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Using a drinking water treatment simulator for operator training

Accelerating the simulated process leads to an increase in learning

MSc Project (ME2590-32)

Michiel van der Wees
wb1043706

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Delft University of Technology

Faculty of Mechanical, Maritime and Materials Engineering
Department of Biomechanical Engineering

UReason

Using a drinking water treatment simulator for operator training

Accelerating the simulated process leads to an increase in learning

A study on the effect of an increase in simulation speed on learning.

Michiel van der Wees
wb1043706

Supervisors:
Peter Wieringa
Joost de Winter
Leen de Graaf

Delft, October 2009

Abstract

The drinking water treatment industry is becoming increasingly centralized and automated. This requires a different operator training approach then the traditional on the job training. To address this requirement a drinking water treatment plant simulator was developed. A major advantage of such a simulator might be that the normally very slow process can be accelerated, giving an increase in feedback to the trainees. In this paper the effectiveness of training on an accelerated simulated process is investigated. Four groups of subjects were trained on the Waterspot Simulator, three groups (of various experience) trained at 60x accelerated simulation speed, and one group trained at real-time simulation speed. The results showed that the Waterspot Simulator could distinguish between experienced operators and laymen and that the groups that trained with 60x accelerated simulation speed outperformed the group that trained at real-time, when they were compared on a real-time quasi transfer of training task.

Preface

This is the graduation work of Michiel van der Wees on the subject of operator training on drinking water treatment plants. It was conducted from January 2009 until October 2009.

The core of the graduation work is the paper: *"Using a drinking water treatment simulator for operator training"* which describes the Master's final project. The final project was preceded by an internship with a report: *"Model Predictive Control in the Drinking Water Industry: a Survey"*, and a literature survey: *"Evaluation of a Water Treatment Plant Simulator for Training of Operators"*, which are included in the supplementary materials section.

I would like to thank the company UReason International BV and to PWN water supply company North-Holland for giving me the opportunity to work on the Waterspot project; Joost de Winter, Leen de Graaf, Ignaz Worm, Peter Wieringa, Tibor Lapikas and Stefan de Groot for providing information and critical notes which contributed to the result; to all subjects for their time and cooperation; and finally to my parents for their support.

Delft, October 2009

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“Using a drinking water treatment plant simulator for operator training”

Using a drinking water treatment simulator for operator training.

Accelerating the simulated process leads to an increase in learning.

M. Van Der Wees[1], J.C.F. De Winter[1], G.I.M. Worm[2,3], L. De Graaf[4] and P.A. Wieringa[1].

Abstract

The drinking water treatment industry is becoming increasingly centralized and automated. This requires a different operator training approach then the traditional on the job training. To address this requirement a drinking water treatment plant simulator was developed. A major advantage of such a simulator might be that the normally very slow process can be accelerated, giving an increase in feedback to the trainees. In this paper the effectiveness of training on an accelerated simulated process is investigated. Four groups of subjects were trained on the Waterspot Simulator, three groups (of various experience) trained at 60x accelerated simulation speed, and one group trained at real-time simulation speed. The results showed that the Waterspot Simulator could distinguish between experienced operators and laymen and that the groups that trained with 60x accelerated simulation speed outperformed the group that trained at real-time, when they were compared on a real-time quasi transfer of training task.

Keywords

Drinking water treatment; operator training; simulator training; evaluation

[1] Delft University of Technology, Faculty of Mechanical, Maritime and Materials Engineering, Department of Biomechanical Engineering, Mekelweg 2, 2628 CD, Delft, The Netherlands

[2] PWN Water Supply Company North-Holland, PO Box 2113, 1990 AC Velserbroek, the Netherlands

[3] Delft University of Technology, Faculty of Civil Engineering and Geosciences, Department of Water Management, PO Box 5048, 2600 GA, Delft, The Netherlands

[4] UReason Netherlands, Poempoenweg 9, 2321 DK, Leiden, The Netherlands

1. Introduction

In the Dutch drinking water industry quality demands are continuously increasing, while profit margins are reduced. To cope with these changes a high level of automation is introduced, up to a level of fully centralized operations (Worm and Rietveld, 2006).

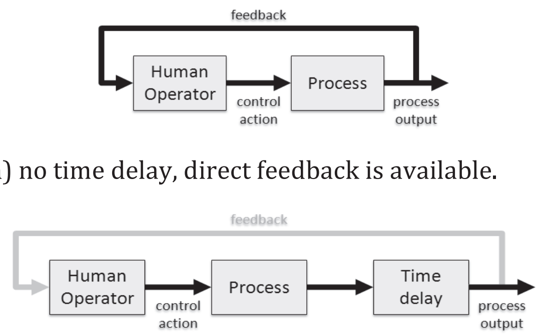
With this automation a conflict is introduced: even highly automated processes require human operators (for supervision, adjustment, maintenance, expansion, improvement and monitoring) and, as such, still remain human-machine systems (Bainbridge, 1983). An automated system is generally more complex than its manually controlled counterpart, because additional complexities are involved, such as sensors, actuators, and control software. The same automation leads to an increase of the "distance" between the operator and the process, diminishing the natural training of the operators and eventually leading to an erosion of their skills. This will lead to operators being unable to perform adequately when upsets occur or when automation fails (Worm and Rietveld, 2006).

Worm and Rietveld (2006) concluded that a simulator was needed for the drinking water treatment sector in the Netherlands. This simulator should offer the operators more insight into the water treatment process and the consequences of possible control actions.

The Waterspot project was started in 2006 to build a simulator for the drinking water industry. The goal is to create a simulator with a role equivalent to that of flight simulators in the aviation industry. With this simulator operators and trainees can manually control a virtual drinking water treatment plant. Various scenarios can be trained on the virtual plant without interfering with the actual plant, allowing the operators to gain hands on experience and thus gain "feeling" for the process again.

It seems evident that a simulator should be a realistic real-time representation of the actual process in order to be effective. Indeed, many simulator developers and users adhere to the assumption "more realistic is better". However, Salas, Bowers and Rhodenizer, 1998 showed that this assumption is not necessarily valid: more realistic simulation does not always imply increasing learning.

In the present study, we set out to investigate a *deliberate deviation from reality*. A major advantage of a simulator might be that the (normally very slow) process speed can be accelerated, resulting in an unrealistic rather than realistic simulation. Due to the accelerated simulation speed, the trainee can get direct feedback during training (Figure 1). As a result, his understanding of the relationships between control actions and reactions of the process might improve faster. However, accelerating the simulation speed might also result in too aggressive control when transferring to the slow, real process.



(a) no time delay, direct feedback is available.

(b) due to the time delay feedback diminishes.

Figure 1. A schemetic illustration of feedback, diminished by time delay.

It is important to validate the Waterspot Simulator for its effectiveness as a training tool. Our evaluation focused on transfer of training from an environment with increased simulation speed, to an environment with normal simulation speed. The hypothesis is:

"Training on the Waterspot Simulator at 60 times the real speed, gives a greater increase of performance than training on the Waterspot Simulator at the real speed".

In addition to investigating training effectiveness, the present study investigated the suitability of the Waterspot simulator as an assessment tool. A second hypothesis was introduced to investigate whether the Waterspot Simulator can make a distinction between good and bad operation:

"Operators having experience on the actual water treatment plant perform better on the Waterspot Simulator than inexperienced participants".

To evaluate these hypotheses a quasi transfer of training experiment was set up with four groups: Experienced Operators, Inexperienced Operators, Laymen training with a simulation speed which was increased 60 times, and a control group of Laymen training with normal simulation time. With this set-up it was possible to compare the first three groups to evaluate the second hypothesis, and to compare the two groups of laymen to evaluate the first hypothesis.

2. Materials and Methods

2.1. Simulated water treatment process

For the evaluation of the Waterspot Simulator we focused on the pellet softening process at the Wim Mensink treatment plant of PWN Water supply North-Holland. This is the most dynamic and complex process of the water treatment (Van Schagen et al., 2006; Van Schagen et al., 2008).

In the pellet softening process the calcium concentration in water is reduced to prevent scaling in household equipment and to reduce the need for detergents. Pellet reactors consist of cylindrical vessels partly filled with seeding material (usually river or garnet sand; see Figure 2). The water is pumped through the reactors in upward direction, keeping the seeding material in a fluidized condition. At the bottom Caustic Soda (NaOH) or Lime (CaOH) is dosed. As a result the Saturation Index (SI) of the water increases as the Calcium Carbonate ($CaCO_3$) gets supersaturated. The supersaturated Calcium Carbonate then crystallizes on the seeding material, forming pellets.

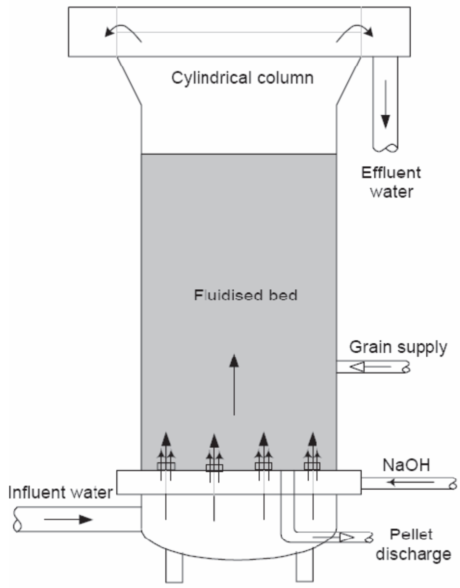


Figure 2. Pellet reactor (Van Schagen et al., 2006).

If the effluent of the pellet reactors is still supersaturated with Calcium Carbonate (SI >> 0) scaling occurs downstream (in filters, valves, pipes and pumps). To prevent this acid (Carbon Dioxide at Wim Mensink) is dosed. The acid will neutralize the remaining Caustic Soda (a base). When too much acid is dosed the Saturation Index drops below zero making the water dissolve pipes and other equipment.

At optimal operation, part of the water is softened more deeply than the required level, and part of the water is bypassed (Van

Schagen et al., 2006), resulting in the desired water quality (Figure 3).

The Softening process is a stable process. By altering the process settings, the equilibrium of the process can be changed as desired.

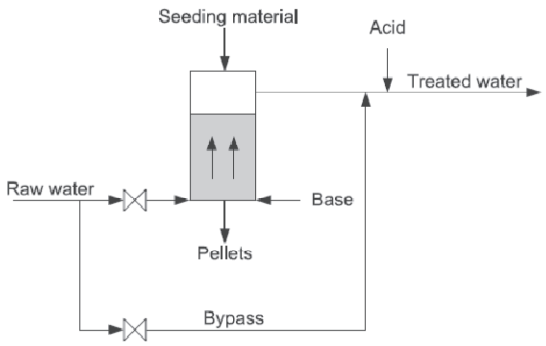


Figure 3. At Wim Mensink part of the water bypasses the softening process (Van Schagen et al., 2008).

2.1.1. Time delays

The softening at Wim Mensink is subject to various time delays. As a result, operators receive little direct feedback on their actions when they manually control the plant

These time delays are caused by the large volumes of water, in the pellet reactors themselves, but also in the sand filters. Because the softened water and the bypassed water are mixed at the very end of the treatment plant, all these volumes contribute to the time delay. In real-time operation, the delay between a control action and the moment that the plant reaches a new equilibrium is typically about 15 minutes.

Because the controlled variables have effect on multiple water quality variables, the time delays have an even greater effect on diminishing feedback. For example, when a participant changes both the amount of active reactors, and changes the dosage of Caustic Soda, within 15 minutes, it is impossible to see the effect of one of them on the resulting water quality.

2.2. Graphical user interface (GUI)

The acceptation of the Waterspot Simulator is largely dependent on the level of simulator fidelity (Farmer et al., 1999). Therefore the GUI of the simulator follows the standards for SCADA[5] system design, as is also used in the actual control room. The GUI consists of a hierarchical set-up of the screens to limit the information per screen and standard icons for the various treatment units.

The present experiment was carried out using the GUI of the Waterspot Simulator on a laptop computer. The Waterspot Simulator was controlled by a standard optical USB-mouse and the keyboard of the laptop computer. A screenshot of the GUI of the simulator is included in Figure 4. The hardware and software specifications are included in Appendix A.

2.2.1. Experiment

Research has shown that affective reactions, utility judgments, and skill demonstration (i.e., quasi transfer of training) correlate with training effectiveness (Alliger et al., 1997). Therefore the experiment consisted of two questionnaires (one pre-experiment questionnaire and one post-experiment questionnaire), three training runs, and two quasi transfer of training runs. The quasi transfer of training runs were performed on the same simulator but under different circumstances in terms of simulation speed and disturbances. As such, the quasi transfer design assumes that the Waterspot Simulator represents a valid replacement for the actual treatment plant.

[5] Supervisory Control And Data Acquisition

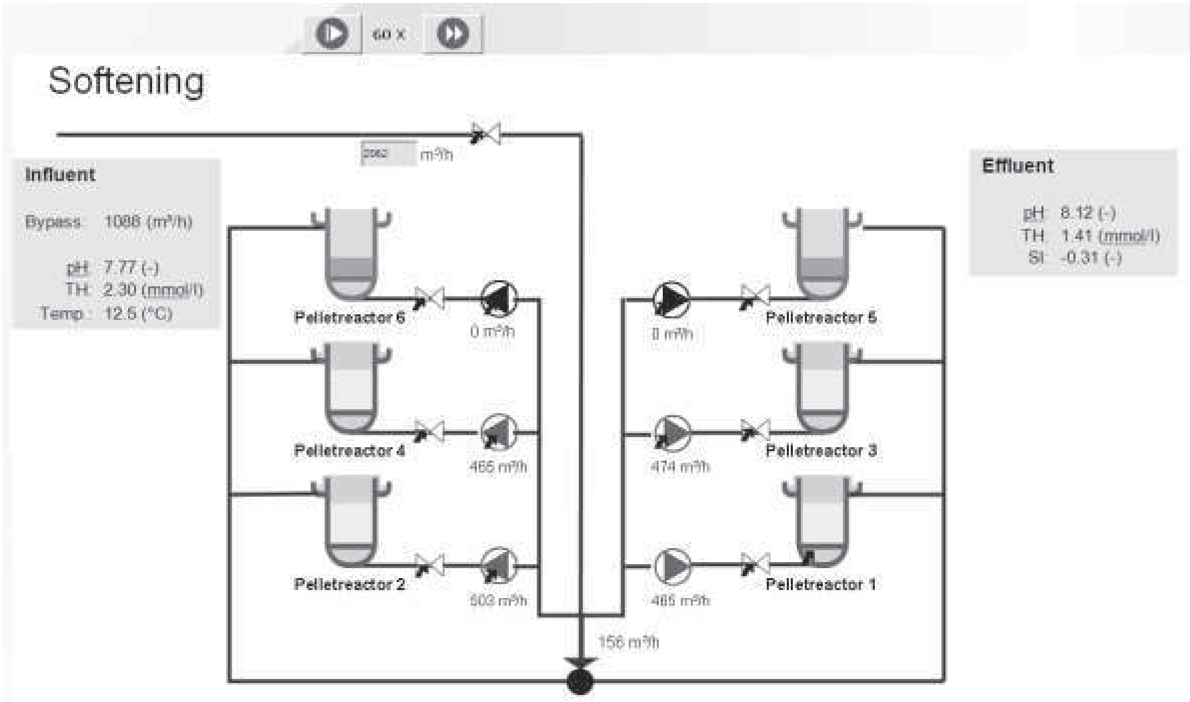


Figure 4. Screenshot of the Waterspot Simulator GUI for the softening step.

2.2.2. Groups

Four groups of participants were created. Each group consisted of four participants. None of the participants were familiar with the Waterspot Simulator.

Group 1: Experienced Operators
Group 2: Inexperienced Operators
Group 3: Laymen
Group 4: Laymen, control group

The Experienced Operators were employees of the treatment plant of Wim Mensink of PWN water company North Holland. The operator's mean number of years of experience at Wim Mensink was 12.5 years (range 4–25 years).

The Inexperienced Operators were from other PWN North Holland water treatment plants, and did not have experience with the Wim Mensink plant operation. In these other plants, softening is performed with Caustic Soda dosage in a reservoir, instead of in pellet reactors.

The Laymen were recruited from the Delft University of Technology student population. None of the Laymen had previous experience with the drinking water treatment process.

2.2.3. Instructions and procedures

Prior to the actual experiment the subjects were given written instructions. It was explained how to control and navigate within the Waterspot Simulator, and the tasks to be performed were described.

At the start of each experiment the participants were asked to fill in a pre-experiment questionnaire to get information about their expectations. The questionnaire contained statements related to utility judgment as well as affective reactions on a five-point Likert scale ranging from strongly disagree to strongly agree. The questionnaire is included in Appendix B-1.

During the experiment the participants were instructed to keep the following three water quality parameters within their operational windows:

- Saturation Index (SI; window: 0.2–0.4),
- Total Water Hardness (TH; window: 1.4–1.6 mmol/l),
- Acidity (pH; window: 7.5–8.5)

The participants could control the following variables:

- The number of active reactors (possible values, 0, 1, 2, …, 6),
- The dosage of Caustic Soda (NaOH; range 0–200 l/h),
- The dosage of Carbon Dioxide (CO_2; range 0–20 Nm^3/hr).

The experiment consisted of five runs of 20 minutes: three training runs and two quasi transfer of training runs, to validate the acquired skills and knowledge in a different situation. An overview of the experiment set-up is included in Table 1.

For groups 1, 2, and 3, the simulation speed during the three training runs was accelerated 60 times. This implied within the 20-minute run, 20 hours were simulated. Group 4 trained with a real-time simulation speed. The simulation speed for the quasi transfer of training runs was real-time for all groups.

During the training runs and the first quasi transfer of training run the ratio between the flow of dune infiltrate and the flow of Reverse Osmosis water was changed.

For the training runs with a 60x accelerated simulation speed this was done at t = 0, t = 5, t = 10, and t = 15 minutes, in which t is time the participant spent behind the simulator. The laymen were expected to need about 5 minutes to bring the process back into its operational window after a change. Due to some simulator lags the intervals in terms of simulated time are little less than 5 hours.

For the runs with a simulation speed of 1x this process change occurred only at t = 0 and t = 10 minutes, because the process itself would require about 10 minutes to return to its operational window after appropriate control actions.

During the first minute of the second quasi transfer of training run, the ratio between the flow through the pellet softening treatment process and the bypass was altered. Because this was a different process change, the participants were required to use a mental model of the process they had practiced, instead of the specific skill they had trained.

