in modeling of the purification process they will be held constant.

- The structures of the WRK III purification plant. These are described in the chapter 2 where the buildings of the purification process are illustrated.

4.4.2 Collected data

The following charts in figure 4.9, 4.10 and 4.11, show the data that have been collected and will be used for the regression for the fuzzy logic model. The data collected are of the period between 1st of January in 1999 until end of March 2000 and collected from the PHD. (The data is collected from the measurements of filter 41.)

![Chart 4.9 Treatment Process Data]

The temperature shows the clear relationship with the seasonal changes. In winter, the temperature is lower than in the summer. It varies between 5 and 20 degrees Celsius. The turbidity starts increasing when the temperature just reached its maximum and starts to drop slowly. This indicates that most of the turbidity is caused by algae as when the temperature drops, a lot of the algae die and makes the water turbid. The turbidity ranges between 1 and 11 FTU. The iron dosage is generally high when the turbidity is high. It ranges between 15 and 35 g/m³. Wispro dosage is either 0.3 or 0.4 g/m³.
Figure 4.10 Filtration data

Figure 4.10 shows the data collected of the filtration. These are the head loss, the runtimes and the filtration flow rate. The runtimes vary between 25 hours and 80 hours. An enlarged figure of figure 4.10 can be found in figure 4.11. It shows about three runtimes in a five day period. The filtration flow rate was at that time relatively high. The fluctuations of the head loss are caused by the filtration flow. The filtration flow depends on two factors. The flow rate that goes to the WRK III water users and the number of filters that are being back washed or are in stand-by.
4.4.3 Validation criteria

The validation data set consists of input and output data that are not included in the training data. To compare different functions of a black box model, simulations are done on the validation set. The acquired output data from the model is then compared to the measured output data.

- **Median absolute error**:\(^{[13]}\)
  The median absolute error is the modal difference between the simulated output and the actually measured output.

  \[
  \text{Median absolute error} = \text{median} (\sqrt[3]{(y-y')^2})
  \]

  \(y\) = process data
  \(y'\) = predicted data

- **Relative percentage median error**
  Relative percentage median error is the percentage of the median absolute error from the actual output data.

  \[
  \text{Median absolute relative error} = \text{median} (100\% \times \sqrt[3]{(y-y')^2}/y)
  \]

- **Variance Accounted For: VAF**:\(^{[14]}\)
  The percentage of the variance accounted for is a measure of how well the predicted output value follows the collected output value. The percentage is a value between 0 and 100 %. The percentage value of 0 % is given if the predicted value is just as good as a constant mean value of the collected output. The percentage value of 100 % is given if the prediction follows the collected output data perfectly. An illustration is shown below in figure 4.12 and 4.13.

![Figure 4.12 VAF of 0 %](image)

![Figure 4.13 VAF of 100 %](image)
Note that the mean absolute errors of both cases have the same value.
The percentage of the variance accounted for is calculated by mainly dividing the
covariance’s of the predicted data by the collected data. The formula of the percentage of the
variance accounted for is shown below.

\[
\text{Covariance} = \frac{\Sigma(y_i - \mu_y)(y'_i - \mu_{y'})}{N}
\]

Where:
\[\Sigma = \text{total from i to N}\]
\[i = \text{initial = 1}\]
\[y = \text{process data}\]
\[y' = \text{predicted data}\]
\[\mu_y = \text{mean value of process data}\]
\[N = \text{number of data}\]

\[
\text{VAF} = 100\% \left( 1 - \frac{\text{cov}(y - y')}{\text{cov}(y)} \right)
\]

4.4.4 Regression methods

One way of acquiring a fuzzy logic model from a data set is to perform regression.
When fuzzy logic regressions takes place, the accuracy of the mapping of the input data onto
the output data depends mainly on the number of fuzzy logic clusters. A low number of
clusters will result in a less accurate mapping because the regression becomes too general.
The high cluster model will result in a less accurate prediction of new output data because of
over fitting. This means the model can only predict accurately on the data of which it is
regressed from. Therefore a midway between these regressions must be found to find the
average model. This could be found by bootstrapping.

The bootstrap method is to obtain the best average fuzzy logic model from the available
data. This will smooth out the error made by the measuring instrument or the collecting of the
data. The bootstrap method starts by first collecting data from a data set. From this data set, a
fixed percentage is taken out to use as the validation data. The rest is used as training data in a
training set. A bootstrap model is produced by regression of the training set. This model then
has to predict the output data of the validation data by only using the input of the validation
data. The relative error and the VAF are calculated between the output of the predicted data
and the output of the validation data. Then the bootstrap is repeated many times (example 50
time) to obtain an average model. The bootstrap method used in this report uses the following
configuration:

- Number of data points in time used in the collected data set: 178 data points
- % of data used in the validation data set: 5 % = 9 data points
- Therefore training data = 169 data points
- Number of bootstraps performed in a session = 50 bootstraps

Another method is the “predict next output in steps” method. This method is to test
the prediction power of the fuzzy logic model. The model simulates the practical use of using
a black box model onto a process. The “predict next output in steps” method is done in the
following way: Data are collected in a data set and are ordered in time. Then the first part of
the data set (first 150) is used as training data. A model is made by one regression of this
training data. The model is then used to predict the next output data, head loss gradient, after
the training data (151st data). The median errors are calculated between the predicted data and
the process data. This procedure is repeated to predict the next data (152nd data), but using a
new model. This new model is made with the regression of the old training data including the new acquired data (data 151). This process continues until the end of the data set. The method is in other words producing a dynamic model, which adjusts from new acquired data as time goes by.

4.4.5 Parameter analysis

Parameter analysis is performed in order to discover which parameters have a bad influence on the prediction and which have an important influence. The following input and output data are used for the analysis.

- Input data: wispro dosage, iron dosage, temperature, turbidity
- Output data: Head loss gradient, dh/dt.

The parameter analysis is performed by first regression of the data to obtain a linear model that predicts the head loss gradient. This linear model uses all the input parameters except one for its regression. Then the linear model is tested on how well it can predict the head loss gradient. It is then compared to the linear model that uses all the parameters for its regression. This would show how important the left out parameter is. If the linear model without one parameter does a much better job in predicting the head loss than the linear model with all the parameters, then the left out parameter is a disturbance and should be left out. This method of leaving one parameter out is performed also on the other parameters. (Everytime leaving only one parameter out of the regression. The results can be seen in figure 4.14.

![Parameter analysis](image)

Figure 4.14 Parameter analysis

The results show in Figure 4.14 that the filter flow is the most important parameter as without filter flow, the linear model will have a median relative error of 25 percent while a linear model with filter flow has a median relative error of about 15 percent. A model without the other parameters show that it makes little difference in using in the regression as the difference between a model without the parameter iron dosage, temperature, turbidity or wispro has the same accuracy in prediction as with using all the parameters. This gives way to not use one of the parameters as it the time for regression will be less with lower set of parameters. However, the explanation for the results is that there is a correlation between the iron dosage, temperature, turbidity and wispro dosage, because the magnitude of the iron dosage, controlled by the operator, depends on the other parameters. Using all the parameters Therefore all the parameters are included in the model.
4.4.6 Number of data

The fuzzy logic model is as good as the data it is regressed on. In order to get a good average model, a large number of data is needed. The least number of data needed in a training set for the regression is found in this chapter. This is found by using the method “predict next output in steps” method with using different amount of data for the regression.

![Figure 4.15 number of data needed](image_url)

The model is based on regression of the data set. The graph shows that the higher the number of data used for the regression, the more accurate the prediction is of the gradient of the filter head loss. Regression with more than 85 data don’t show much more improvement of the prediction.