Finally the participants were asked to fill in the post-experiment questionnaire. The statements from the pre-experiment questionnaire were translated from expectation type statements to experience type statements (e.g., "I expect that training on the Waterspot Simulator is educational," became: "Training on the Waterspot Simulator is educational"). The post-

Table 1. Experiment set-up

groups		Training runs (3x)	skill demonstration 1	skill demonstration 2
		changes on ratio between dune and RO water	changes on ratio between dune and RO water	change on ratio bypass flow
group 1	Experienced Operators	60xspeed, 4 changes	1xspeed, 2 changes	1xspeed, 2 changes
group 2	Inexperienced Operators			
group 3	Laymen (60xspeed)			
group 4	Laymen (1xspeed)	1xspeed, 2 changes		

experiment questionnaire is included in Appendix B-2.

2.2.4. Performance indicators

The following performance indicators were defined for the different runs:

- Integral of the Error
- Error from first guess
- Error from final guess
- Number of control actions

Integral of the Error

For each of the runs at 60x accelerated simulation speed, the performance was calculated by taking the integral of each of the three quality parameters (SI, TH, Ph) outside of their operational window (Figure 5). For each quality parameter, this yielded a vector of 36 (3 runs * 4 participants per group * 3 groups) integral-error scores; these vectors were standardized into *z*-scores. These *z*-scores were summed across the three quality parameters, yielding 36 Integral of the Error scores.

At real-time simulation speed the Integral of the Error score was not applicable: as a result of the large delays in the system, this measure would be insensitive to the participant's actions. Furthermore, it would be effective to oversteer the process in order to have it within bounds sooner, neglecting the fact that the process might grow out of bounds as time passes beyond the duration of the run. Therefore, three other measurements were defined:

Error from first setting

The Error from first setting is defined as the error outside the operational window of the quality parameters when the process is at equilibrium, given the first settings a participant chose in a run. The first setting was defined as the first choice a participant made for all three input settings, within the first 30 seconds after the first change of a run. The Error from first setting was calculated after the experiment, by applying the first settings on the Waterspot Simulator at 60x accelerated simulation speed and waiting for the equilibrium.

Again the errors resulting from the three quality parameters were normalized and summed to give a total error score.

Error from final setting

The Error from final setting was the same as the Error from first guess, however given the final settings the participant chose during a run.

Number of control actions

The number of control actions is obtained by counting the changes in control settings during a run. Though not an actual performance indicator, it can be used as an indicator for the control effort.

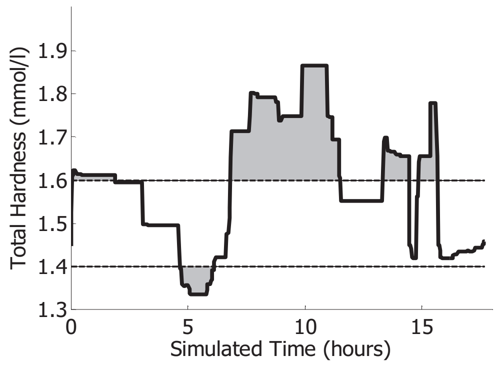


Figure 5. Integral of the Error for Total hardness.

2.2.5. Analyses

The performance indicators were used to compare the various groups and runs with each other.

Groups 1, 2, and 3 were compared after the first training run and both the transfer runs to investigate whether there existed performance differences between these groups.

Groups 3 and 4 were compared using the scores of the transfer runs to investigate the amount of learning of these groups. All statistical comparisons were performed with *t* tests.

3. Results

An example of a run with a 60x accelerated simulation speed is shown in Figure 6. It shows the recorded Total Hardness, NaOH dosage, and Number of active reactors. It can be seen that when a change of water total hardness occurred, the operator acted soon after in order to compensate for these changes and to keep the hardness within the operational window.

3.1. Results comparing groups 1, 2, and 3.

To evaluate the second hypothesis, groups 1, 2, and 3 (Experienced Operators, Inexperienced Operators, and Laymen 60x) were compared.

Learning effects

Figure 7 shows the learning curves of the Integral of the Error score for the 3 training runs at 60x accelerated simulation speed. The corresponding means and *SD*s are included in Table 2.

Table 2. Learning effects during training runs on the indicator Integral of Error score

	Experienced Operators		Inexp. Operators		Laymen 60x	
run	*M*	*(SD)*	*M*	*(SD)*	*M*	*(SD)*
1	1.22	(3.65)	-0.63	(2.77)	12.6	(23.70)
2	-3.28	(0.46)	-0.12	(3.90)	-0.57	(3.78)
3	-3.31	(0.62)	-2.52	(0.61)	-3.38	(0.30)

No statistically significant difference was found when the Experienced Operators were compared with the Inexperienced Operators or when the 8 operators were compared to the 4 laymen ($p > .05$).

The results in Figure 7 do show that the mean performance improved per run. Means (with standard deviations in parentheses) of 11 participants of the first versus the third run were 0.43 (2.88) and -3.03 (0.64) respectively (Participant 10 was omitted due to his extreme error score of 48 in run 1). A paired *t* test showed that the performance in run 3 was significantly better then the performance in run 1 (p = .024).

Error from first setting.

The Errors from first setting for the first three groups, for transfer runs 1 and 2 are shown in Figure 8 and Table 3.

Table 3. Errors from first settings for transfer runs 1 and 2.

	Experienced Operators		Inexp. Operators		Laymen 60x	
run	*M*	*(SD)*	*M*	*(SD)*	*M*	*(SD)*
1	1.64	(3.60)	0.52	(3.96)	-1.39	(0.15)
2	-1.88	(0.44)	-1.79	(0.55)	1.39	(2.79)

For transfer run 1, no statistically significant difference was found when the Experienced Operators were compared with the Inexperienced Operators or when the 8 operators were compared to the 4 laymen ($p > .05$).

For transfer run 2, Experienced Operators did not perform differently from Inexperienced Operators ($p > .05$), but when all 8 operators were compared to the 4 Laymen 60x it was found that the operators performed statistically significant better then the Laymen 60x (p = .007).

Error from final setting.

The results for Error from final setting for the first three groups for transfer run 1 and 2 are shown in Figure 9 and

Table 4.

Table 4. Errors from final settings for transfer runs 1 and 2.

	Experienced Operators		Inexp. Operators		Laymen 60x	
run	*M*	*(SD)*	*M*	*(SD)*	*M*	*(SD)*
1	-1.35	(0.98)	0.35	(2.19)	1.84	(2.46)
2	0.03	(2.96)	-1.29	(0.81)	-1.41	(0.87)

No significant difference was found when comparing the Experienced Operators with the Inexperienced Operators or when comparing the 8 operators with the laymen for both of the transfer runs ($p > .05$).

Number of actions.

The results for Error from final setting for the first three groups are shown in Figure 10 and Table 5.

Table 5. Number of actions for transfer runs 1 and 2.

	Experienced Operators		Inexp. Operators		Laymen 60x	
run	*M*	*(SD)*	*M*	*(SD)*	*M*	*(SD)*
1	11.5	(6.1)	9.8	(4.8)	19.8	(5.3)
2	10.8	(2.2)	6.8	(2.6)	16.0	(6.6)

The Experienced Operators and the Inexperienced Operators performed comparable for both transfer runs ($p > .05$). When the 8 operators were compared to the 4 laymen it was found that the laymen made significantly more actions during transfer run 1 ($p = .017$) and transfer run 2 ($p = .024$).

3.2. Results comparing groups 3 and 4.

To evaluate the first hypothesis groups 3 and 4 (Laymen 60x and Laymen 1x) were compared. This comparison was based on the quasi transfer of training runs, which were equal for all groups.

Quasi transfer of training run 1

The Error of the first setting (E1S), the Error of the final setting (EFS) and the Number of Actions (NoA) for transfer run 1 are shown in Figure 11 and Table 6. There were no significant differences between the two groups.

Table 6. Indicator scores comparing Laymen 60x with Laymen 1x during transfer run 1.

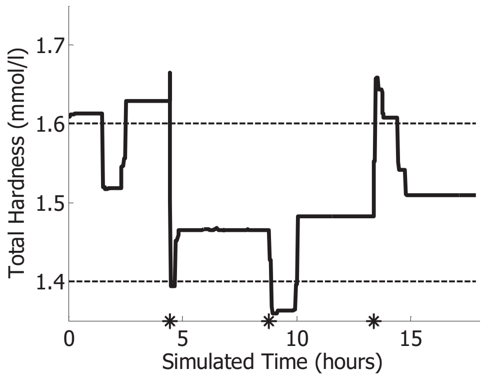
	Laymen 60x		Laymen 1x		*p*
	M	*(SD)*	*M*	*(SD)*	
E1S	-1.39	(0.15)	-0.67	(1.59)	.403
EFS	1.84	(2.46)	-0.72	(2.19)	.171
NoA	19.8	(5.3)	31.3	(12.3)	.135

Quasi transfer of training run 2

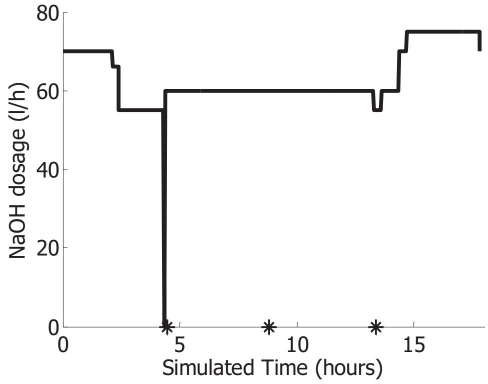
Figure 12 and Table 7 show the results for transfer of training run 2. Although the differences of the Error from the first setting showed no significant difference, they were in the expected direction: the Laymen 60x chose better first settings. For the Error from final setting and the Number of actions statistically significant differences ($p < .05$) were found in the expected directions: the Laymen 60x performed significantly better (in terms of error scores) than the Laymen 1x when transferring to a novel situation, while the Laymen 1x used significantly more actions.

Table 7. Indicator scores comparing Laymen 60x with Laymen 1x during transfer run 2.

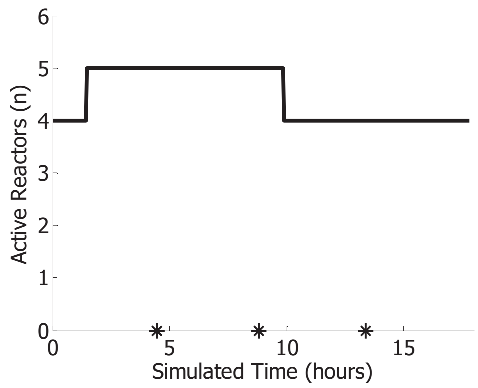
	Laymen 60x		Laymen 1x		*p*
	M	*(SD)*	*M*	*(SD)*	
E1S	1.39	(2.79)	2.45	(3.23)	.637
EFS	-1.41	(0.87)	2.80	(2.47)	.018
NoA	16.0	(6.58)	32.8	(8.66)	.022



(a) Total Hardness. The operational window is represented by the horizontal lines.

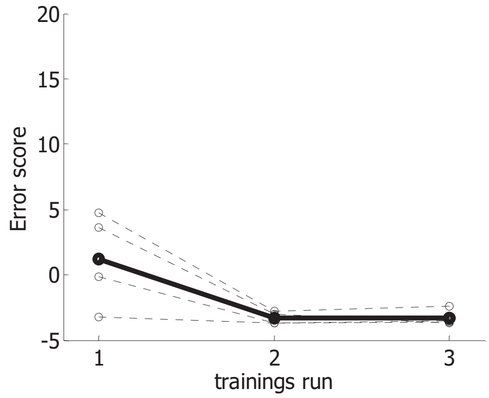


(b) NaOH dosage

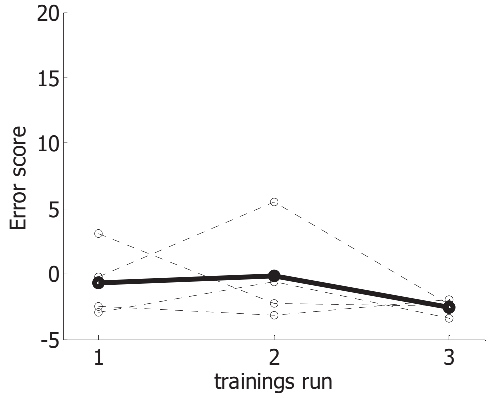


(c) Active Reactors

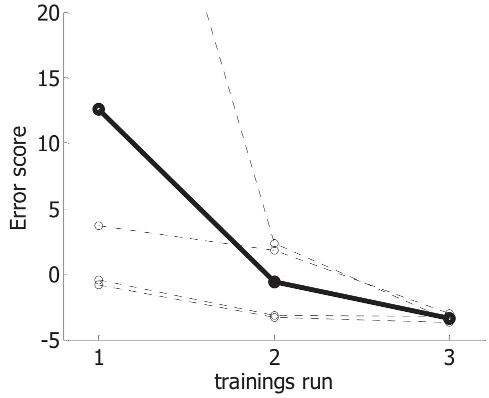
Figure 6. Recordings of a typical run (stars mark the process changes).



(a) Experienced Operators

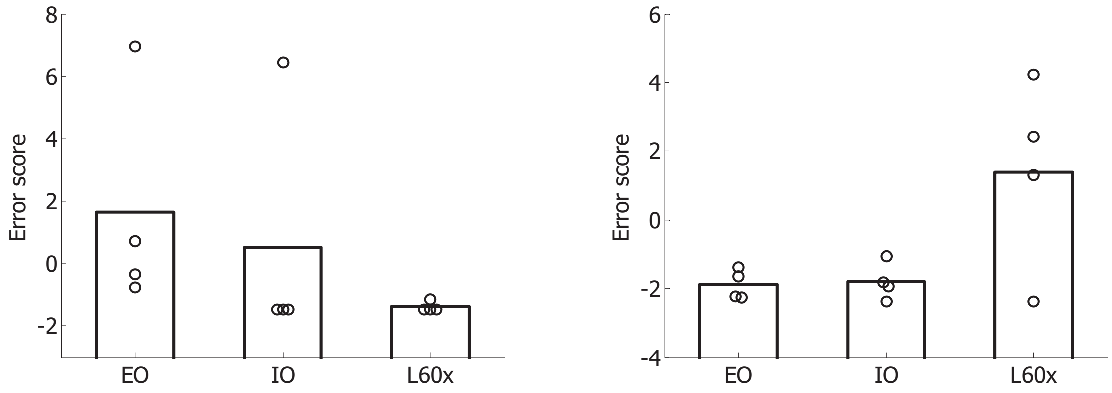


(b) Inexperienced Operators



(c) Laymen 60x

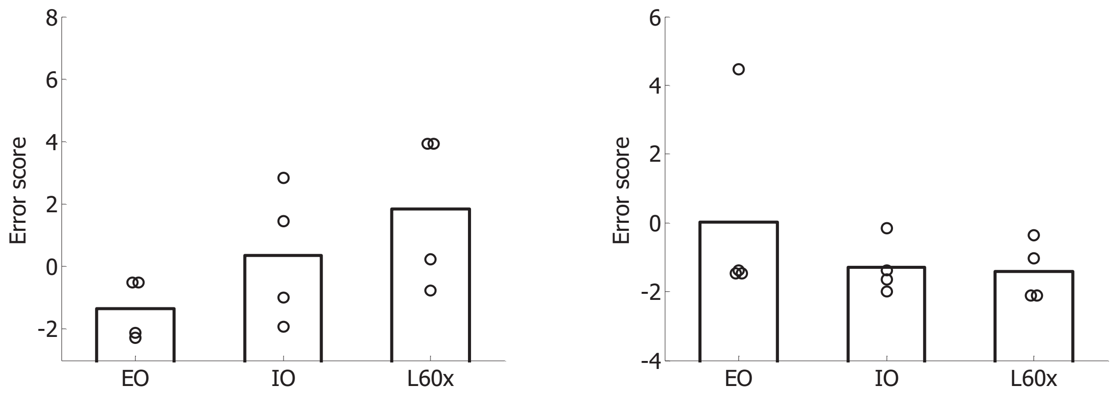
Figure 7. Integral of the Error scores for the training runs. Bold lines indicate mean scores.



(a) Transfer run 1

(b) Transfer run 2

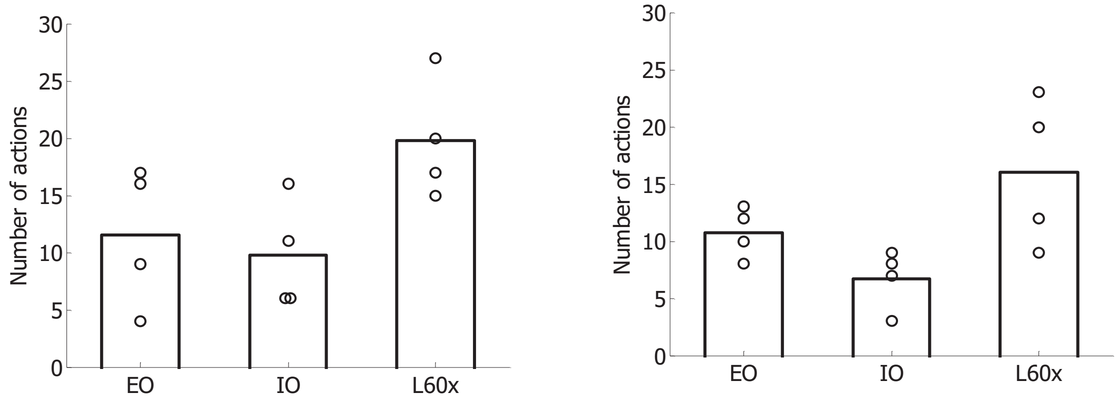
Figure 8. Errors from first setting for Experienced Operators (EO), Inexperienced Operators (IO) and Laymen 60x (L60x), during the transfer tasks. Bars indicate mean scores.



(a) Transfer run 1

(b) Transfer run 2

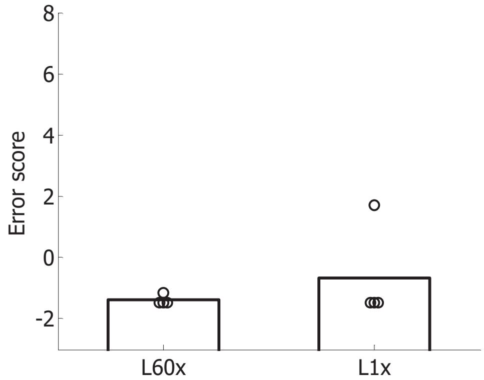
Figure 9. Errors from final setting for Experienced Operators (EO), Inexperienced Operators (IO) and Laymen 60x (L60x), during the transfer tasks. Bars indicate mean scores.