4.4.7 Average model by Bootstrapping

The first analysis is to determine how many bootstraps should be performed in order to acquire the best average model. This is found by comparing the standard deviation of the accuracies of the bootstrap models. For example, 50 bootstraps are performed. Each bootstrap designs a model from the data. These bootstrap models are tested on their accuracy. The model with the median error of the 50 bootstraps is chosen. This process is repeated again with 50 bootstraps to acquire another median model. This is repeated 200 times. The accuracies of the 200 model are compared with each other by calculating the standard deviation. This shows how different the models are in their prediction. The standard deviation is recorded. Finally, this whole process is repeated again, but then with 60 bootstraps, 70 bootstraps, 80 bootstraps and so on. Everytime the standard deviation is calculated. Results are found in figure 4.16. It shows that the more bootstraps are performed, the lower the standard deviation between the predictions. At least 40 bootstraps should be performed, as more bootstraps do not lower the standard deviation of the predictions. It is decided to do 50 bootstraps.
Matlab toolbox fuzzy logic is used. This uses subtractive clustering in order to acquire a fuzzy logic model. This means that the radius of the influence of clusters should be defined before the regression can take place. The best cluster radius is found by bootstrapping with systematically different cluster radii. The accuracy of the prediction of the head loss gradient by the bootstrap model is then recorded and shown in figure 4.17.

Figure 4.17 shows that the radius of the clusters between 0.9 and 1.5 give the best results as then the median relative error is lowest and the median VAF are highest at those values.

The radius of each parameter can be of a different value in order to acquire better predictions. By using the method described in the last paragraph, the following radiiuses were found:

- Filtration flow 0.9
- Iron dosage 0.7
- Temperature 0.7
- Turbidity 0.8
- wispro 10
- Head loss gradient 0.9

Wispro has a radius of 10 because the wispro dosage had only two values, 0.3 and 0.4 g/m³. A radius of 10 would make the wispro rule linear.
Figure 4.18 shows how the error is distributed over the data. The relative error chart shows that the prediction is more often less than the actual head loss gradient then more. The median relative error is found at 9.9% and the VAF is found at 88.7%.

Figure 4.18 Distribution of the accuracy of the model.

Figure 4.19 illustrates how accurate the predicted data is plotted against the measured data. The predicted head loss gradient is calculated back into the runtime of the filtration. This is then plotted against the measured runtimes. As can be seen in the figure, the predicted runtime follows the measured runtime well, but at one peak, data point 30 it overestimates the runtime by nearly 50 hours. At this point the data

Figure 4.19 Predicted vs. measured runtimes.

The structure of the model is shown in figure 4.20. The structure of the model has three clusters and three rules that use the logical term AND rule. The rules are shown in figure 4.27. The three rules can be linguistically be explained
- Rule 1: if relative high flow and high iron dosage and high temperature and medium turbidity and any wisp dosage then high head loss gradient.
- Rule 2: if relative low flow and low iron dosage and low temperature and low turbidity and any wisp dosage then lowhead loss gradient.
- Rule 3: if relative low flow and medium iron dosage and high temperature and low turbidity and any wispro then medium head loss gradient.

![Figure 4.20 Head loss gradient prediction model structure](image)

4.4.8 Fuzzy logic vs. linear comparison

The models acquired by fuzzy logic and by the linear modelling are compared with each other. The accuracies of predicting the head loss gradient are shown in figure 4.21. The fuzzy logic model predicts the head loss gradient better by the median relative error of 1.5 % and by a VAF of 4 %. The fuzzy logic model predicts better than a linear model.

![Figure 4.21 Fuzzy logic vs linear model](image)
4.5 Model design

4.5.1 Mapping
The fuzzy logic regression maps the input data onto the output data. This mapping can be shown in 3 dimensional graphs, shown in this chapter. These graphs will give insight on how the input parameter influences the gradient head loss. The following three-dimensional figures show how the fuzzy logic model maps the data. The y axis is the filter flow and the z axis is the head loss gradient. The x-axis is the parameter of which its influence is looked at.

Figure 4.22 iron dosage mapping

Figure 4.22 shows that at a low flow rate of 400 m$^3$/h, when the iron dosage is at 25 g/m$^3$ that the head loss gradient is largest. At higher flow rates, the iron dosage doesn't seem to influence the runtimes much. How the head loss gradient varies with varying iron dosage is very non-linear. The cause could be that the iron dosage was controlled by the operator and was constantly adjusted which would reach a filtration runtime that were similar.

Figure 4.23 Temperature mapping
Figure 4.23 shows that the temperature has a large influence on the gradient of the head loss as at any flow rate, a change in the temperature result in a change in the head loss gradient. At low flow rates of about 400 m³/h the higher the temperature, the higher the head loss gradient. However, the picture changes when the flow rate is high. The higher the temperature, the lower the head loss gradient.