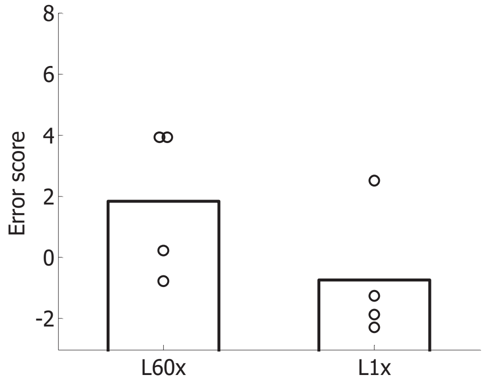
(a) Transfer run 1

(b) Transfer run 2

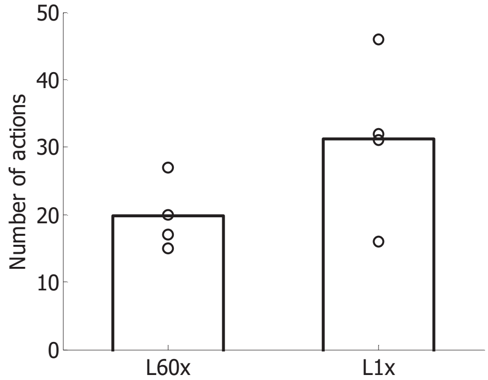
Figure 10. Number of control actions for Experienced Operators (EO), Inexperienced Operators (IO) and Laymen 60x (L60x), during the transfer tasks. Bars indicate mean scores.



(a) Error from first setting

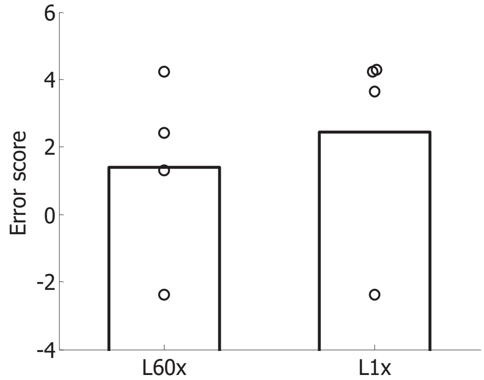


(b) Error from final setting

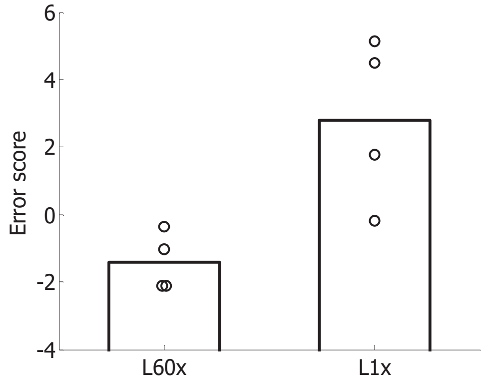


(c) Number of actions

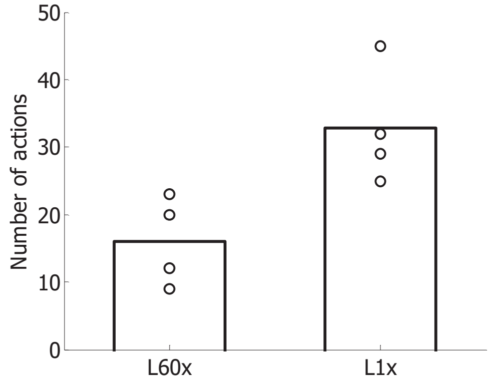
Figure 11. Performance indicators for Laymen 60x (L60x) and Laymen 1x (L1x), for quasi transfer of training run 1. Bars indicate mean scores.



(a) Error from first setting



(b) Error from final setting (p = .018)



(c) Number of actions (p = .022)

Figure 12. Performance indicators for Laymen 60x (L60x) and Laymen 1x (L1x), for quasi transfer of training run 2. Bars indicate mean scores.

3.3. Questionnaires

The results of the questionnaires are included in Appendix C. For all statements, the total mean ratings amongst all 16 participants were between 3.4 and 4.2, indicating good utility judgment and effective reactions. An exception was the statement "Training on the Waterspot Simulator can replace the current training method completely." This statement had a mean rating of 2.6.

The highest mean rating (4.3) was obtained for: *"Training on the Waterspot Simulator challenges to increase my insight in the treatment process"*. This indicates that the participants not only liked training on the Waterspot Simulator, but were intrinsically motivated to increase their insight in the treatment process.

There were no noticeable differences between the four groups; except for the statement: "*When the simulation speed of the Waterspot Simulator is accelerated I lose my feeling of the process*," the Experienced Operators were more concerned for this effect than the other groups. Furthermore the Laymen 1x were less concerned for this effect than the Laymen 60x.

4. Discussion

4.1. Questionnaire

The Waterspot Simulator yielded satisfactory rates for both utility judgment as affective reaction related questions. Participants valued the fact that the simulator provided additional insight in the water treatment process, but did not think that the Waterspot simulator could replace current training completely. The Experienced Operators and Laymen 60x group were concerned that training with increased speed yielded a loss of feeling of the actual process. In this experiment, this concern turned out to be unwarranted for the laymen who trained at 60x speed, because this group outperformed the laymen who trained at normal speed.

4.2. Assessment with the Waterspot Simulator.

The significant differences found between training run 1 and 3 for the operators and the Laymen 60x and the significant differences found between the first three groups, using the various performance indicators support the hypothesis:

"Operators having experience on the actual water treatment plant perform better on the Waterspot Simulator than inexperienced participants".

For the Error from final setting no significant difference was found between these groups. However a significant difference was found between the two groups of laymen for this indicator. The Laymen 60x seem to have gained enough process knowledge to find the appropriate settings at the end of a run, where the Laymen 1x seem to lack this knowledge.

During the experiment we observed that Experienced Operators showed recognition of the process after one run and started to control other variables to prevent "wear" of the simulated treatment plant which were not included in the instruction set. This indicates high simulator fidelity and thus increases the change of acceptance (Farmer et al., 1999).

The distinguishing capacity of the used performance indicators seems to be too coarse to make a distinction between Experienced and Inexperienced operators. This might be due to the small groups that were used in this research. Also noise was introduced in the task for the Experienced Operators due to the recognition of the process (which triggered them to control more variables, making their task more difficult).

Furthermore a more complete control task (e.g., adding other system boundaries throughout the water treatment plant) will be able to make a finer distinction between the various groups.

4.3. Training with an accelerated simulation speed.

The found differences in control actions between the two groups of laymen support the first hypothesis:

"Training on the Waterspot Simulator at 60 times the real speed, gives a greater increase of performance than training on the Waterspot Simulator at the real speed".

Combined with the shown ability of the Laymen 60x to find appropriate settings for the second quasi transfer of training run, which was clearly not accomplished by the Laymen 1x.

The direct feedback of the accelerated simulation allowed the Laymen 60x to gain process knowledge effectively during the training runs, whereas the Laymen 1x lacked this feedback, preventing them from learning.

For quasi transfer of training run 1 both groups of Laymen had comparable error scores, which may be due to the fact that quasi transfer of training run 1 is the same as the training run for the Laymen 1x. But when the disturbance changed for both groups of laymen in quasi transfer of training run 2, Laymen 60x were better able to find appropriate settings (comparable to the Operators, see Figure 9b). Contrary, the Laymen 1x used roughly twice as many actions without being able to find appropriate settings.

5. Conclusion

This research showed that training with 60x accelerated simulation speed at the Waterspot Simulator leads to better performance when transferring to a novel situation. Due to the accelerated simulation speed, feedback becomes available to the trainees. This gives them the opportunity to directly see what effects various settings have on a long term scale. Without this direct feedback it is difficult for them to see which effect was caused by which action. For stable processes it is desired that the final result of possible actions is available within seconds. Accordingly, we showed that a departure from realism enhanced training effectiveness of the simulator.

Participants indicated that the Waterspot Simulator is a helpful tool to increase their insight in the treatment process, and the research showed the Waterspot Simulator is possible to discriminate between various levels of performance on some of the performance indicators.

Recommendations

More research with larger groups is required to make a finer distinction between different levels of performance possible with the Waterspot Simulator. The tasks to be performed in future research can also be made more difficult by including other process properties throughout the water treatment plant.

For operator training on slow processes in general it is recommended that more research is done on training instable processes on an accelerated environment.

Acknowledgement

The "Waterspot" project started in February 2007, will end in November 2009, and is in cooperation with PWN, Waternet, Vitens, Dunea, UReason, DHV, ABB, Delft University of Technology and KWR. This research was co-funded by SenterNovem, an agency of the Dutch Ministry of Economic Affairs with an Innowator subsidy.

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Appendix A: Hardware and software availability

The Waterspot Simulator runs on a Dell Vostro V1510 Laptop, Intel(R) Core(TM)2Duo CPU T8100 @ 2.10GHz, 3.00 GB of RAM. The software used is included in Table A-1.

Table A-1. Used software

Software	Version	Website
EPANET	2.00.12	www.epa.gov/nrmrl/wswrd/dw/epanet.html
Jasper reports	3.1.0	www.sourceforge.net/projects/jasperreports
MySQL Community Version	5.1.3	www.dev.mysql.com/downloads/mysql/5.1.html
Stimela	6.5.59	www.stimela.com
Stimela OPC Server	1.0	
Matlab®	6.5R13	www.mathworks.com
Simulink®	5.0R13	www.mathworks.com
Waterspot	1.0	www.waterspot.nl
USE®	2.4_2	www.ureason.com
Microsoft Windows XP®	2002/SP3	www.microsoft.com

Appendix B: Questionnaires (1 = totally disagree, 5 = totally agree).

B-1. pre-experiment questionnaire

	EO		IO		L60x		L1x		Total
	mean	*(SD)*	mean	*(SD)*	mean	*(SD)*	mean	*(SD)*	mean
I expect that training on the Waterspot Simulator…									
is educational.	3.5	(1.0)	4.0	(0.8)	3.5	(1.0)	4.0	(0.0)	3.8
increases my insight in the water treatment process.	3.3	(1.0)	3.8	(0.5)	3.3	(1.5)	3.5	(0.6)	3.4
is fun.	3.8	(0.5)	3.8	(0.5)	4.0	(1.4)	4.3	(0.5)	3.9
I expect the chosen set-up to be a good way to increase my insight in the softening process.	3.8	(0.5)	3.8	(0.5)	3.0	(1.4)	3.5	(0.6)	3.5
I expect that the Waterspot Simulator is a good tool to train new operators.	4.3	(0.5)	3.8	(0.5)	4.0	(0.8)	4.5	(0.6)	4.1
I expect that training with an accelerated simulation speed gives an increase in learning for controlling the drinking water treatment process.	4.0	(0.8)	3.8	(0.5)	3.5	(1.3)	4.3	(0.5)	3.9

B-2. post-experiment questionnaire

	EO		IO		L60x		L1x		Total
	mean	*(SD)*	mean	*(SD)*	mean	*(SD)*	mean	*(SD)*	mean
Training on the Waterspot Simulator…									
is fun	4.5	(0.6)	4.0	(0.0)	4.0	(0.0)	4.0	(0.0)	4.1
is educational	3.8	(1.3)	4.0	(0.8)	4.0	(0.8)	4.0	(0.0)	3.9
gives an increase on the insight of the water treatment process	4.3	(0.5)	4.3	(0.5)	4.3	(0.5)	4.0	(0.0)	4.2
can replace the current training method completely.	2.5	(0.6)	2.5	(1.0)	3.0	(0.0)	2.5	(0.6)	2.6
is a good addition to the current training method.	4.0	(0.0)	4.0	(0.0)	3.3	(0.5)	4.0	(0.8)	3.8
chalenges to optimize the treatment process.	4.0	(0.8)	4.3	(0.5)	3.8	(0.5)	4.5	(0.6)	4.1
chalenges to increase my insight in the treatment process.	3.8	(1.3)	4.3	(0.5)	4.5	(0.6)	4.5	(0.6)	4.3
To increase my knowledge about the water treatment process I like to…									
study from books.	3.5	(1.0)	3.5	(0.6)	3.8	(0.5)	3.3	(0.5)	3.5
walk along with more experienced operators.	3.0	(1.4)	4.5	(0.6)	4.0	(0.8)	4.3	(0.5)	3.9
train on the Waterspot Simulator.	3.5	(1.0)	4.3	(0.5)	3.8	(0.5)	4.0	(0.0)	3.9
To increase my knowledge about the water treatment process it is effective to…									
study from books.	3.5	(1.0)	3.5	(0.6)	3.8	(0.5)	3.8	(0.5)	3.6
walk along with more experienced operators.	3.0	(0.8)	4.3	(0.5)	4.3	(0.5)	4.3	(0.5)	3.9
train on the Waterspot Simulator.	3.3	(1.0)	3.8	(0.5)	4.0	(0.0)	4.3	(0.5)	3.8
The Waterspot Simulator									
can be used to discriminate between good and bad operation.	3.3	(0.5)	3.5	(1.0)	3.8	(0.5)	3.5	(0.6)	3.5
is a good approximation of the reality.	3.8	(0.5)	4.0	(0.8)	2.8	(0.5)	3.8	(0.5)	3.6
When the simulation speed of the Waterspot Simulator is accelerated									
different settings can quickly be tested. This gives an increase of my insight in the process.	4.0	(0.8)	4.5	(0.6)	4.3	(0.5)	3.8	(1.0)	4.1
I lose my feeling of the process.	3.5	(0.6)	1.8	(0.5)	3.5	(1.3)	2.5	(0.6)	2.8
Average of both questionnaires, excluding the last (negative) question	3.6	(0.9)	3.8	(0.7)	3.7	(0.8)	3.9	(0.7)	3.8

2.

Supplementary Materials

2.1

Literature survey: *"Evaluation of a Water Treatment Plant Simulator for Training of Operators"*

L1181
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Evaluation of a Water Treatment Plant Simulator for Training of Operators

Literature Study (ME2510)

Michiel van der Wees
Wb1043706

December 2008

Delft University of Technology

Abstract

Drinking water treatment plants are increasingly automated. As a result operator skills decay and natural training diminishes. To counter this undesired side effect, extra operator training is required. The Waterspot project was started to create a simulator of a drinking water treatment plant: the Waterspot Simulator. This simulator will serve as a training tool and as a decision support system for operators and technologists. It is the first water treatment plant simulator where quality, quantity and control models are combined into one simulator. Making it easy to evaluate various scenarios and control strategies. To prove the effectiveness of the Waterspot Simulator as a training tool, evaluation is necessary.

In this literature study theories of learning were investigated. Skill versus practice in general seems to follow an exponential fit. This exponential law might describe the learning curve of the Waterspot Simulator well, giving an indication of the learning rate on the simulator.

Next evaluation methods were compared. Four frameworks were found; all based on, and including, Kirkpatrick's (1979) four level model. This model describes four steps of evaluation: reaction, learning, behavior and results. With each evaluation step the effectiveness of a training method is evaluated more thoroughly and the correlation of the result of the evaluation with the actual result of the training, gets stronger.

Finally performance measurements are necessary for evaluation of the Waterspot Simulator. Performance can be (subjectively) indicated by trainers, can be measured by rating the decisions taken by trainees or can be measured by measuring the result of the trainee's actions. The latter is found preferred since it gives the most objective, quantitative measurement.

It was concluded that evaluation of the Waterspot Simulator should be done on the basis of the augmented framework of Alliger et al. (1997): affective reactions, utility judgments and skill demonstration. A correlation study by Alliger et al. (1997) indicated that these three levels have a significant correlation with transfer of training. Therefore they are expected to be useful for indicating transfer of training.

Preface

This literature study is part of the final year of the Mechanical Engineering program of the Delft University of Technology, specialization Bio-Mechanical Design. It is connected to the final thesis.

It is written at the small Dutch software company UReason. Leen de Graaf provided useful notes and information, contributing to the result.

From the faculty Mechanical Engineering Joost de Winter and Stefan de Groot reviewed the work and provided useful remarks.

Delft, Januari 2009

Search Criteria

To find suitable literature, there was searched for the following topics and combinations of them:

- Simulators
- Training
- Operators
- Evaluation
- Control Room
- Decision Making

As the search progressed cited authors where also used. About 60 publications were found, of which 17 were used for this work.

Farmer et al. (1999) served as the major basis for this study.

Table of Contents

1. Introduction

Modern Drinking Water Treatment Plants (WTP's) are becoming fully automated to increase efficiency and produce a higher and more stable quality of the end product (Worm & Rietveld, 2006a). However, even highly automated processes require human operators for supervision, adjustment, maintenance, expansion, improvement and monitoring (Bainbridge, 1983).

Another result of automation is that the traditional operators adopt the role of supervisor, with a larger time span of control and less natural training; instead of sitting behind the control rods, he or she sits at home, only receiving messages when automation fails or the process is out of its operational window.

Due to this lack of natural training, skills of present operators decay and that of future operators are likely to never develop to a desired level at all (Bainbridge, 1983). Obviously this will lead to operators unable to perform adequate when upsets do occur.

To tackle this problem Worm and Rietveld (2006b) concluded that an operator training and support simulator is desired. In the Waterspot project such a simulator has been developed. With this simulator trainees can control a virtual plant; they can train various scenarios without having to upset the actual plant (which is obviously not desired for various reasons).

In the Netherlands there are 10 drinking water companies, serving 7.6 million connections. They produce over 1.2 billion cubic meters per year giving a turnover of 1.4 billion Euro (Vewin, 2008). In appendix 3 some automation projects on drinking water are described.

It might seem evident that the Waterspot Simulator is a suitable tool for training of operators. However, three often made assumptions about simulators as a training medium are:

- Simulation is all you need;
- more realistic is better;
- if the trainee's or trainers likes it, it is good,

all of which are invalid as stated by Salas et al. (1998). Therefore the Waterspot Simulator needs to be evaluated to judge if it is an effective tool for operator training. Two hypotheses are formulated:

- "Training on the Waterspot Simulator gives an increase in operator performance."
- "Training on the Waterspot Simulator gives an increase in the performance of students up to the level of experienced operators"

In this literature study, methods are evaluated in order to investigate these hypotheses. In chapter 2 an introduction to the Waterspot project is given. In chapter 3 the softening process (the water treatment step this research will focus on) is described. In chapter 4 some background is presented on training in general. In chapter 5 the training evaluation methods are discussed followed by required performance measurement methods in chapter 6. In chapter 7 the found methods are evaluated and a research proposal is made for evaluating the Waterspot

Simulator as a training tool. The conclusion of this literature study is given in chapter 8.

2. Waterspot

The Waterspot project was started to create a real-time WTP simulator to train the operators and provide them with a decision support system. The Waterspot Simulator should offer them more insight into the consequences of possible control actions, and be able to provide simulator based operator training. The Waterspot simulator is developed by a consortium of nine Dutch companies; four water supply companies: Duinwaterbedrijf Zuid-Holland, Waternet, PWN Waterleidingbedrijf Noord-Holland and Vitens; and Software developer UReason, DHV Water Engineers, ABB, Delft University of Technology and KWR are involved.