![Figure 4.24 wispro dosage mapping](image1)

Figure 4.24 shows how the wispro dosage effects the head loss gradient. At low flow rates, a different wispro dosage has relatively little effect on the head loss gradient, but at higher flow rates of 700 m³/h, the higher wispo dosage causes a higher head loss gradient. This is logical as a higher wispro dosage will clog the filters quicker.

![Figure 4.25 turbidity mapping](image2)

Figure 4.25 turbidity mapping

In figure 4.25 the turbidity gives the reverse picture of the temperature figure in figure 4.20. This could have been caused by the influence of the water temperature to the turbidity.
4.5.2 Simulink model

The simulation of the prediction of the filtration runtimes is programmed in a Simulink/Matlab environment. The simulink model can be in figure 4.23.

![Simulink model of the runtime prediction](image)

Figure 4.26 Simulink model of the runtime prediction

The model goes through four stages, from left to right in figure 4.26.

The first stage is the input stage, all the data is collected of the model parameters. These data come from the PHD database.

The next stage is calculating the average of the data during 15 hours. The model shows the value of the average data in small screens of each parameter. The delay blocks are used to calculate which period the average of the data is needed. This could be 15 hours before the runtime or 15 hours after the runtime. (Feed back or feed forward)

In the third stage the model predicts the filtration runtime. This model predicts the time when the filtration head loss reaches 1.8 meters. The input parameters to the fuzzy logic model are the average wispro dosage, iron dosage, water temperature, filtration flow rate and the inlet turbidity.

The prediction starts with the model recording the clean bed head loss of the filtration at the start of the runtime. Then the fuzzy logic predicts the head loss gradient. The fuzzy logic model block can be seen in figure 4.26 by the block named fuzzy logic controller. The fuzzy logic model is made by the bootstrapping method beforehand. It predicts the head loss gradient by "if--- then" rules and these can be seen in the ruleviewer [13] shown in figure 4.27.
The more the chart is filled up of the rule, the more that parameter contributes to the head loss gradient. For example, rule 1 has the following consequence:

**Example rule 1.**

Rule 1 is shown in the top row. The first five graphs represent the antecedent. The consequent is in the graph to the right of the last antecedent. The rule of rule 1 is: if a relative high filtration flow rate and a high iron dosage and a high temperature and a medium turbidity and a medium wispro dosage then the head loss gradient will be high. The input data is a flow rate of 333.5 m³/h, an iron dosage of 20 g/m³, a temperature of 5.6 degrees Celsius, a turbidity of 0.868 FTU and a low wispro dosage of 0.3 g/m³, which are shown by the vertical line. The area shaded in the antecedent graphs shows how much the rules influence the consequent. The consequent in this case is about 10% filled. Aggregating all consequences of the three rules gives the average output result of the head loss prediction of 0.0107 m/m.

From the Head loss gradient prediction, the runtime is calculated by:

Runtime = (1.8 meters – clean bed head loss) / head loss gradient. The calculations are performed in block “subsystem 8” in figure 4.26.
The last stage is representing the prediction and the measured runtimes in one chart so that they can be compared with each other. The predicted head loss is represented as a straight line and shows when the head loss reaches 1.8 meters. The accuracy of the predictions is decided by observing the simulations.

When simulating, the model showed a few times that the predictions were clearly wrong. Having another sub-model solved this problem. This sub-model monitors the difference between the fuzzy logic head loss gradient and the real head loss gradient. It is shown in the figure in block “sumsystem”. If the difference between the two gradients were found to differ more than 30% at the point when the real head loss reaches 1 meter, then the sub-model intervenes. 30% is used because even at 29% difference, the fuzzy logic model had still a good prediction as the real head loss changed after the 1 meter head loss. The sub-model bases its prediction on the real head loss gradient when the real head loss has reached 1 meter. It uses this gradient and extrapolates to predict when the head loss reaches 1.8 meters.