The central component of Waterspot is the UReason environment USE which is fed with simulator data from the Stimela model (water quality; described in section 2.1) as well as from EPANET (water quantity; described in section 2.2).

2.1. Stimela

Stimela is a modeling environment built in Matlab/Simulink that is developed by DHV Water BV and the Delft University of Technology. It is especially designed for water quality modeling (Helm and Rietveld, 2002).

For each treatment process modular models have been developed, which can be interconnected to form entire WTP's.

2.2. EPANET

EPANET is a public domain software tool, developed by EPA's Water Supply and Water Resources Division (EPANET, 2008). It is a modeling tool, containing models of various components, like pipes, tanks, valves, pumps and reservoirs, which can be connected to one another forming a network. When properties of the network are send to the EPANET environment, EPANET will give quantitative data in return, such as mass flows and levels.

For the Waterspot project EPANET is used to model the water distribution and flow networks of the WTP's.

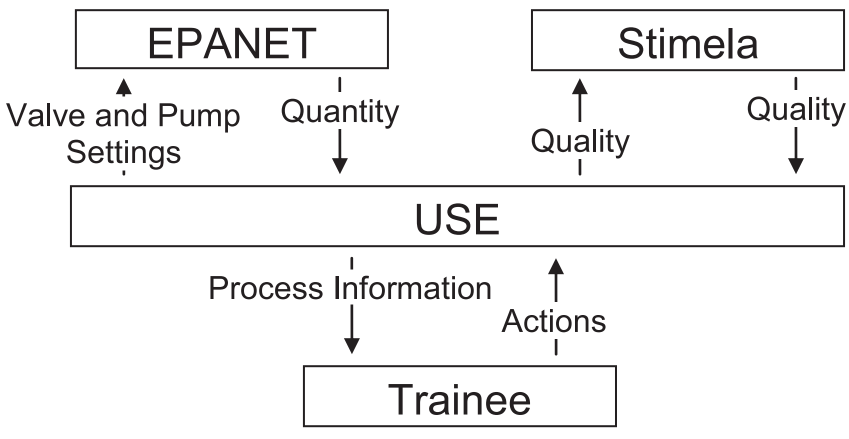

Figure 1: Schematic model of the Waterspot Simulator

3. Softening

In the water treatment process the water hardness is reduced in a softening step. This prevents limestone from forming in various types of household equipment. At the Weesperkarspel treatment plant (WPK), the water is softened in pellet reactors (Figure 2). At WPK the softening stage consists of 8 parallel pellet reactors, which can be turned on and off depending on water demand and maintenance.

These pellet reactors are highly sensitive to temperature fluctuations of the influent water (which occur on a yearly basis) and to demand fluctuations (as they occur on a daily basis). These slow (temperature) and fast (demand) fluctuations of the softening process makes it prone to produce upsets while at the same time making it hard to control. Therefore the research will focus on the Waterspot Simulator as a tool for training operators to control the pellet reactors.

A pellet reactor consists of a cylindrical vessel partly filled with seeding material. The seeding material consists of small grains, between 0.15 and 0.35 mm (usually river or garnet sand). The water is pumped through the reactor in upward direction, keeping the seeding material in a fluidized condition. At the bottom chemicals are dosed (usually caustic soda) so calcium carbonate becomes supersaturated and crystallizes on the seeding material, forming pellets.

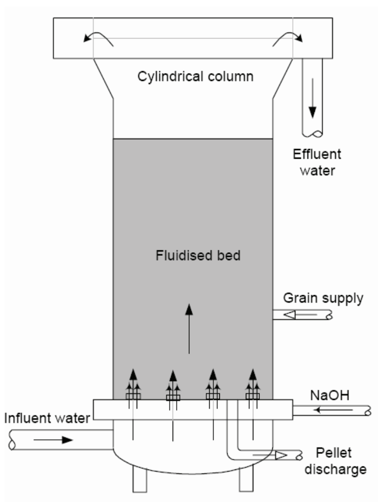

Figure 2: Pellet reactor

The softening process is optimal when the bed height is maximal, however an overflow might cause grains to be washed away with the affluent water. Since both crystallization rate and bed height are highly dependent on temperature (a low temperature gives a slow reaction rate and a higher bed height due to viscous properties) the water flow, need to be adjusted during the year. However, due to the long retention time of the pellets (typically around 100 days) future process states have to be part of the decision process. For example, when the operator wants to ad grains to raise the bed height in spring, he or she should bear in mind that the bed height will already increase due to the rise of temperature.

Usually the softening in the reactor is deeper than the required level (especially during summer temperatures), so part of the water can be by-passed and mixed with the effluent water of the pellet reactors.

Due to the limited contact time of the water with the pellets, the effluent water can still be supersaturated with calcium carbonate as it leaves the pellet reactor. The Saturation Index (SI) (the difference between the actual pH and the saturation pH of calcium carbonate) is used as an indicator for this supersaturation. To reduce the SI acid (mostly CO_2 or HCl) is added to the effluent water so limestone will not form downstream of the pellet reactors.

Because of the long retention time of the pellets, significant temperature changes during the year and fast demand fluctuations, a steady state process is never reached in the pellet reactors. However process disturbances have a major impact on the fluidized bed, and cause a decrease in process efficiency. The non steady state characteristics of the softening process, combined with the sensitivity to process disturbances make adequate control of this process of particular importance. And in the case of an automation failure (e.g. when pumps or automated valves fail) the human operator will have to be able to take adequate actions to prevent major disturbances in the fluidized bed's and limestone forming downstream of the softening process.

The possible consequences of automation failure in the softening step make it of particular importance for operator training, where the non steady state, dynamic characteristics make it also an interesting case for training evaluation.

4. Training of Operators

For a good evaluation of a training method, knowledge of training principles is mandatory. The following chapter describes the training process, in section 4.1 the mental model is briefly discussed, followed by Rasmussen's (1983) model of skill, rule and knowledge based behavior. The learning curve is explained in section 4.3, and in section 4.4 the use of simulators as training medium are described.

4.1. Mental model

A central theme in operator training approaches is that trainees have to acquire a mental model of the task, an integrated representation of the knowledge, structure, and principles underlying task performance (Farmer et al. 1999, p. 86; Dixon & Gabrys, 1991). In a study on differences between conceptual and operational knowledge Dixon and Gabrys (1991) concluded that operational knowledge is important for transfer of training, i.e. when subjects learn a task with operational similarity to a previously trained task, they may show positive transfer. Furthermore they note that there is little evidence that conceptual knowledge of a task has impact on future performance. This suggests that structuring the task itself (by hands on training), instead of actual knowledge about working principles (by studying from books for example), leads to increasing performance and transfer of training.

4.2. Skill, Rules, Knowledge based behavior

As the operators get trained at certain tasks, their behavior shifts from knowledge based to rule and skill based behavior (Rasmussen, 1983). The direct characteristics of skill based behavior (act without reasoning), frees up mental capacity and thereby reduces the stress the operator encounters (Farmer et al. 1999, p. 261). This process is also referred to as overtraining. However, a trap lies in skills or rules that might be applied, when they are actually not applicable, e.g. pouring milk into the sugar bowl.

4.3. The learning curve

Unsurprisingly tasks get faster and more accurate with practice. However, it is surprising that the rate and shape of this improvement is fairly the same for a great number of different tasks. From short perceptual tasks to team-based longer term tasks of building ships, the rate that people improve with practice appears to follow a similar pattern. Figure 3 shows such a learning curve for a simple task.

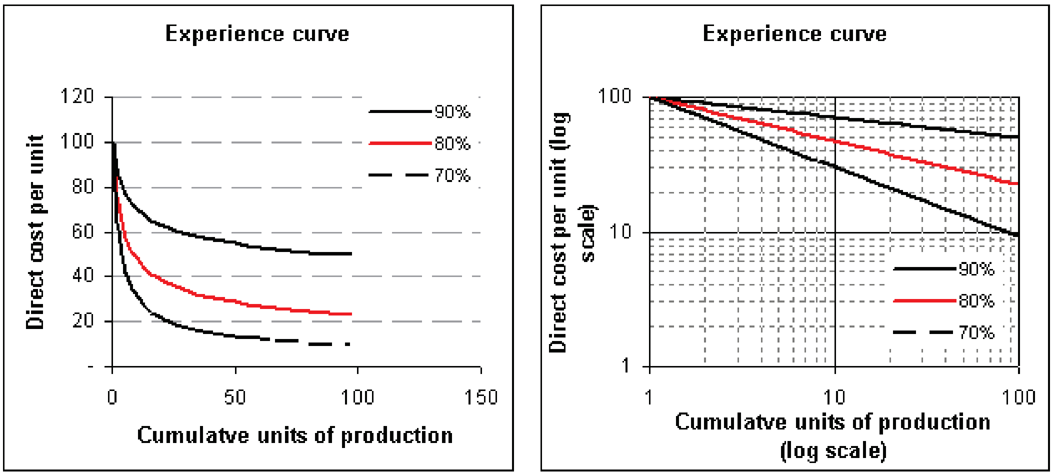

Figure 3: A typical Learning Curve (wikipedia.org)

Newell and Rosenbloom (1981) proposed the log-log law of practice to describe this curve:

$$Log\ T = Log\ B - a \cdot Log\ n \quad ,$$

where:

T is the time required to perform the task
B is the performance time on the first trial
a is the slope of the line, i.e., the learning rate
n is the trial number

This equals to the (generally excepted) power law of practice (Newell and Rosenbloom, 1981):

$$T = B \cdot n^{-a}$$

Due to the wide variety of tasks where this power law applies it is also known as 'the ubiquitous law of practice'.

However recent studies show that the power law of practices is actually an artifact arising from averaging over control groups, and is poor in describing individual learning. An exponential function might give a better fit (Ritter and Schooler, 2002):

$$T = a \cdot e^{-n-P},$$

where P is the previous practice.

The exponential fit indicates that learning per trial equals a fixed percentage of what is left to be learned in stead of just slowing down as it would if it follows a power law.

4.4. Simulators as a training medium

Simulators are increasingly used as training media in various types of industry: operator control rooms, aviation, various types of medical interventions (ranging from endoscopy to anesthesia and labor), car driving, and are even used for dynamic pricing in the sales industry (Dimicco et al., 2003). Some practical reasons for using simulators as a training medium, instead of real life training, are given by Farmer et al. (1999, p. 61):

1. Real life is too dangerous (e.g., emergency procedures)
2. Conditions are not available in real life (e.g., training desert operations in the Netherlands)
3. Insufficient opportunities to train on the real system
    a. Too expensive
    b. Insufficient time available on the real system
    c. Circumstances required for training do not occur frequently enough
    d. Possibilities for training are restricted by environmental regulations (noise, pollution…)
    e. Safety regulations preclude the execution of particular tasks or maneuvers (high speed chase).

Next to these practical reasons several didactic reasons for using simulators as training media are given:

1. Control of the type and timing of training events that are presented and, hence, the learning experiences that are offered to the trainee(s). This enables the provision of more learning experiences per unit of time and the planned distribution of learning experiences.
2. Adapting the training task to the performance of the trainee(s).
3. Providing augmented cueing and feedback, i.e. cues and feedback extrinsic to the (training) task.
4. Objectively registering and diagnosing trainee performance (e.g., for debriefing and/or administrative purposes).
5. Automating the process of training and instruction and consequently improving efficiency.

Usually some level of knowledge is required to perform the simulator task at all. Initial training is usually provided by instructors in a classroom, by a textbook, or sometimes by part-task simulators to train the various subtasks. As the experience of the trainees increases, trainees become able to handle more tasks simultaneously and the complexity of the scenario's can be increased accordingly.

4.5. Conclusion

This chapter provided an overview of learning theories. It seems that operators acquire operational models of the practiced tasks, allowing them to act on basis of previously encountered similarities. This makes their behavior shift from knowledge toward skill based behavior, and they no longer have to reason towards actions to take, making them increasingly time efficient in their task.

Next the learning curve was discussed. It was shown that performance during practice runs can be described with a learning curve model. When a good fit can be found during training on the Waterspot Simulator, it might be able to use this curve to make some predictions of how learning will progress after more extensive training. It might thereby give an indication of the benefit of more extensive training. This might be useful in evaluating training on the Waterspot Simulator.

5. Evaluating training

Evaluation of training programs is important since it can help to justify the training budget of organizations by demonstrating of the added value. It might discover areas of training programs that fail to meet expectations, providing opportunities for future improvement. And it might prove generally accepted assumptions about training programs wrong (Salas et all., 1998). In literature various evaluation guidelines where found, however all of them are based on Kirkpatrick's four level evaluation model (Kirkpatrick, 1979).

In section 5.1 the Four Step Evaluation Model of Kirkpatrick is elaborated, followed by a discussion on this model in section 5.2.

5.1. The four step evaluation model of Kirkpatrick (1979).

The evaluation model of Kirkpatrick consists of four steps. As the evaluation progresses, the result of the evaluation gives more guarantee that the training program worked. However they are increasingly difficult to perform. The four steps are described as follows:

- Step 1: Reaction
- Step 2: Learning
- Step 3: Behavior
- Step 4: Results

The next section elaborates on these four steps.

Step 1: Reaction

In the four level model of Kirkpatrick reaction is defined as how well the trainees and trainers like a particular training program. Favorable reaction is important because:

1. Decisions on future activities are frequently based on the reactions of one or more key persons.
2. Trainees are more likely to pay attention and learn the principles facts and techniques if the reaction is favorable.

Furthermore reactions can help the training director to improve future programs.

The reaction of the trainees can be measured by the use of rating charts of which some examples are given. They are included in appendix 1. In the opinion of Kirkpatrick the charts need to be designed so that they meet the standards below:

1. Determine what you want to find out.
2. Use a written comment sheet covering those items determined in step one above.
3. Design the form so that the reactions can be tabulated and quantified.
4. Obtain honest reactions by making the forms anonymous.
5. Encourage the conferees to write in additional comments not covered by the questions that were designed to be tabulated and quantified.

When the reactions measured are found positive the first step of evaluation is finished. However, there is no insurance that actual learning has taken place. Therefore the next step of Kirkpatrick is to evaluate the learning.

Step 2: Learning

As the reaction is measured, the next step of the evaluation process is to evaluate the actual learning that occurred in the training program. In Kirkpatrick's four level model learning is defined as follows: "What principles, facts, and techniques were understood and absorbed by the conferees?" In other words: the transfer from these principles, facts and techniques to on the job behavior is of no interest yet. They will be evaluated in step 3.

For learning evaluation a measurement procedure needs to be established. Some guidelines are given:

1. The learning of each conferee should be measured so that quantitative results can be determined.
2. A before-and-after approach should be used so that any learning can be related to the program.
3. As far as practical, the learning should be measured on an objective basis.
4. Where practical, a control group (not receiving the training) should be used to compare with the experimental group which receives the training.
5. Where practical, the evaluation results should be analyzed statistically so that learning can be proven in terms of correlation or level of confidence.

These guideposts indicate that learning evaluation is already more difficult as reaction evaluation. For statistical relevance large groups of subjects might be needed and a method has to be defined for an objective measurement of the learning.

Step 3: Behavior

Now that both reaction and learning are evaluated, it might be concluded that the training program is successful. However this is not necessarily the case. Learning in a training program does still not ensure improved behavior on the job. It seems five requirements need to be met before a person is going to change his/her behavior on the job:

1. He must want to improve.
2. He must recognize his own weaknesses.
3. He must work in a positive climate.
4. He must have some help from someone who is interested and skilled.
5. He must have an opportunity to try out the new ideas.

To evaluate a training program in terms of behavior improvement again five guidelines are given:

1. A systematic appraisal should be made of on-the-job performance on a before-and-after basis.
2. The appraisal of performance should be made by one or more of the following groups (the more the better):
    a. The persons receiving the training.
    b. Their superior/superiors.
    c. Their subordinates.
    d. Their peers or other people thoroughly familiar with their performance.
3. A statistical analysis should be made to compare before-and-after performance and relate changes to the training program.
4. The post-training appraisal should be made three months or more after the training so that the trainers have an opportunity to put into practice what they have learned. Subsequent appraisals may add to the validity of the study.
5. A control group (not receiving the training) should be used.

It is evident that behavior is even more difficult to evaluate than learning. Again large groups of subjects need to be measured, but they also need to be measured three months after the training program is completed. On top of that drinking water treatment plants are operated by only a hand full of operators, making it impossible to draw a statistical relevant conclusion.

Step 4: Result

Most training programs are set up to reach a certain goal: reduction of costs; reduction of turnover and absenteeism; increase in quality and quantity of production. Therefore it is most useful to finally evaluate training programs in terms of "results". This is however is most difficult to measure. At first there has to be made an before-and-after evaluation of the specific variable (lets say production costs) and secondly, all influential factors other than training have to be excluded to be sure the difference between the measurement can be attributed to the training.

5.2. Discussion on the Four Step Evaluation Model of Kirkpatrick.

Kaufman

Kaufman (1996) argued that the four level model of Kirkpatrick is not complete and should include a fifth level, describing societal improvements.

Holton III

According to Holton III (1996) the main problem of the four level model is the absence of causal relations between the various levels. He proposes a new evaluation model which describes all influences on the levels of Kirkpatrick (Figure 4). The first level of Kirkpatrick was excluded from this model since no significant correlation was found between reaction and outcome. Although this model might give a complete representation of the training process, due to the large number of influences and relations it is merely practical for evaluation.

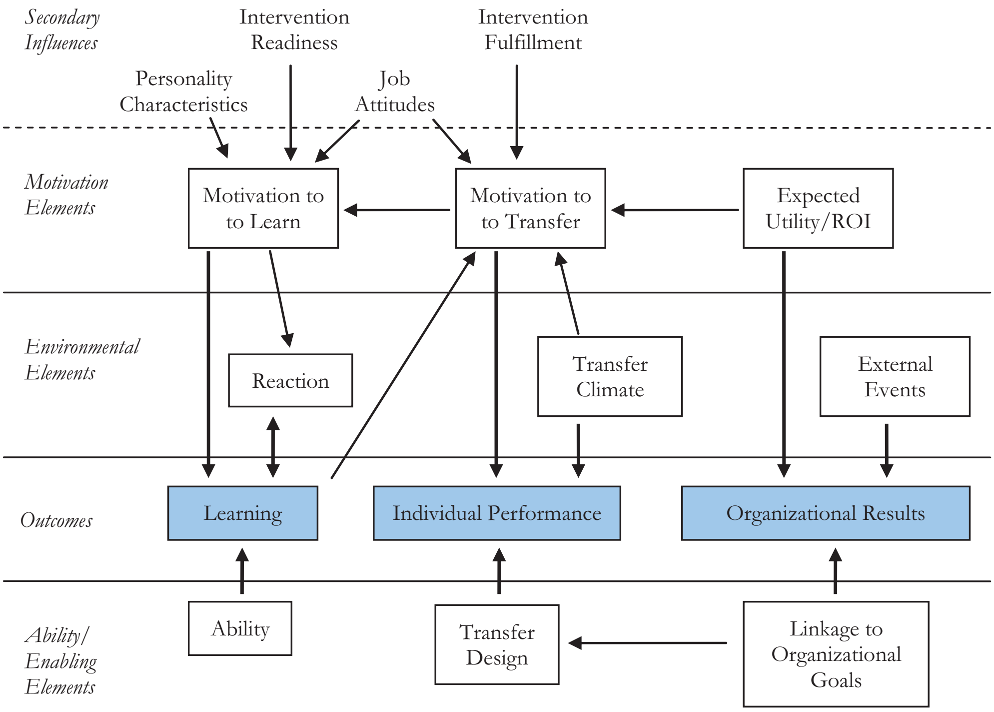

Figure 4: Model by Holton III (1996)

Alliger

Despite the discussed problems of Kirkpatrick's model and proposed new models, the four level model still serves as a major basis for evaluation. To get a deeper insight in the relation among the training criteria Alliger et al. (1997) performed a study. At first they presented an augmented taxonomy based on Kirkpatrick's taxonomy. The goal of this augmented framework was to provide a finer distinction among training criteria for the meta-analysis that followed.

Table 1: Training Criteria Taxonomies (Alliger et al. 1997).

Kirkpatrick's taxonomy	Augmented framework
Reactions	Reactions
	Affective reactions
	Utility judgments
	Combined judgments
Learning	Learning
	Immediate knowledge
	Knowledge retention
	Behavior/skill demonstration
Behavior	Transfer
Results	Results

A table with the found correlations is included in appendix 2. As expected it was found that from the reactions utility judgments have the highest correlation with transfer. With a correlation of 0.18 about 3% of the variance between the results of various training evaluations is explained. When corrected for reliability these correlations are expected to be larger. It should be noted that the correlations are found across various training methods where large differences in setup are suspected. Therefore large correlation coefficients are not to be expected in this study. Affective reactions are uncorrelated to other indicators. However, affective reactions are still of importance in evaluating a training program. Negative affection is likely to have an adverse effect on willingness to learn (and thereby affecting learning).

Surprisingly, the correlations found for immediate knowledge (0.11) and knowledge retention (0.08) actually have a lower correlation with respect to transfer than utility judgments. A possible explanation is that trainees' utility reactions are influenced by their knowledge of the work environment, whereas the measurements of immediate knowledge and knowledge retention might not naturally have this link. Behavior/skill demonstration shows the same correlation with transfer as utility judgment (0.18). Note the relation of behavior/skill demonstration with operator knowledge and the relation of immediate knowledge and knowledge retention with conceptual knowledge from section 4.1. There were only four studies found providing correlation on results, therefore Alliger et al. had not focused on that level.

In an evaluative study on training evaluation, performed by Haccoun and Saks (1998) it was found that the augmented framework of Alliger et al. (1996) might be a useful update to Kirkpatrick's model. Furthermore they confirmed that trainers should measure the utility judgments of trainees, since they will provide early indicators of transfer.

6. Performance Measurement

To measure skill improvement during a training intervention, performance measurement is essential. Furthermore, effective performance measurement can be a useful tool to provide trainees and trainers with accurate feedback to improve performance.

This chapter briefly discusses some performance measurement techniques as discussed by Farmer et al (1999). In section 6.1 requirements for the Waterspot Simulator are discussed, followed by a discussion on possible methods in section 6.2. A conclusion is given in section 6.3.

6.1. Requirements for performance measurement

In psychology, performance experiments initially followed a 'small and simple' paradigm, in which attempts were made to study individual elements of performance such as memory of motor control. However, even simple laboratory tasks do not allow study of single mental processes in isolation. Although this might suggest that study of the complex task is preferable, this will prove even more problematic. Performance on such tasks is difficult to measure and may involve a large number of variables.

Three problems of performance measurement are indentified:

- The nature of the skill: perceptual-motor skills are easier to measure than cognitive skills, such as decision making that may be associated with little overt activity.
- Timelocking of responses to external stimuli: In complex tasks, the external events that triggered particular actions cannot always be clearly identified.
- Definition of optimal performance: In decision-making tasks it may be difficult to define clear and unequivocal criteria for optimal performance.

For evaluation of the Waterspot simulator performance of the trainees should be measured during the training. The measured performances should be comparable, and it should be possible to fit a learning curve through the performance data. Therefore objective quantitative performance data is preferred.

6.2. Available methods for performance measurement

Various methods are available for performance measurement. The most appropriate performance measurement depends on the nature of the task to be trained. For cognitive tasks, like operating a plant, Farmer et al. gives roughly three ways of measuring performance:

- verbal, subjective reports;
- measures of the process involved in decision making;
- measurement of outcome.

Subjective measures, usually based upon a rating scale, represent the opinion of experts or trainees and will provide qualitative data. Objective measures might be collected directly from performance, such as deviation from a required track, and will provide quantitative data.

Subjective measures are usually easier to implement and expert evaluation can take specific circumstances into account. However, subjective measures are likely to be influenced by biases, pre-conceptions and memory limitations. Moreover they may be unevenly rated by large performance peaks and objective comparison between subjective measures is impossible. Subjective measures are mainly applicable for reaction measurement.

The process measures are also mainly based on rating scales and checklists. Correct and incorrect actions are defined and given specific weights. Although this gives semi-objective data, it still gives highly qualitative data which is hard to compare.

For simulators measurements of outcome are more readily provided objectively. The various variables of the process (for example cost of resources or the deviation of the optimal path) can be incorporated in a cost function which in turn gives an overall performance measure. This quantitative measurement can be used to compare before and after performance and to find learning curves.

6.3. Conclusion

In this chapter requirements and methods for performance measurement were discussed. To be able to compare various performance levels, quantitative information is required. Measurements of outcome might give this quantitative information, if performance is determined on basis of specific process variables (hardness of the effluent, costs of production) or a cost function of various output variables.

For reaction, objective measurements of outcome are not applicable, therefore they will need to be measured on a subjective, qualitative basis with the use of rating scales.

7. Evaluating the Waterspot Simulator

7.1. Evaluation framework

To evaluate the hypotheses evaluation is required. In chapter 5 some evaluation models where discussed. To find the most suitable model for evaluating the Waterspot Simulator a comparison is made of the found models on the basis of their strengths and weaknesses.

Kirkpatrick (1979)

Strength:

- Widely applied do to appealing look.

Weaknesses:

- Most of the times only the first two levels are applied, due to the increasing impracticality of the higher two levels.
- Lack of evidence for correlation between the various levels.

Holton III (1996)

Strength:

- Very complete model, describing all relevant aspects of training and their interactions, making it useful to find weaknesses of a training program.

Weakness:

- The completeness makes it also very cumbersome to implement.

Kaufman (1996)

Weakness:

- Actually the same model as Kirkpatrick, however with inclusion of a fifth level, even less practical as the third and fourth level of Kirkpatrick.

Alliger et al. (1997):

Strength:

- Based on the appealing model of Kirkpatrick, with some division in level 1 and level 2.
- Supported by correlations.

Considering these findings it can be concluded that an evaluation on the basis of Alliger et al. (1997) is the most appropriate choice for evaluation of the

Waterspot Simulator. The completeness of Holton III (1996) might also look appealing; however the goal of the present research is not to improve the training program but only to check if it is an effective program. Therefore the underlying relations are not of interest.

The correlations found by Alliger et al. (1996) indicate a positive relation between utility judgments and skill demonstration versus transfer of training. Utility judgments are generally easy to measure using tabular questionnaires. Skill demonstration can be readily easy measured within the Waterspot Simulator itself, by the use of performance measurement of outcome as discussed in chapter 6. Therefore the evaluation of the Waterspot Simulator will focus on these two levels. Furthermore, due to the acknowledged importance of affective reactions, these will also be evaluated.

Table 2: Levels to be used for evaluation of the Waterspot Simulator (indicated in bold).

Kirkpatrick's taxonomy	Augmented framework by Alliger et al. (1996)	
Reactions	Reactions	
		Affective reactions
		Utility judgments
		Combined judgments
Learning	Learning	
		Immediate knowledge
		Knowledge retention
		Behavior/skill demonstration
Behavior	Transfer	
Results	Results	

The affective and utility reactions will be measured after the training with tabular questionnaires. This will give qualitative information about the training program, able to indicate whether the training was effective in teaching the trainees the required skills.

Skill demonstration will be measured before, during and after the training. They will be measured on an outcome basis as discussed in chapter 6. Various variables (e.g. effluent water quality, the use of resources, control actions) will serve as performance indicators. A cost function will serve to extract a final performance measurement of the various data. Experts will be counseled to give the variables weight factors in this cost function.

The skill demonstration measurements will provide quantitative data about the performance of the trainee, making them suitable to compare the performance of the trainee before and after the training. And as it can be measured during trainng sessions as well it might also provide useful data for fitting learning curves and give information about the rate of learning on the simulator.

7.2. Training Scenario's

For the training program scenarios need to be designed. Experts will be counseled to find useful scenarios for training, such as pump failures, temperature changes and demand fluctuations.

To make sure unwilled side effects of overtraining (section 4.2) will be noticed in the evaluation of the training, different scenarios will be created which might trigger the same skill based behavior. This will increase the change of mislapses to occur, and makes it possible to identify them.

8. Conclusion

In this literature study two hypotheses where stated: “Training on the Waterspot Simulator gives an increase in operator performance.” and “Training on the Waterspot Simulator gives an increase in operator performance up to the level of experienced operators”. Goal of this literature study is to find evaluation methods to evaluate these hypotheses.

To answer the first hypothesis four models were found and discussed. It was concluded that the evaluation of the Waterspot Simulator should be done with the use of three levels of the augmented framework of Alliger et al. (1997). Reaction measurement (both utility judgments as affective reactions) should be done on basis of a tabular questionnaire and skill measurement on the basis of outcome measurements and some cost function (yet to be defined).

To answer the second hypothesis deeper insight in the learning is required. Therefore performance measurements of outcome (which will give objective and quantitative data) will also be measured during training runs on the Waterspot Simulator. These measurements will than be used to analyze the learning curve of the trainees on basis of the Power Law of Learning. The learning curve will give more quantitative information about the amount of learning on the Waterspot Simulator, to support the second hypothesis.

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Appendix

1. Examples of rating charts (Kirkpatrick, 1979)

Figure 1 Rating chart.

Leader Subject

Date

1. Was the Subject Pertinent to Your Needs and Interests?

☐ No ☐ To Some Extent ☐ Very Much So

2. How Was the Ratio of Lecture to Discussion?

☐ Too Much Lecture ☐ O.K. ☐ Too Much Discussion

3. How About the Leader?

	Excellent	Very Good	Good	Fair	Poor
A. How well did he/she state objectives?					
B. How well did he/she keep the session alive and interesting?					
C. How well did he/she use the blackboard, charts, and other aids?					
D. How well did he/she summarize during the session?					
E. How well did he/she maintain a friendly and helpful manner?					
F. How well did he/she illustrate and clarify the points?					
G. How was his/her summary at the close of the session?					

What Is Your Overall Rating of the Leader?

☐ Excellent ☐ Very Good ☐ Good ☐ Fair ☐ Poor

4. What Would Have Made the Session More Effective?

____

____

____

Figure 3 Oscar Mayer & Co. evaluation form.

Key	Programs
A	Modern Leadership for Middle Management
B	Supervisors' Leadership in Cost Control
C	Developing Supervisory Skills
D	Human Relations for Foremen & Supervisors
E	Leadership and Growth
F	Creative Thinking for Supervisors
G	Human Relations for New Foremen
T	Totals

	A	B	C	D	E	F	G	T
Questionnaires returned:	3	3	5	11	5	1	1	29
1. I thought the program was:								
A. Very well organized and helpful	3	3	5	11	5	1	1	29
B. It was of some value								
C. It was poorly organized and a waste of time								
2. In reference to the subject content:								
A. It was all theory and of little practical value								
B. It was both theory and practical	3	2	2	3	1			11
C. It was very practical and useful	0	1	3	9	4	1	1	19
3. Concerning the quality of the instruction:								
A. The instruction was excellent	2	3	4	11	4	1	1	26
B. I would consider the instruction average			1		1			2
C. The instruction was of poor quality								

Figure 4 Supervisory Institute Program evaluation form.

IN GENERAL

1. How worthwhile was the Institute(s) for you?
   - ☐ Very worthwhile
   - ☐ Fairly worthwhile
   - ☐ Not very worthwhile
   - ☐ A waste of time
2. Did the Institute have:
   - ☐ Too much theory and not enough of the practical
   - ☐ Too much of the practical and not enough theory
   - ☐ About the right combination of theory and practice

HOW THE INSTITUTE WAS CONDUCTED

3. On the whole, the course was conducted
   - ☐ Very well
   - ☐ Fairly well
   - ☐ Poorly
   - ☐ Very poorly
4. Lecture and discussion
   - ☐ Too much lecture
   - ☐ Too much discussion
   - ☐ About the right amount of each
5. Discussion leaders
   - ☐ Too many from the University
   - ☐ Too many from business and industry
   - ☐ O.K.
6. Visual aids
   - ☐ Not enough movies, charts, etc.
   - ☐ Too much use of demonstrations, blackboards, movies, charts, etc.
   - ☐ O.K.

APPLICATION OF THE COURSE

7. Did the Institute apply to your particular operations?
   ☐ Yes ☐ Partly ☐ No

FOLLOW-UP

8. Would you like to attend another Institute?
   ☐ Yes ☐ No

COMMENT

9. Should these Institutes run for ☐ 5 days ☐ 4 days ☐ 3 days.
10. Please list 3 of your main problems:
    1. ______________________________
    2. ______________________________
    3. ______________________________
11. Comments or suggestions
    ____
    ____
    ____

2. Correlations found by Alliger et al. (1997).

Mean Sample-size Weighted Correlations Among Training Criteria

	Reactions						Learning							
	Affective		Utility		Combined		Immediate		Retained		Behavior		Transfer	
	r	n	r	n	r	n	r	n	r	n	r	n	r	n
<u>Reactions</u>														
Affective	.82 (.81)	12	.34 (.28)	3			.02 (.01)	11			.03 (.01)	9	.07 (.03)	6
Utility			.86 (.85)	5			.26 (.20)	6			.03 (−.08)	3	.18 (.12)	3
Combined					.82 (.80)	5	.14 (.09)	6			.12 (.07)	8	.21 (.16)	9
<u>Learning</u>														
Immediate							.77 (.75)	14	.35 (.29)	2	.18 (.16)	13	.11 (.08)	16
Retained									.58 (.53)	2	.14 (.05)	2	.08 (.03)	4
Behavior											.85 (.84)	9	.18 (.11)	7
<u>Transfer</u>													.86 (.85)	13

Note: Values in parentheses show lower 95% confidence bound for mean correlation; n is number of studies combined in calculating each mean correlation. Empty cells indicate that one or fewer correlations were available. Reliabilities are on the diagonal.

3. Model Predictive Control in the Drinking Water Industry

2.2

Internship report: ***"Model Predictive Control in the Drinking Water Industry: a Survey"***

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Model Predictive Control in the Drinking Water Industry: a Survey

Michiel van der Wees

Abstract

Water Treatment Plants are increasingly automated. As a result operators more often take the role of supervisors, who mainly just monitor the plant instead of continuously controlling it. As a result natural training becomes absent and the skills of the operators deteriorate. Therefore it was concluded that a simulator should be built to provide training and decision support for the operators. This simulator is currently being developed within the project Waterspot. The models developed for this simulator might also be used for optimizing the (currently still mainly heuristic) automated control of the treatment plants. They might provide predictions for a model predictive controller (MPC). MPC uses this predictions iteratively to find an optimal control strategy. This gives the controller the opportunity to adept its strategy to (expected) future changes.

This report provides an overview of the current progress of MPC in the drinking water industry. In literature MPC has already shown to be effective for different steps and aspects of the drinking water treatment. However since the model currently used in the Waterspot project is too slow to be used in one MPC controlling the whole plant, it might be preferable to use various controllers in a hierarchical structure. This could both enhance the speed of the models and also create better insight in the control strategies. Furthermore temperature and water demand models should be included for more effective control of the Drinking Water Treatment Plant.

Keywords: drinking water treatment, model predictive control, Waterspot

1. Introduction

Water Treatment Plants (WTP's) are more and more fully automated. As a result efficiency is increased and a higher and more stable quality of the end product is reached (Worm et al. [4]). This requires robust control, able to anticipate on process changes with a very wide range of time delays, as they exist in typical WTP's. These different time ranges make it difficult (if not impossible) for simple PID-like controllers, without any information on future process states, to control the WTP in an optimal way. It is for the controller as it would be for a rally driver without a navigator to tell him what corners are to be expected next.

Models of the processes to be controlled might provide a solution to this problem. They can be incorporated in a (numerical) simulation which can give the operator valuable information about future states. This will give him the possibility to look beyond the scope of hours into the scope of weeks and even months or longer. This will provide better insight in the problem and will help the operator to make an optimal decision. Therefore the Waterspot project was set up to develop a simulator of WTP's.

The next step would be controllers that are aided by these models and the information they give about the (near) future: Model Predictive

Controllers (MPC's). This type of controller uses the models of the process and expected disturbances to find an optimal control strategy for the near future.

This report provides and overview of the current progress of MPC in the drinking water industry.

The paper is organized as follows. At first an introduction to the Waterspot project is given in section 2, followed by a description of the treatment processes as they are found within the treatment plant Weesperkarspel in the Netherlands in section 3. The current control strategy is then briefly described in section 4, followed by a brief description of Model Predictive Control in section 5. In section 6 an overview of MPC in the drinking water industry is given, followed by a discussion in section 7. Finally a conclusion and recommendations are given.

2. Waterspot

Due to the increase in automation in WTP's a shift in operation is introduced. The traditional operator will more often adopt the role of a supervisor with a larger time span of control but less natural training, since he does not take part in daily operation. Therefore it was concluded by Worm and Rietveld [1] that a WTP simulator is desired. The Waterspot project was started to create a WTP simulator to train the operators and provide them with a decision support system which offers them more insight into the consequences of possible control actions. The Waterspot project is developed by a consortium of nine Dutch companies, four water supply companies: Duinwaterbedrijf Zuid-Holland, Waternet, PWN Waterleidingbedrijf Noord-Holland and Vitens. Furthermore Software developer UReason, DHV Water Engineers, ABB, Delft University of Technology and KIWA Water research are involved.

The central component of Waterspot is the UReason environment USE which is fed with simulator data from the Stimela model (water quality; described in section 2.1) as well as from EPANET (water quantity; described in section 2.2).