4.6 Simulation and results

The accuracy of the simulations is tested by observation of the charts generated by the model. The runtime predictions are considered either good prediction or a bad prediction. A prediction is considered good when the predicted head loss line rises similarly to the rise of the real head loss line on the charts. The following criteria are used to consider the predicted head loss good:

- The difference between the real runtime and the predicted runtime is less than 5 hours.
- If the measured filtration reaches the 1.8 meter head, but continues its runtime for a while, the simulation is considered good if the difference of the runtime at the moment the measured runtime reaches 1.8 meters is 5 hours separating.
- If the measured filtration has its back-washed sooner than the 1.8 meter head loss, than the simulation is considered good if the difference in the runtime is less than 5 hours at the head loss level when the measured runtime is back washed.

The result of the simulation produces charts where the actual head loss of the filtration is shown and where the predicted head loss is also shown. The y-axis shows the head loss of the filtration. The runtimes can be seen on the x-axis. The simulation was done for the year 1999. An example of the result of one runtime is shown in figure 4.28. The dotted line is the measured filtration head loss while the black line is the predicted head loss.

![Figure 4.28 Head loss predictor.](image-url)
Other examples of the simulations can be seen in figures 4.29 to 4.34. The charts show a tendency that the prediction has a little lower head loss gradient than the measured head loss gradient. However, a good prediction is still observed because the filters are flushed at the predicted time.

![Figure 4.29 simulation 1 results](image)

Runtime 42 hours; Iron dosage = 25 g/m³; Temperature = 17.9 °C; Average filtration flow = 378 m³/h;
Turbidity = 5.6 FTU; Wispro = 0.4 g/m³

The first simulation (see figure 4.29) gives a very good prediction. The filtration flow rate was quite stable. The predicted runtime of 48 hours was also measured.

![Figure 4.30 simulation 2 results](image)

Runtime 44 hours; Iron dosage 27 g/m³; Temperature 18.3°C; Average filtration flow 363 m³/h;
Turbidity 5.0 FTU; Wispro = 0.4 g/m³

The second simulation (figure 4.30) has the prediction a little earlier than the measured runtime. This is caused by the flow rate that suddenly lowers at the end making the runtime longer. Still the prediction is considered good, as the difference is small.
Figure 4.31 simulation 3 results
Runtime 33 hours; Iron dosage 27 g/m³; Temperature 19°C; Average filtration flow 434 m³/h;
Turbidity 3.0 FTU; Wispro 0.4 g/m³

The third simulation (figure 4.31) prediction is a little different than the measured head loss. However, the measured prediction is not flushed exactly at 1.8 meters, but at about 1.9 meters. The runtime is prolonged. The measured time the filters are flushed is about the same. Therefore the predicted runtime is considered good.

Figure 4.32 simulation 4 results
Runtime 25 hours; Iron dosage = 30 g/m³; Temperature = 20.5°C; filtration flow rate = 500 m³/h
Turbidity = 1.54 FTU; Wispro = 0.4 g/m³

Simulation 4 (figure 4.32) seems to show that the predicted runtime is longer than the measured runtime. However, just at the end, the measured head loss has a lower head loss gradient, which causes the measured to be the same as the predicted runtime. The reason for the lower gradient is caused by the lower filtration flow rate at the end of the runtime.
Figure 4.33 simulation 5 results
Runtime 30 hours; Iron dosage =28 g/m³; Temperature =6.7°C; Average filtration flow =523 m³/h;
Turbidity = 7.3 FTU; Wispro =0.4 g/m³

Simulation 5 (figure 4.33) shows a measured head loss that fluctuates a lot because of the fluctuating filtration flow rate. This could ruin the prediction, but because the prediction is based on the average of the history of the runtimes, the prediction is still good.

Figure 4.34 simulation 6 results
Runtime 46 hours; Iron dosage =23 g/m³; Temperature=4.8°C; filtration flow rate =400 m³/h;
Turbidity = 6.9 FTU; Wispro dosage =0.4 g/m³

Simulation 6 (figure 4.34) has a prediction that is totally different than the measured runtime. The prediction is intervened by the sub-model and corrects the prediction. When redoing the simulation, but then with using the average input data during the filtration runtime (normally the average of the last 15 hours is taken), the model still predicted the same runtime. The error lies in the missing critical data on which the fuzzy logic model does its regression. The errors happen when there was a very high filtration flow or a very low filtration flow or when the there are large fluctuations in filtration flow.
In the year 1999, 193 filter runs were performed. The following results were found:

- 163 runs were predicted accurately within 5 hours
- 121 runs were predicted accurately within 2 hours
- 30 runs were predicted wrongly and were supported by the sub-model in order to correct the prediction.