2.1. *Stimela*

Stimela is a modeling environment built in Matlab/Simulink that is developed by DHV Water BV and the Delft University of Technology. It is especially designed for water quality modeling [5].

For each treatment process models are being developed. The models are dynamic making it possible to monitor changes in time. This also makes it possible to use the various models for real time control.

Stimela contains different modular components for the various treatment steps, which can be interconnected to form entire WTP's. To illustrate this Stimela was actually named after the Zulu word for train.

2.2. *EPANET*

EPANET is a public domain software tool, developed by EPA's Water Supply and Water Resources Division [2]. It is a modeling tool, containing models of various components, like pipes, tanks, valves, pumps and reservoirs, which can be connected to one another forming a network.

For the Waterspot project EPANET is used to model the water distribution and flow networks of the WTP's.

3. Water Treatment Process

Drinking water treatment generally consists of a

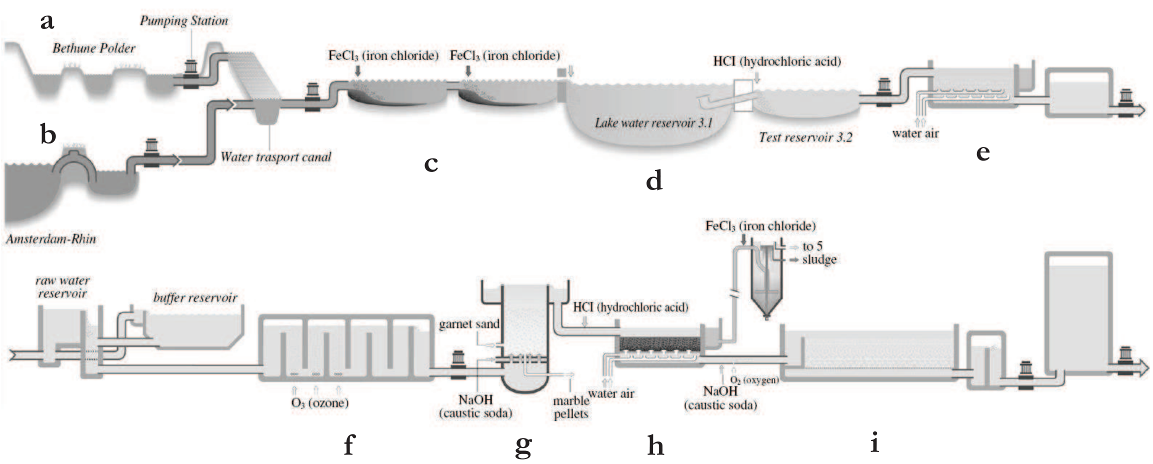

Figure 1: The process scheme of the drinking water production plant of Weesperkarspel [6].

number of steps, with various time constants and dependencies. As an example the Weesperkarspel Treatment Plant (WPK) is described (Figure 1). This WTP accounts for about 31 million m^3 per year. The drinking water is distributed without residual chlorine (as stated by Dutch regulations).

Water from the Bethune Polder (Figure 1a) and sometimes from the Amsterdam Rhine Canal (Figure 1b), is pretreated before it is transported to WPK. It is coagulated with ferric chloride in a settling tank, removing suspended solids, phosphate and heavy metals (Figure 1c). Further quality improvement is reached by sedimentation, biodegration and other auto purification processes in a reservoir of 130 hectares and a retention time of 100 days (Figure 1d). Rapid sand filtration (removal of ammonium, suspended solids and algae) finishes the pretreatment, and the water is transported to WPK (Figure 1e).

3.1. Ozonation (Figure 1f)

The first treatment process at WPK is ozonation. Ozonation is applied for disinfection, oxidation of natural organic matter, degradation of organic micro pollutants and for color, taste and odor improvement.

During ozonation byproducts can be formed such as bromate and biological degradable organic matter. The bromate forming is dependent on the bromide content of the influent water, and is often limited by legal standards. This limits the ozone dosage. The biological degradable organic matter has a positive influence on dissolved organic carbon (DOC) removal in biological filtration (see 3.3) but a negative influence on the biological stability of water and on clogging of biological filters [10]. The solubility of ozone in water is dependent on the water temperature; ozone is less soluble in warm water then it is in cold water.

3.2. Softening (Figure 1g)

After the ozonation process the water hardness is reduced in a softening step. This prevents limestone from forming in various types of household equipment as well as in the following treatment steps. The water is softened in pellet reactors (Figure 1 (bottom middle) and Figure 2). At WPK the softening stage consists of 8 parallel pellet reactors, which can be turned on and off depending on water demand and maintenance.

A pellet reactor consists of a cylindrical vessel partly filled with seeding material. The seeding material consists of small grains, between 0.15 and 0.35 mm (usually garnet sand). The water is pumped through the reactor in upward direction, keeping the seeding material in a fluidized condition. At the bottom chemicals are dosed (caustic soda) so calcium carbonate becomes supersaturated and crystallizes on the seeding material, forming pellets.

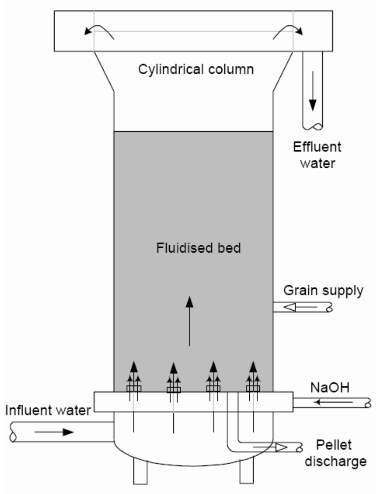

Figure 2: Pellet reactor [8]

The softening process is optimal when the bed height is maximal, however an overflow might cause grains to be washed away with the affluent water. Since the crystallization rate is highly dependent on temperature (a low temperature gives a slow reaction rate), the water flow, and thereby the fluidized bed height, need to be adjusted during the year. However, due to the long retention time of the pellets (typically around 100 days) future process states have to be part of the decision process. For example, when the operator wants to ad grains to raise the bed height in spring, he or she should bear in mind that the bed height will already increase due to the rise of temperature.

Usually the softening in the reactor is deeper than the required level (especially during summer temperatures), so part of the water can be by-passed and mixed with the effluent water of the pellet reactors.

Due to the limited contact time of the water with the pellets, the effluent water is still supersaturated with calcium carbonate as it leaves the pellet reactor. The Saturation Index (SI) (the difference between the actual pH and the saturation pH of calcium carbonate) is used as an indicator for this supersaturation. To reduce the SI hydrochloric acid is added to the effluent water so limestone will not form downstream of the pellet reactors.

Because of the long retention time of the pellets, significant temperature changes during the year and fast demand fluctuations, a steady state process is never reached in the pellet reactors.

3.3. *Biological Activated Carbon Filtration (BAC) (Figure 1h)*

The third step at WPK is an active carbon filtration step. Activated carbon is able to adsorb a part of the remaining organic matter containing micro pollutants as well as odor, taste and color producing compounds.

Activated carbon is a substance with a high carbon concentration (e.g., pit coal, turf). It is carbonated under high temperatures, where it is partially transformed into carbon monoxide and water. This gives the activated carbon its open structure with a large internal surface (Figure 3). Hence, a large part of the adsorbed substances is adsorbed inside the carbon.

Once in a couple of years the carbon gets saturated with adsorbed organic matter and the carbon needs to be regenerated. For this regeneration process the carbon has to be removed from the installation and heated to 1000 °C.

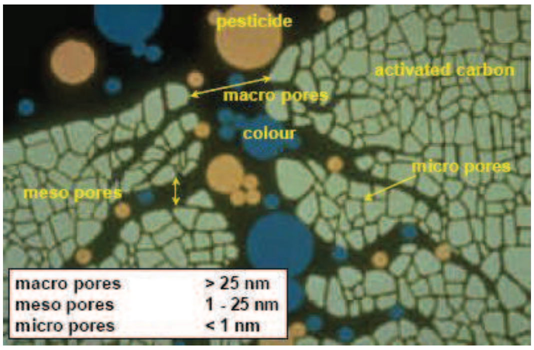

Figure 3: The open structure of activated carbon.

Activated carbon filters are mostly downflow operated. The contact time is the most important parameter for good adsorption; therefore filters are often executed with high beds, so the surface area can be kept small. to reduce the surface area. This makes gravity forces insufficient for operation and an extra pumping phase is required.

Bacteria that grow on the carbon will decompose organic material, effectively increasing the filter run time as well as the removal of organic matter. Due to the previous ozonation step the carbon is oxidized enhancing the biological activity; it is said to be "biological activated".

Because of the increased biological activity on the carbon the organic macro pollutants (DOC) will occupy less adsorption space and more space is left for the persistent organic micro pollutants. Some micro pollutants can even be decomposed after ozonation. The biological activity is temperature dependent meaning that the adsorption process will be strong in winter. However, organic material adsorbed in the winter might actually be decomposed in the summer. This phenomenon is called bio-regeneration.

As the various pollutants are decomposed, Assimilable Organic Carbon (AOC) is formed that will stimulate bacterial growth. Break through of AOC must be avoided to prevent regrowth of bacteria in the piped network. In addition bacteria can be eroded from the carbon surface into the effluent water, increasing the colony count. Therefore a disinfection step is required.

Besides the organic matter being adsorbed other suspended materials are filtered out of the water as well. These clog the filter bed and need to be washed out by backwashing (§ 3.5).

3.4. *Slow Sand Filtration (Figure 1i)*

The final step at WPK is slow sand filtration for further reduction of suspended solids. This is also the second important barrier against pathogens, especially pathogens with low susceptibility for ozone (such as the Cryptosporidium) as an alternative to chemical disinfection.

The filter has a small grain size (0.2 to 0.6 mm) and a filtration rate below 1 m/h. Therefore the filter has a large filtration area compared to other types of filtration. Slow sand filtration occurs mainly in the top layer of the filter where a biological "Schmutzdecke" is formed.

Due to this schmutzdecke backwashing is not suitable for cleaning slow sand filters. Instead the upper layer of about 1 cm has to be scraped. Since the slow sand filters are placed after various other filters the effluent water is hardly loaded with impurities, resulting in a filter runtime of several years.

3.5. *Backwashing*

During operation, the pores in filter beds become filled with accumulated suspended solids. As a result the porosity as well as the resistance are increased and the effluent water quality is degraded. This can be reversed by back washing the filter with clean water (filtrate).

When a filter is backwashed the water supply and the filter drainage are blocked. Next the backwash process is started. A combination of water and air is pumped through the filter bed in upward direction, cleaning the filter bed. When the filter bed is sufficiently clean the water flow is stopped and the filter is put into normal operation mode again. The effluent water shortly after backwashing is normally of poor quality, therefore it is drained to waste for a short period (the repending period).

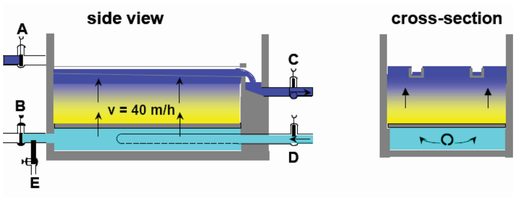

Figure 4: Backwashing

Due to the backwashing process the filter does not produce any effluent for 30 to 60 minutes. The back washing it self lasts about 20 minutes.

4. Current Control Strategy

The current control strategy at WPK is mainly heuristic. The water flow through the various process steps is controlled by simple PI controllers, dependent on the various water levels on the filter beds and reservoirs. This is done locally as well as globally. The efferent flow of a BAC is controlled by the water level on it and the flow into the first step of the plant (the ozonation) is controlled by the water level on the slow sand filters (on the end of the cleaning process). These water levels also act as a buffer for possible fluctuations.

The chemical dosages of ozone and caustic soda are controlled flow dependent; the amount of chemical per amount of water is kept constant; again using PI controllers. And the Saturation Index of the effluent water from the pellet reactors controls the dosage of hydrochloric acid with a PI controller.

An exception to the simple control structure of WPK is the control of the pellet reactors. More details on the recently implemented control strategy on the pellet reactors are found in 6.1.

5. Model Predictive Control

When a model of the process to be controlled is available, model predictive control (MPC) can be applied. Various types of MPCs exist as found in literature ([14], [15] & [16]) but the general principle is about the same:

Using a model of the system its response is calculated. This response is optimized given the possible control actions and the desired system state, with the use of a cost function. This cost function can contain criteria such as the amount of chemicals used, de deviation of the target quality of the end product, aggressiveness of control actions and other. The first step of the found control is implemented and the MPC algorithm starts over again (given the new system state), leading to a new control strategy.

MPC is an advanced control strategy, capable of handling non linear systems as well as system constraints.

When the model is too slow to provide this online control, offline MPC can be used to find an optimal control strategy. In offline MPC a simulation is used to find the optimal control strategy. This strategy is then implemented in the controller of the real process. A drawback of offline MPC is the loss of flexibility since new control strategies have to be calculated as the system is changed. When online MPC is used, only the model has to be updated.

A drawback of MPC is the effort that has to be put in modeling and tweaking of the controller. MPC's have a relatively large set of parameters such as the time over which the system response has to be calculated, the time over which the control actions have to be calculated, and setting up a cost function. All these different aspects of MPC affect the final performance of the operator.

6. Current research on MPC for WTP's

6.1. PROMICIT

In the PROMICIT project the aim is to achieve a breakthrough in drinking water quality control by developing an integral, dynamic model of the total water treatment plant and to use of this model as a basis for integral control of the goal factors quality, quantity, environmental impact, cost and redundancy and flexibility [6]. WPK of Amsterdam Water Supply is subject of this project.

Boskopper et al. [6] describe two case studies at WPK. In a case study on pellet softening it was concluded that considerable improvements in water quality as well as costs might be realized when control strategies are optimized. A decrease in operational costs of 10% is expected when MPC is applied.

The second case study was on Biological Activated Carbon filtration (BAC). It showed a positive effect of the use of ozone on the amount of biodegradable components in the BAC and an extension on the lifetime of the activated carbon. An increase of filter run times was demonstrated at WPK of 70%, with an applied ozone dosage of 1.5 mg/l!

Van Schagen et al. [7],[8] & [9] did further research on the pellet reactors step. A nonlinear model of the water softening process served as a basis for a Linear Model Predictive Controller for the softening process for drinking water treatment [7]. The model was calibrated using full-scale process measurements. The model was linearized for use in an MPC. This Controller was extensively validated in nonlinear simulations. Resulting in smoother operation of the process compared to the previously used heuristic controller and operator strategies.

Van Schagen et al. [8] proposed a hierarchical control structure existing of three levels of control. The top level is the total production of the plant, which is mainly determined by the reservoir levels and drinking water consumption. The intermediate level of control is the distribution of water over the various parallel process lanes and the lowest level is the control of the individual processes in each lane, which should be optimal for the set points given by the intermediate level controller.

Van Schagen et al. [9] focused on control of the fluidized bed height. This resulted in a controller where the caustic soda dosage controls the total hardness of the treated water (reactor plus bypass) and keeps it at a constant value of 1.5 mmol/l. The acid dosage after the treatment step keeps the Saturatinon Index of the treated water at a constant value of 0.3. Garnet sand dosage keeps the fluidized bed at the maximum height of 4.5 m for maximum crystallization surface and the pellet discharger uses the pressure drop over the bottom 40 centimeters, as a control input. The most important difference from the original operation is that the bed height is kept at the maximal 4.5 m and the pressure drop over the total height of the bed is not controlled.

For WPK, with an average production of 2800 m^3/h, the identified optimal solution leads to eight reactors in operation at 0° C. However an increase of water temperature will give an increase of the reaction rate, therefore more calcium carbonate can be extracted per pellet reactor. At a water temperature of 30° C this results in an optimal solution with only six reactors in operation (and an increase in bypass ratio) to remove the same amount of calcium carbonate.

It was concluded that the performance can be improved when the pellet size and bypass-ratio are kept at an optimal value, while maximizing the fluidized bed height. The main disturbance is the temperature of the effluent water, where the optimal pellet size and bypass-ratio show only small temperature dependencies, giving only small improvements in operator costs. For optimal control of the pellet diameter, prediction of the temperature variations is therefore necessary. An unexpected decrease of temperature will increase the bed height up to 1% per 1°C, which can only be corrected by discharging additional pellets, thus increasing the operational costs.

The final, and significant, remark states: "Small changes in water quality have large influences on the long term performance and control actions have influence on the fluidized bed composition weeks after the control action. It is therefore difficult to control the plant with only simple feedback control loops (normal reaction times in minutes) and the human eye (normal reaction time in hours) at an optimal operation point at all times". This makes MPC a very suitable control strategy!

Van der Helm et al. [10] calibrated and validated a model, describing ozonation of the water cleaning process. The model was capable of predicting ozone decay and ozone exposure, decrease in UVA_{254}, increase in AOC concentration and bromate formation on the basis of the applied ozone dosage. The model will be used at drinking water treatment plants at Weesperkarspel and Leiduin of Waternet for operational support of the current ozonation processes. It is also implemented in an MPC of a pilot ozonation plant at WPK (15m^3/h).

6.2. *Other research*

Abbas [11] did research on MPC for a reverse osmosis (RO) desalination unit. For the single variable case, where the permeate flow rate was controlled by the feed pressure, he found that use of the Dynamic Matrix Control (DMC) algorithm gave much better results as a control system based on conventional PI controllers. A faster response was produced by the DMC as well as less aggressive control of the manipulated variable resulting in less wear.

A second case study where both flow rate and product quality were controlled by manipulating the feed pressure and the pH showed a substantially better performance for the DMC algorithm compared to the conventional PI controllers.

Duzinkiewicz et al. [12] did a proposal for a two level hierarchical MPC that integrates quality and quantity control of a drinking water distribution system (DWDS) using chloride injections. The upper level controller operates according to the receding horizon strategy. Quantity and quality state information of the DWDS as well as the consumer demand prediction for the next 24 hours are send to the controller. The controller then calculates the optimal chlorine injections for the booster stations as well as optimal valve and pump settings, and sends the found control actions for the next two hours to the local controllers. Local disturbances are however unavoidable, therefore local controllers use online quality measurements as direct feedback and adjust their control accordingly.

This controller has been simulated in a DWDS, giving good results and performance of the controller. Further research should be concentrated on how to convert the demand prediction uncertainty into the modification of model parameter bound envelopes.

Price and Hankins [13] investigated the effect of controlling the pre-coagulation regime on the performance of downstream membrane filtration. For filter membranes with hollow fiber configuration, fouling is partially reversible by backwashing. Irreversible fouling however, requires chemical cleaning. This is cumbersome, requires shutdown of the cleaned unit for several hours, produces a waste stream and might affect the membrane life.