When using the criteria for considering a simulation a good simulation, defined in the last paragraph, the fuzzy logic model predicted 163 runtimes correct. The sub-model intervened 30 times in the prediction of fuzzy logic model.

4.7 Conclusion and discussion

The accuracy of the head loss gradient prediction has a median relative error of 9.9 % as shown in chapter 4.4.7 and a VAF of 87.8 %. The accuracy of the prediction is practical enough as seen in the simulation.

In the results of the simulations in chapter 4.7, the created fuzzy logic model can effectively simulate the treatment process and predict the runtimes but needs the help of an extra model to correct the prediction at certain situations. The extra model extrapolates the gradient of the head loss in order to predict the runtime. Of the 193 runtimes, 30 were intervened by the extra model. The reason why the extra model has to intervene is because the fuzzy logic model didn't have the vital regression data to predict at that particular situation. The situation was usually a very low filtration flow or a very high filtration flow. The solution to the problem is to acquire a larger range of data so as to be able to predict better. The data collected were under controlled circumstances, where the iron dosage is correlated to the rest of the parameters. A better range of data could be collected if the iron dosage was not controlled, but the water users might not accept this experiment.

An operator, who bases its control on experience, needs a lot of different situations and experience to be able to predict the treatment process. If the fuzzy logic model is updated continually, then the model becomes a learning model just as an operator. The error could also lie in that fuzzy logic model does its prediction based on the data of the average 15 hours before the filtration runtime. This means that the parameters during the filtration runtime do not correspond to the parameters that fuzzy logic uses. However, when a simulation was tried with the prediction based on the runtimes, the extra model had to intervene just as many times.

The fuzzy logic model describes how the various parameters interact with each other as in the 3D charts in chapter 4.5.1. The charts give insight on how the parameters influence the treatment process at different flow rates and temperatures. The WRK III does not yet have any documentation how the runtimes of the filters vary with different parameters. The charts can give rules to the operators how to control the filtration runtimes as the charts also show how the runtimes vary with different iron dosage and wispro dosage. When examining figure 4.19, the chart shows how the head loss gradient changes with the iron dosage. The chart suggests that a dosage of 25 g/m³ at a low filtration flow will cause a high head loss gradient. Therefore the dosage should be more or less 25 g/m³ to avoid a high head loss gradient. (The higher the head loss gradient, the lower the runtime. When there is a high filtration flow, then the iron dosage should be as low as possible as then the head loss gradient is lowest.

A warning sign could be given when the filter has to be back washed, for example the model predicts that in 5 hours the filter has to be back-washed. The accuracy of the prediction is about 10 % so the accuracy of the predicted runtime is then half an hour, which is practical enough. The prediction shows the time when more than two filters have to be backwashed at the same time. A control system may then decide to backwash one filter earlier in order to avoid having a filter on stand-by. (Maximum 2 filters can be back washed at a time). To be
able to do this, the WRK III has to make a fuzzy logic model each of the 18 filters as these filters are not identical to filter 41.

If the transport regime uses the buffer capacities of the reservoirs as shown in the transport model simulations, then the fuzzy logic model can make better predictions of the runtimes as then the filtration flow is not so fluctuating.
References

[1] Ir. L. W. P. Bianchi/ P Bustraan, Pompen, Haarlem


Appendix I: Pump Characteristics

The Luceer model is a model written in an excel spreadsheet. It calculates the theoretical energy use by the filtrate cellars. The reason for having such a model is to check on the use of the filtrate pumps. If the power usage of the filtrate pumps is not the same as the theoretical power usage, then there is a strong possibility that something in the transport network has failed. For example if the power usage of the pumps at a certain flow rate is much lower than the theoretical energy use, then this could indicate a possible leakage in the pipelines. The Luceer model is also quite reliable because it is also calibrated to the actual power usage. Therefore, the Luceer model is the best model available to calculate the power usage.

The following information shows the dimensions of the transport network. Table 1 shows the length, diameter and elevation of the pipelines to Hoogovens and PWN. The pipeline to Hoogovens is the pipeline that will be used to calculate the energy use of the filtrate pumps, as this is the transport to be researched.

<table>
<thead>
<tr>
<th>Tract</th>
<th>Length [m]</th>
<th>Diameter [m]</th>
<th>Elevation [kPa]</th>
</tr>
</thead>
<tbody>
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<td>Andijk- Wognum</td>
<td>19800</td>
<td>1.4</td>
<td>-17.5</td>
</tr>
<tr>
<td>Heerhugowaard-Heemskerk</td>
<td>17225</td>
<td>1.4</td>
<td>-33.4</td>
</tr>
<tr>
<td>Heemskerk-Beverwijk</td>
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<td>1.4</td>
<td>112.7</td>
</tr>
<tr>
<td>Beverwijk – Hoogovens cellars</td>
<td>4548</td>
<td>1.5</td>
<td>-28</td>
</tr>
<tr>
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<td>1</td>
<td>13</td>
</tr>
<tr>
<td>Beverwijk – Ouf {PWN}</td>
<td>100</td>
<td>1</td>
<td>53</td>
</tr>
<tr>
<td>Beverwijk – Oruf {PWN}</td>
<td>100</td>
<td>1</td>
<td>53</td>
</tr>
</tbody>
</table>

The Luceer model uses the following formulas to calculates the energy usage of the filtrate pumps

Power usage of the filtrate pump

\[
P = \text{Pump hydraulic power use} / \eta
\]

where:

\[
\eta = \text{pump rendement}
\]

Pump’s hydraulic power use = \(Q/60^2 \times \text{discharge head loss}\)

where

\[
Q = \text{flow rate}
\]

Discharge head loss = pump pressure + pump height - (filtrate water level + 0.42) \times 10 - (Q/116.152)^2

where:

0.42 m = pumps position
pump pressure = suction head loss + pressure head loss + elevation

where:

suction head loss = \((Q^{1.328})/3212\)
The pipe flow head loss is calculated by the formula of Shields and Stokes

\[ H = \lambda \times \frac{L}{D} \times \frac{v^2}{1000 \times \frac{v^2}{2 \times g \times 100}} \]

where:
- \( H \) = pipe flow head loss
- \( L \) = length of the pipeline
- \( D \) = Diameter of the pipeline
- \( v \) = velocity
- \( g \) = gravitational acceleration
- \( \lambda \) = lambda

first estimate
\[ \lambda = 0.23 \times \left( \text{lining friction/ 1000/Re/diameter} \right)^{0.125} \]

second calculations
\[
\lambda = \frac{0.25}{\left( \ln \left( \frac{k}{3700 \times \bar{d}} \right) + \frac{1}{0.4 \times \text{Re} \times \sqrt{\lambda \times 1}} \right)^2}
\]

- \( \mu \) = Kinematic viscosity
  - \( = 1.33935 \times 10^{-3} \text{ m}^2/\text{s} \)
- \( k \) = Pipelining friction, Nikuradse
  - \( = 0.2 \text{ mm} \)
- \( v \) = flow rate / area
  - \( = Q/(\pi \times r^2) \)
- \( r \) = pipe radius

elevation is found in table I.
Example calculation

To illustrate the calculations, an example is shown below.
Assume the following

Kinematic viscosity
\[ \mu = 1.33935E-06 \text{ m}^2/\text{s} \]
 Pipelining friction, Nikuradse
\[ k = 0.2 \text{ mm} \]
 Hoogovens elevation (see table 1) =
 Water level in cellar = 1.2 meters.
\[ H_{\text{elevation}} = 45 \text{ kPa} \]
 Assume
 Flow one pump flow rate \( Q = 4000 \text{ m}^3/\text{h} \)
 Water temperature = 10 °C
 One pipeline to Hoogovens, (see table I.)