Inclusion of a pre-coagulation phase will improve the removal of constituents that produce irreversible fouling. However suboptimal coagulation conditions might lead to small colloidal and iron species present in the water, which will affect and clog the membrane, increasing the cleaning and operation costs.

The research has shown that the zeta potential (giving an indication of the electrical charge of the colloidal particles) can be used to detect changes in the coagulation process, and hence to determine appropriate dosage levels.

7. Discussion

In this paper an overview was given of the current development of MPC in the Drinking Water Industry. This gave an idea of it's advantages and disadvantages with respect to the traditional control strategies. For the Waterspot project it is concluded that it is an interesting development which might have major advantages in terms of operational costs and quality of the end product. However the current models are still to slow for overall online MPC control.

Control strategies in the Drinking Water Industry are still mainly heuristic. This makes it impossible to find an optimal control strategy to control a water treatment plant.

For an optimal control strategy, models of the various processes are needed. These models are currently being created within the Stimela and EPANET environment and integrated within the Waterspot WTP simulator. These models can also be used in Model Predictive Controllers, able to handle the non linear system properties, the various system constraints, the batch behavior of the filter beds (due to backwashing and regeneration) and last but not least: models of expected disturbances such as water temperature and water demand.

As was shown in the PROMICIT project, MPC is effective in the softening process. The large process dependencies of foreseeable process disturbances make it useful to model the future behavior of the process and of the disturbances to optimize the control inputs. For example, the rising water temperature in the summer will lead to an increase of the bed height. A controller should be aware of this long term system response, to prevent it from unnecessary grain dosing, which will only lead to extra pellet discharge. Various studies have already been done on the softening process at WPK showing promising results. Another WTP will probably implement an MPC in the softening process soon as well. With their current control strategy they have so little confidence in their control that they do not dare to adjust them to the fluctuating demand. Instead they soften deeper as required and reinject the overdose into the ground. There the water will reharden again, diminishing the treatment effect. The extra costs of this strategy are estimated around € 700,000 annually.

For plants with an ultra filtration phase MPC has shown effective for optimizing coagulant dosage in the pre coagulation phase. This illustrates the effectiveness of MPC in combining various treatment processes to find optimal control. This might also be of great importance for the ozonation process since this has influence on the biological activity in the BAC filtering.

For the various filter processes, the batch behavior (due to backwashing, regeneration and scraping) makes MPC an effective control algorithm. It might be effective for finding optimal moments for backwashing, BAC regeneration, and scraping. Furthermore, the temperature dependence of the slow biological processes in the BAC and the Slow Sand Filter makes MPC superior to PI control. For example, when the BAC filter bed is suspected to be saturated at the end of the winter, rising temperatures might activate bio-regeneration. This might delay the need for regeneration and thus improve the filter run time.

On a notebook (Intel Core 2 Duo, T7400 running @ 2.16GHz with 2GB of RAM and Windows XP SP2) the total Waterspot model of WPK runs at most 3600 times real-time. As a result the calculation of the response for about a year (which is required to take account for the slow nodes of the WTP) takes up to 02:26 hours, much slower as the fast nodes of the WTP and therefore not useful for effective MPC.

Other strategies might prove to be more effective than integral MPC. Instead various processes might be decoupled, and combined in an hierarchical structure as proposed and proven effective on a smaller scale in literature ([7],[8],[12]). Apart from enhancing the speed of the control this might also give more insight in the found control strategy.

Another way to reduce the computational demand is Offline MPC as described in §5, or calculating step responses using the found models, and then using the found responses in a step response based model for the MPC. However this might result in a black box controller with little insight in the actual process, and might therefore not be preferable for the operators. Furthermore this would make is far less adaptable to possible process changes.

The various models might give a good possibility for MPC, however an overall MPC might not be preferable. Instead a hierarchical control structure with the use of various MPC's should give good results. As they have in various other cases. Furthermore the Waterspot model should be extended with a temperature and demand prediction model to enhance the effectiveness of MPC control.

For the ozone dosage no significant improvements are expected when MPC is applied due to the absence of long time delays. However since it influences the BAC further on in the process, MPC on the combined process of ozone dosage and BAC might give large improvements on the BAC filtration process.

In the softening process several studies on MPC have been done, all indicating major improvements when MPC is applied.

The BAC performance might be effectively increased by controlling the ozone dosage with an MPC, as discussed previously. MPC might be used on the BAC process to find the optimal time for starting the backwashing process as well as the regeneration process. This is particularly of interest since the BAC filters might bio-regenerate in spring due to rising temperatures, which might prolong their life significantly, increasing their overall up time, and effectively reducing the costs of regeneration. If this is combined with MPC control of the ozone dosage the bio-regeneration of the BAC might even be further optimized on expected temperatures.

For the slow sand filters the most important control action is when to scrape the top layer of the filter bed. However since the mainly biological process is not yet fully understood, models don't yet exist. As a result its dependencies are not known and the impact of MPC on the slow sand filters is hard to predict. But it seems apparent that the biological filtering process is temperature dependent, as well as the regeneration of a new "schmutzdecke", which makes MPC a suitable control strategy.

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Abbreviations

WTP	(drinking) Water Treatment Plant
WPK	drinking water treatment plant at Weesperkarspel
DWDS	Drinking Water Distribution System
RO	Reverse Osmosis
NOM	Natural Organic Matter
BAC	Biological Activated Carbon
DOC	Dissolved Organic Carbon
AOC	Assimilable Organic Carbon
TOC	Total Organic Carbon
THM	trihalomethanes
SI	Saturation Index
UVA_{254}	UV absorbance at 254 nm
MPC	Model Predictive Control
NMPC	Non Linear Model Predictive Control
LMPC	Linear Model Predictive Control
DMC	Dynamic Matrix Control
MBC	Model Based Control
PID	Proportional–Integral–Derivative Controller
LQR	Linear Quadratic Regulator

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Other Interesting Literature

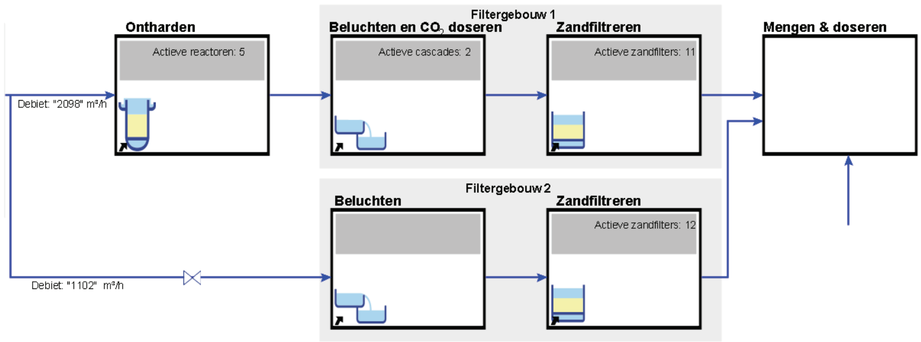
[17] C.W. Baxter, Q. Zhang, S.J. Stanley, R. Shariff, R-R.T. Tupas and H.L. Stark (2001) *Drinking water quality and treatment: the use of artificial neural networks.* NRC Research Press Website
[18] Alan Hugo *Limitations of Model Predictive Controllers*

2.3

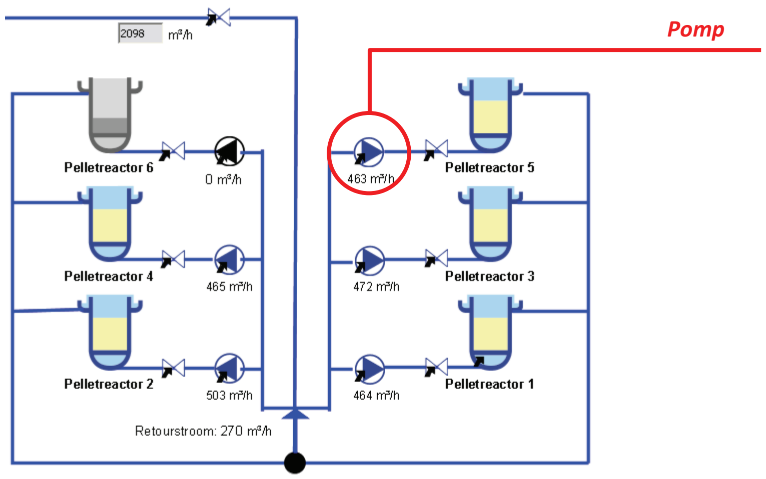
Instruction set as given to the subjects

Bediening Waterspot Simulator

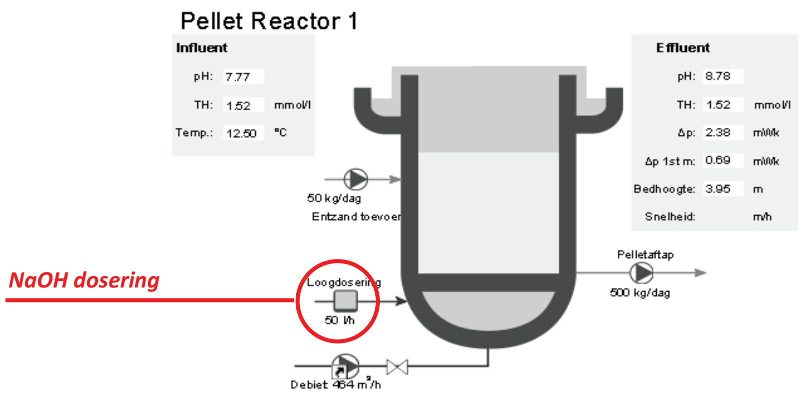
In de Waterspot Simulator kan genavigeerd worden door op de betreffende substappen te klikken (telkens een enkele klik, soms duurt het een moment voor het nieuwe scherm opent). Zo kan er bijvoorbeeld van figuur 1 naar figuur 2 genavigeerd worden, of van figuur 2 naar figuur 3.



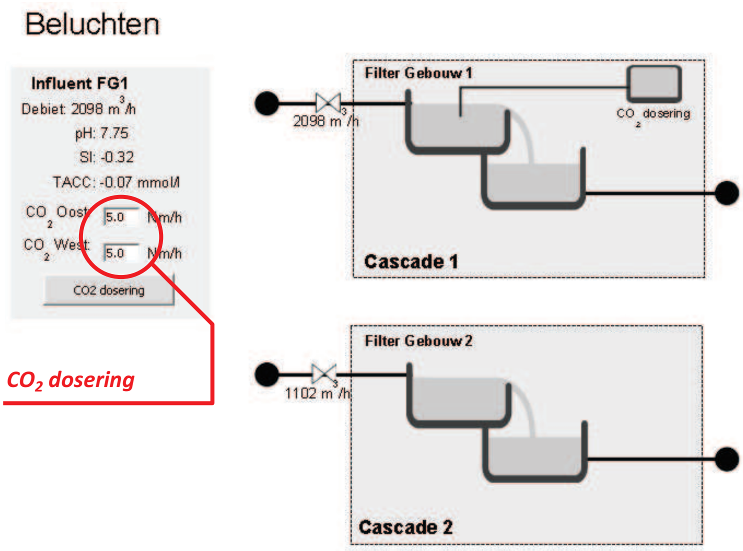
Figuur 1: Overzicht waterreiniging



Figuur 2: De opstelling van 6 onthardingsreactoren bij pompstation Wim Mensink.

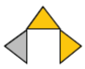


Figuur 3: Onthardingsreactor



Figuur 4: Beluchting en CO_2 dosering.

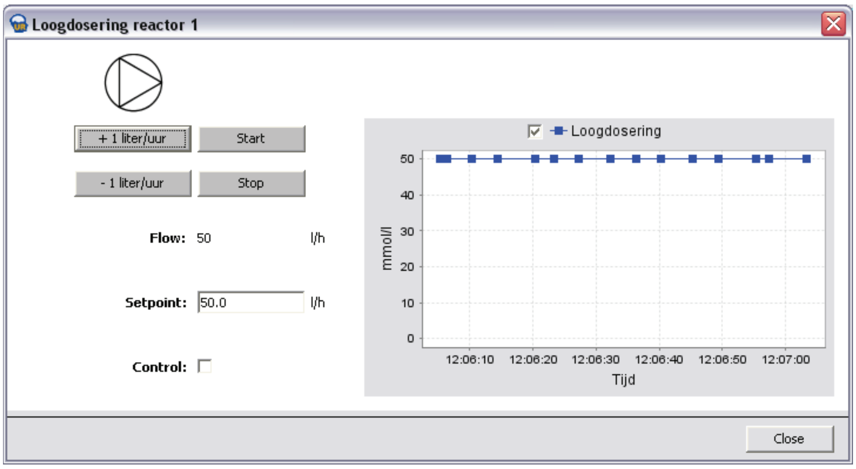
Verder kan er met behulp van de drie driehoekjes (zie figuur 5) worden genavigeerd. Met de pijl naar boven naar het bovenliggende niveau, met de pijl naar links tegen de stroom in (bijvoorbeeld van de beluchting (figuur 4) naar de ontharding (figuur 2)) en met de pijl naar rechts met de stroom mee (vice versa).



Figuur 5: Navigator

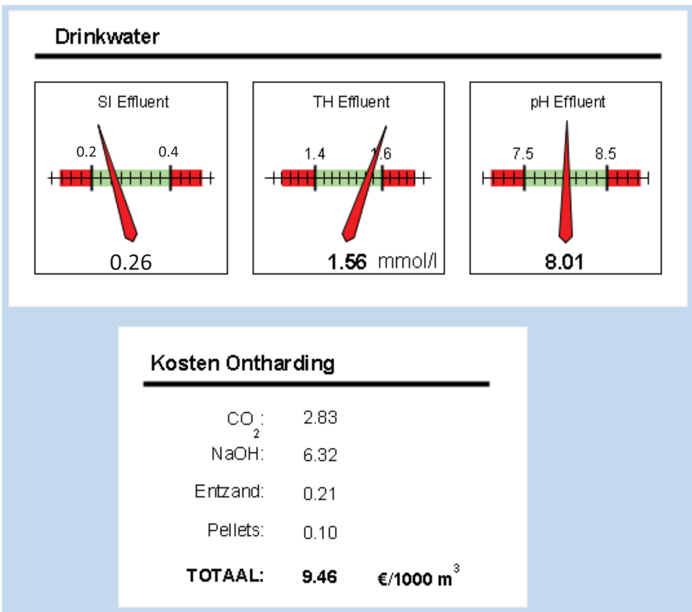
*LET OP: Om de benodigde rekenkracht te minimaliseren is er slechts één onthardingsreactor gemodelleerd, reactor 2 t/m 6 kopieren de kwaliteitskenmerken van het ontharde water van reactor 1. Als gevolg heeft alleen reactor 1 een subniveau (*figuur 3*). Vanuit dit subniveau wordt de Natronloog en entzand dosering, en de pelletaftap voor alle actieve reactoren geregeld. Een ander gevolg is dat reactor 1 niet uitgezet mag/kan worden.*

Bediening van de pompen en dosering van chemicaliën geschiedt door op de desbetreffende pomp te klikken. Er verschijnt dan een popup (figuur 6) waar pompen in en uitgeschakeld kunnen worden en de flow kan worden aangepast. De onthardingsreactoren worden in en uitgeschakeld door het in en uitschakelen van de bijbehorende pomp.



Figuur 6: Bediening Loogdosering

Tenslotte kunnen de (hardheids) kwaliteitskenmerken van het geproduceerde drinkwater, en de kosten die gemaakt worden voor het ontharden, overal opgevraagd worden door op het € symbool te klikken. Hierdoor wordt figuur 7 opgeroepen. Kosten zijn welliswaar van ondergeschikt belang ten opzichtge van de waterkwaliteit, maar worden mogelijk gebruikt als maat voor de efficientie van de gekozen bedrijfsvoering.



Figuur 7: Kwaliteitskenmerken en kosten

De Scenario’s

Trainingssessie 1:

Eerst wordt er 3 keer een trainings scenario afgelegd van 20 minuten. Tijdens deze training is de simulatiesnelheid verhoogd tot 60x de werkelijke snelheid. Elke 5 minuten vind er een wijziging plaats op de RO stroom uit Heemskerk, de influent stroom uit de duinen zal voor het totale volume compenseren (De uitganssituatie is 850 m^3/h uit Heemskerk en 3150 m^3/h uit de duinen). Hierdoor zal de drinkwaterkwaliteit (na verloop van tijd) niet meer voldoen aan het gestelde operationele venster (zie bijlage).

Tijdens sessie 1 mogen er onthardingsreactoren in en uitgeschakeld worden, en mogen de NaOH dosering en CO_2 dosering geregeld worden. Het doel is om tijdens deze sessies de waterkwaliteitskenmerken TH, pH en SI (zie bijlage) te optimalizeren bij minimaal gebruik van grondstoffen (proces kosten). Per run wordt er een prestatiescore bepaald aan de hand van de kwaliteitskenmerken en gerbruik van grondstoffen gedurende de run.

Na de drie runs worden er 2 testruns afgelegd. Tijdens de testruns wordt het scenario op werkelijke snelheid afgespeeld (gedurende 20 minuten, echte tijd). Bij testrun 1 wordt er aan het begin, en nog eens na 20 minuten een wijziging in de RO stroom uit Heemskerk aangebracht, bij testrun 2 wordt er een verstoring aangebracht in de verdeling van het water over Filtergebouw 1 en Filtergebouw 2. Wederom aan jou de taak om de drinkwater kwaliteit te optimaliseren bij een minimaal gebruik van grondstoffen.

Tussen de trainingsruns is er steeds 5 minuten pauze. Na trainingssessie 1 is er 20 minuten pauze.

Trainingssessie 2:

Trainingssessie 2 is in feite een vrije training van 40 minuten. Tijdens deze sessie mag de versnelling worden aangepast tussen 1x en 600x werkelijke snelheid. Verder mag naast het in en uit schakelen van reactoren en aanpassen van de doseringen NaOH en CO_2, de entzand dosering en pellet aftap ook geregeld worden. De entzand dosering en pellet aftap mogen hier ook tijdelijk onrealistisch hoge waarden (bijvoorbeeld 1 miljoen kg/dag of zelfs meer) gegeven worden om zo de bedhoogte aan te passen, wanneer de gewenste bedhoogte is bereikt moet deze dosering uiteraard wel weer teruggezet worden naar reeele waarden (helaas is dit nog niet op een eenvoudigere manier mogelijk).

Het doel van deze trainingssessie is om exploratief verschillende bedrijfsvoeringen uit te proberen die leiden tot hetzelfde drinkwater kwaliteit, maar met verschillend gebruik van grondstoffen.

Afronding:

Wanneer alle runs voltooid krijg je wederom een korte vragenlijst om de Waterspot Simulator te evalueren.