Then :
Reynolds
\[ \text{Re} = \frac{Q}{\mu} \]
\[ = 829590 \]
Flow rate speed
\[ v = \text{flow rate }/\text{area} \]
\[ = \frac{Q}{(\pi \times r^2)} \]
\[ = 0.721927 \text{ m/s} \]
First estimate of \( \lambda \)
\[ \lambda = 0.23 \times (k/1000/\text{Re}/D)^{0.8} \]
\[ = 0.1384 \]
second calculation:
\[ \lambda = \frac{0.25}{\left( \ln \left( \frac{k}{3700 \times d} \right) + \frac{1}{0.4 \times \text{Re} \times \sqrt{\lambda}} \times \frac{1}{2.3} \right)^2} \]
\[ = 0.0419 \]

Pipe head loss
\[ H_{\text{pipe}} = \lambda \times \frac{L}{D} \times 1000 \times \frac{v^2}{2 \times g \times 100} \]
\[ H_{\text{pipe}} = 161 \text{ kPa} \]
The suction head loss is calculated by the following calibrated formula
\[ H_{\text{suction}} = (h_{\text{cellar}} + 1.2).10 - (Q^{1.328})/3212 \]
\[ = 2.8 \text{ kPa} \]
Pressure loss = \( H_{\text{suction}} + H_{\text{pipe}} + H_{\text{elevation}} = -1.8 \]
\[ = 208.8 \text{ kPa} \]
Filrate water level is at 2 m.
Discharge head loss = pressure loss + -1.8 - (filtrate water level + 0.42)*10 -(Q/1103.844)^2
\[ = 196.93 \text{ kPa} \]
Example calculation

Hydraulic power loss = \( \frac{Q}{3600} \) * discharge head loss
= \( \frac{4000}{3600} \) * 196.93
= 218.81 kPa

Energy usage = \( \frac{\text{discharge head loss}}{\eta} \) * 1 hour
= 218.8/0.88
= 247 kWh

When this value is compared with the energy used that was measured, it is nearly the same. This can be seen in figure 1.

The calculations of Lucieer also includes the effect of the throttle valve. The pumps cannot operate under a pump revolution below 500 RPM. This means that the throttle valve has to increase the discharge head when the demand for the flow rate is below a certain point. This point is at 3100 m\(^3\)/h. The way Lucieer model incorporates the effects of the throttle valve is to calculate the pump revolutions from the data. Then a discharge head is added to the equation until the pump revolution is above 500 revolutions. The energy usage then calculated is the energy usage belonging to that flow rate. The WRK III records the opening of the throttle valve. This can be seen in figure 1.

![Figure 1 throttle valve opening vs flow rate](image)

As can be seen in figure 1, the opening of the valve is totally open when the flow rate reaches 3200 m\(^3\)/h, as only then the valve is 100 % open. After 3200 m\(^3\)/h, the valve is used to quickly lower the flow rate in order to keep the water levels in the Hoogovens cellars in check. This is only done when a rapid decrease of the flow rate is needed. Otherwise the filtrate pump lowers its revolutions to lower the filtrate flow rate.
The effects of the throttle valve can also be seen in figure 2. The WRK III records the energy use of each pump and also records the flow rate. This can then be compared with each other to see how accurate the theoretical energy usage of the pumps are to the real situation. Figure 1 show that he theoretical energy usage is very close to the measured energy usage.

![Figure 2 Energy use of the filtrate pumps](image)

The inlet pumps have a much different energy usage than the filtrate pumps. Most of the energy used by the inlet pumps is to elevate the water to about 5 meter. This means that the power usage can be written as

\[ P = k \cdot \rho \cdot g \cdot Q \cdot H^2 / \eta \]

As the Head loss \( H \) is the elevation and is kept constant, the energy usage greatly depends on the efficiency of the pumps at different flow rates. Therefore the theoretical energy usage is found in the Q-h curve pump characteristics made by the manufacturer. As the pumps are of the variable flow rate type, the Q-h curve is as linear as possible. The energy usage of the pumps are measured and recorded by the WRK III. These are shown in the units kVA, which
is not exactly as the energy usage expressed in kWh. However the energy curves are plotted in the same graph and is shown in figure 3.

Figure 3 Inlet pumps theoretical energy usage vs. measured energy usage

As can be seen in figure 3, the theoretical energy usage is show as slightly larger than there was measured. This is because the measured energy usage did not yet take into account the pumps’ efficiency. If this was included, the measured energy usage must be multiplied by about 1.1 to 1.4. This then plots the measured energy usage on top of the theoretical energy usage.