Ten slotte wint de 'beste' bedrijfsvoerder een fles wijn.

	tijdsduur	scenario	versnelling	te regelen grootheden
Sessie 1				
trainingsrun	20 min	wijziging RO stroom (4x)	60x	aan/uit schakelen reactoren CO2 dosering NaOH dosering
trainingsrun	20 min	wijziging RO stroom (4x)	60x	
trainingsrun	20 min	wijziging RO stroom (4x)	60x	
testrun 1	20 min	wijziging RO stroom (2x)	1x	
testrun 2	20 min	wijziging Bypass stroom (1x)	1x	
Sessie 2				
vrije training	40 min	-	1x-600x	aan/uit schakelen reactoren CO2 dosering NaOH dosering Entzand dosering Pellet afvoer

Tabel 1: Overzicht opzet Evaluatie Waterspot Simulator

Bijlage: Variabelen, Operationeel Venster en Kosten

De afhankelijke variabelen:

SI (Saturatie Index) $0.2 < SI < 0.4$	De SI geeft een maat voor de agressivieteit van het water. Bij een SI groter dan 0 zal het water kalk afzetten, maar bij een SI lager dan 0 zal het o.a. leidingen aantasten. De SI van het geproduceerde water moet tussen 0.2 en 0.4 zitten.
pH (zuurtegraad) $7.5 < pH < 8.5$	De zuurtegraad van het water wordt beinvloed door de dosering van NaOH (een base) en de dosering van CO_2 (een zuur). Voor het geproduceerde water moet deze tussen 7.5 en 8.5 zitten.
TH (Totale Hardheid) $1.4 < TH < 1.6$	De hardheid van het water, gemeten in graden duitse hardheid in mmol/l. Deze moet tussen 1.4 en 1.6 zijn voor het in Heemskerk geproduceerde drinkwater.

De onafhankelijke variabelen:

actieve reactoren	Het aantal ingeschakelde onthardingsreactoren *Meer actieve reactoren geeft een diepere ontharding, maar brengt ook hogere kosten met zich mee.*
NaOH dosering	De dosering van NaOH *Een hogere NaOH dosering leidt tot:* *een snellere reactie → een lagere TH* *een hogere SI* *een hogere pH*
CO_2 dosering	De dosering van CO_2 *Een hogere CO_2 dosering leidt tot:* *een lagere SI* *een lagere pH*

2.4

Programming code in Matlab used to calculate performances.

```
% A 'brief' overview of the used Matlab code The code used to calculate the
% TH, SI and pH related scores was the same. Therefore the calculations
% regarding SI and pH are supressed. In this overview this is indicated by
% %[+SI+pH]


%% Load database to structure Subject
% function DBVar.m is called to connect to the SQL-database, (see the end
% of this document)

Run_ids;
load('16Subjects.mat');
for jj=1:16;
    for ii=1:6;
        if(Subject{jj}.Run_ids(ii)~= 0)
% Quality parameters
             [Subject{jj}.Run{ii}.TH.Data Subject{jj}.Run{ii}.TH.TimeStamp Subject{jj}.↙
Run{ii}.TH.T Subject{jj}.Run{ii}.TH.Data_id] = DBVar(Subject{jj}.Run_ids(ii), '01: TH↙
drinkwater (mmol/l)');
             [Subject{jj}.Run{ii}.SI.Data Subject{jj}.Run{ii}.SI.TimeStamp Subject{jj}.↙
Run{ii}.SI.T Subject{jj}.Run{ii}.SI.Data_id] = DBVar(Subject{jj}.Run_ids(ii), '02: SI↙
drinkwater (-)');
             [Subject{jj}.Run{ii}.pH.Data Subject{jj}.Run{ii}.pH.TimeStamp Subject{jj}.↙
Run{ii}.pH.T Subject{jj}.Run{ii}.pH.Data_id] = DBVar(Subject{jj}.Run_ids(ii), '03: pH↙
drinkwater (-)');

% User actions
             [Subject{jj}.Run{ii}.ActRea.Data Subject{jj}.Run{ii}.ActRea.TimeStamp↙
Subject{jj}.Run{ii}.ActRea.T Subject{jj}.Run{ii}.ActRea.Data_id] = DBVar(Subject{jj}.↙
Run_ids(ii), '05: Aantal actieve reactoren');
             [Subject{jj}.Run{ii}.NaOH.Data Subject{jj}.Run{ii}.NaOH.TimeStamp Subject↙
{jj}.Run{ii}.NaOH.T Subject{jj}.Run{ii}.NaOH.Data_id] = DBVar(Subject{jj}.Run_ids(ii),↙
'06: NaOH dosering');
             [Subject{jj}.Run{ii}.CO2W.Data Subject{jj}.Run{ii}.CO2W.TimeStamp Subject↙
{jj}.Run{ii}.CO2W.T Subject{jj}.Run{ii}.CO2W.Data_id] = DBVar(Subject{jj}.Run_ids(ii),↙
'08: CO2 dosering West');
             [Subject{jj}.Run{ii}.CO2O.Data Subject{jj}.Run{ii}.CO2O.TimeStamp Subject↙
{jj}.Run{ii}.CO2O.T Subject{jj}.Run{ii}.CO2O.Data_id] = DBVar(Subject{jj}.Run_ids(ii),↙
'07: CO2 dosering Oost');

        end
    end
    disp(['Subject ' num2str(jj) ' loaded.']);
end
clear ii jj

%% Median Filter
% to filter out some 'simulator spikes' (the simulator gave some
% unrealistic values sometimes, these were only given for an instant (most
% of them are single values) and are not expected to influence the
% experiment.

for ii = 1:12
    for jj = 1:3
        temp = medfilt1(Subject{ii}.Run{jj}.TH.Data, 5);
        clear Subject{ii}.Run{jj}.TH.Data
```

```
        Subject{ii}.Run{jj}.TH.Data = temp;
        clear temp

%[+SI+pH]

    end
end


%% Cut runs 1,2 and 3 in 4 pieces

% the start and end indices of the pieces were acquired by looking at plots
% of the quality parameters and entered in matlab:

cuts(:,:,1) = [  1   1   1
               135 140 142
               268 277 278
               392 410 414
               528 549 550];

cuts(:,:,2) = ...
cuts(:,:,3) =

% etc. For all 3 training runs of groups 1, 2 and 3 (EOP, IOP, L60x).

% Next the data set was cut into pieces using the cuts matrix:

for ii=1:12;
    for jj=1:3;
        for kk=1:4;

            Subdata = [cuts(kk,jj,ii) cuts(kk+1,jj,ii)];
            Subject{ii}.Run{jj}.Part{kk}.TH.Data        = Subject{ii}.Run{jj}.TH.Data↙
(Subdata(1):Subdata(2));
            Subject{ii}.Run{jj}.Part{kk}.TH.TimeStamp   = Subject{ii}.Run{jj}.TH.↙
TimeStamp(Subdata(1):Subdata(2));
            Subject{ii}.Run{jj}.Part{kk}.TH.T           = Subject{ii}.Run{jj}.TH.T↙
(Subdata(1):Subdata(2));
            Subject{ii}.Run{jj}.Part{kk}.TH.T           = Subject{ii}.Run{jj}.Part{kk}.↙
TH.T - Subject{ii}.Run{jj}.Part{kk}.TH.T(1);
            Subject{ii}.Run{jj}.Part{kk}.TH.Data_id     = Subject{ii}.Run{jj}.TH.↙
Data_id(Subdata(1):Subdata(2));
%[+SI+pH]

        end
    end
end

%% Load Operational Window (min/max of quality params)
OW.TH.max = 1.6;
OW.TH.min = 1.4;
OW.TH.av = 1.5;
OW.SI.max = 0.4;
OW.SI.min = 0.2;
OW.SI.av = 0.3;
OW.pH.max = 8.5;
```

```
OW.pH.min = 7.5;
OW.pH.av = 8.0;

%% Get Integral of Error scores (groups 1, 2 and 3, training runs)

% TH Error outside OW
Subject{Subject_Nr}.Run{Run_Nr}.TH.Error.MinMax = (abs(Subject{Subject_Nr}.Run{Run_Nr}.↙
TH.Data - OW.TH.min)...
                                                  + abs(Subject{Subject_Nr}.Run{Run_Nr}.↙
TH.Data - OW.TH.max)...
                                                  - (OW.TH.max - OW.TH.min))/2;
Errors.MinMax.Subject{Subject_Nr}.Run{Run_Nr}.TH = trapz(Subject{Subject_Nr}.Run↙
{Run_Nr}.TH.T,...
                                                         Subject{Subject_Nr}.Run↙
{Run_Nr}.TH.Error.MinMax)...
                                                       / max(Subject{Subject_Nr}.Run↙
{Run_Nr}.TH.T);
%[+SI+pH]

for Part_Nr = 1:4
% TH Error outside OW
    Subject{Subject_Nr}.Run{Run_Nr}.Part{Part_Nr}.TH.Error.MinMax  = (abs(Subject↙
{Subject_Nr}.Run{Run_Nr}.Part{Part_Nr}.TH.Data - OW.TH.min)...
                                                                   + abs(Subject↙
{Subject_Nr}.Run{Run_Nr}.Part{Part_Nr}.TH.Data - OW.TH.max)...
                                                                   - (OW.TH.max - OW.↙
TH.min))/2;
    Errors.MinMax.Subject{Subject_Nr}.Run{Run_Nr}.Part{Part_Nr}.TH = trapz(Subject↙
{Subject_Nr}.Run{Run_Nr}.Part{Part_Nr}.TH.T,...
                                                                         Subject↙
{Subject_Nr}.Run{Run_Nr}.Part{Part_Nr}.TH.Error.MinMax)...
                                                                     / max(Subject↙
{Subject_Nr}.Run{Run_Nr}.Part{Part_Nr}.TH.T);

%[+SI+pH]
end

%% Get 1 Matrix of minmax errors per quality parameter

%TH
ErrorTHparts = NaN(4,3,12);
for ii = 1:12
    for jj = 1:3
        for kk = 1:4
            ErrorTHparts(kk,jj,ii) = [Errors.MinMax.Subject{ii}.Run{jj}.Part{kk}.TH];
        end
    end
end
%[+SI+pH]

%% Standardize to z-score
% zscores of TH
clear tmp
tmp = shiftdim(ErrorTHparts,1);
tmp = reshape(tmp, 144,1);
tmp = zscore(tmp);
```

```
tmp = reshape(tmp, 3,12,4);
zErrorTHparts = shiftdim(tmp,2);
zErrorTHSum = sum(zErrorTHparts);

%[+SI+pH]

zError = shiftdim(zErrorpHSum + zErrorTHSum + zErrorSISum);

zErrorExpOp = zError(:,1:4);
meanErrorExpOp = mean(zErrorExpOp,2);
zErrorInexpOp = zError(:,5:8);
meanErrorInexpOp = mean(zErrorInexpOp,2);
zErrorStud = zError(:,9:12);
meanErrorStud = mean(zErrorStud,2);
meanErrorAll = mean([zErrorExpOp zErrorInexpOp zErrorStud],2);

% The Error from final settings and Error from first settings were
% gotten from plots of the settings. The resulting quality parameters
% were put in excell and handled there.





function [DBVariable TimeStamp T Data_id] = DBVar(run_id, var_name)
%% get data from waterspot sql database
%
% syntax: [DBVariable TimeStamp T Data_id] = DBVar(run_id, var_name)
%
% Where run_id is the desired run id and var_name the variable name, see
% below. T gives the time since start of the run in seconds.
%
% 01: TH drinkwater (mmol/l) 02: SI drinkwater (-) 03: pH drinkwater (-)
%
%

run_id=num2str(run_id);

%get connection
conn=database('Waterspot','root','waterspot','com.mysql.jdbc.Driver','jdbc:mysql:↙
//localhost:3306/');

%set up query and get specified data
query = ['select * from run_data where run_id = ' run_id ' and tag = ''' var_name↙
''''];
Data=fetch(conn,query);

%get data column to DBVariable
Temp = Data(:,4);
DBVariable = cell2mat(Temp);

%get data id to Data_id
Temp = Data(:,8);
```

```
Data_id = cell2mat(Temp);

%get timestamp column to TimeStamp
Temp = Data(:,1);
TimeStamp = cell2mat(Temp);
Temp = timestamp2day(TimeStamp)*24*60*60;
T = Temp - Temp(1);

close(conn);
```

2.5

Two examples of programming in the USE environment.

Programming in the USE Environment

Programming in the USE Environment is mainly done with several building blocks as illustrated by Figures 1 and 2. For complicated tasks Java script can also be used within scripting blocks. Some java programming is included after Figure 2.

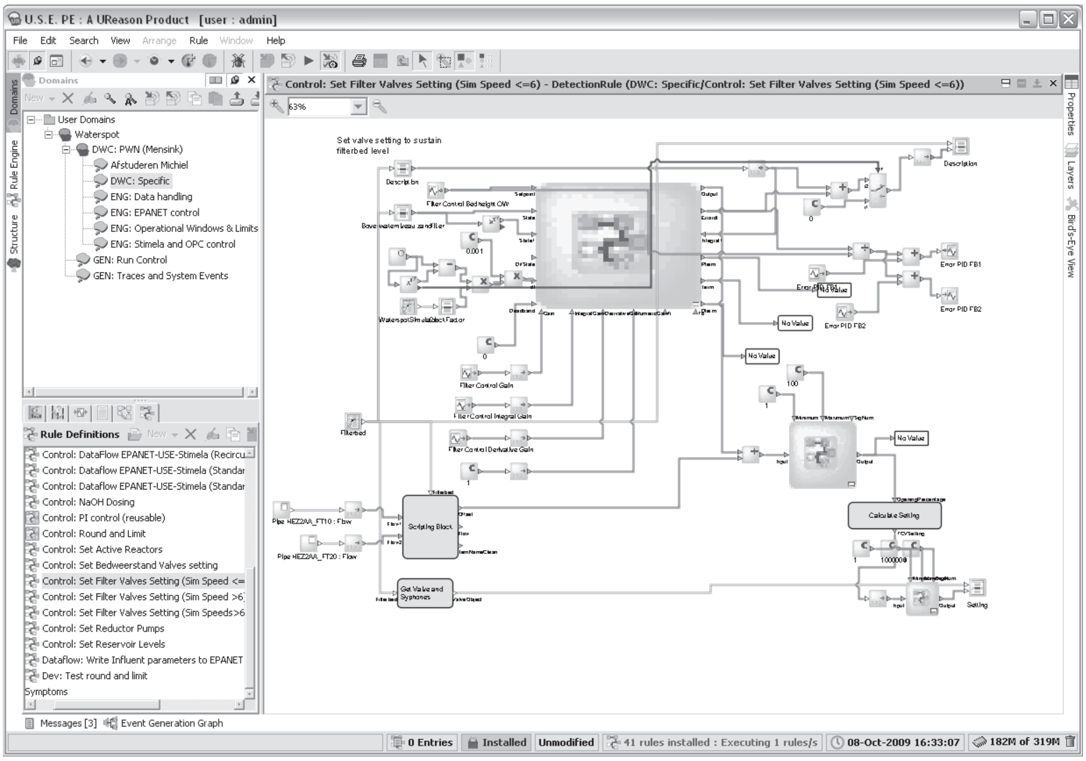


Figure 1. Stabilizing filter beds for 60x acceleration.

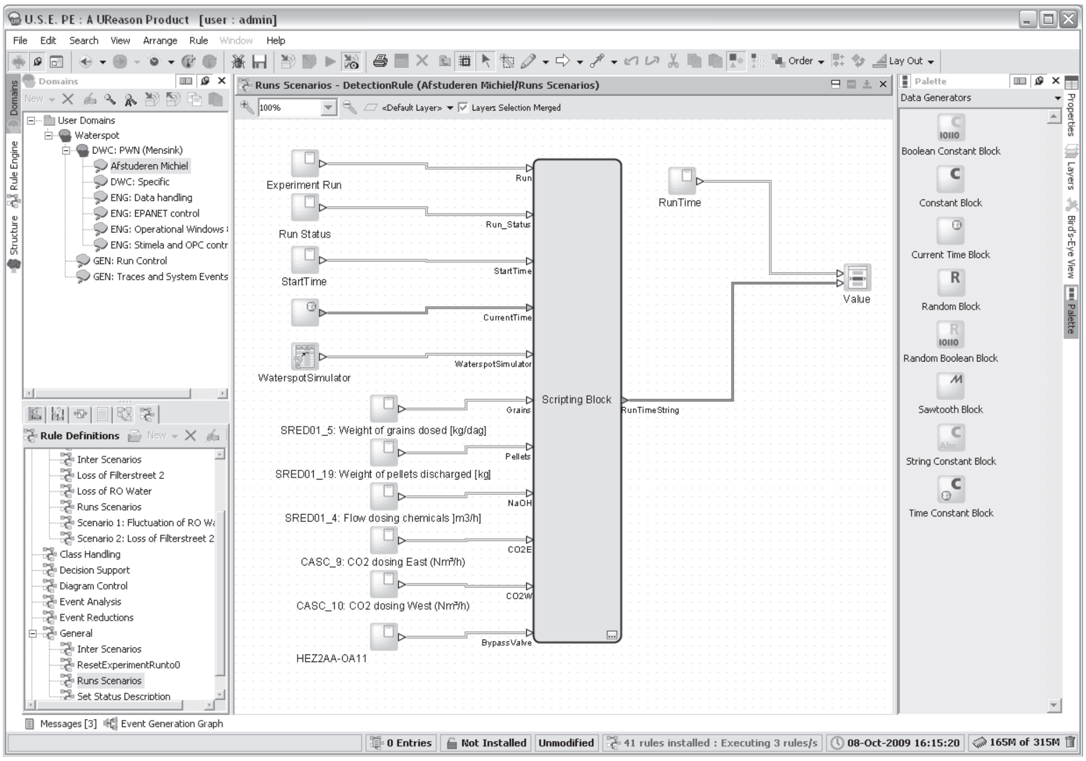


Figure 2. The “supervising block” of the Experiment, part of the script contained in the scripting block is included on the next page.

The “ supervising block” runs the experiment. It starts and stops the various runs, sets the simulation speed and the process changes. Part of the Java programming of the scripting block of the supervising block is given:

```
if(Run_Status.Value == 0){
  for(ii = 1; ii <= 6; ii = ii + 1){
    Pump = getCachedModelObjectByFieldValue("Name", "HEZ30" + ii + "_OP10", "Pump","includeparentmodels")
    Softener = getCachedModelObjectByFieldValue("Name", "Pelletreactor " + ii, "Softening Reactor","includeparentmodels")
    if(ii<=4){
      Pump.Speed = 1;
      Softener.Active = 1;
    }
    else{
      Pump.Speed = 0;
      Softener.Active = 0;
    }
  }
  NaOH.Value = 70;
  CO2W.Value = 5;
  CO2E.Value = 5;
  Grains.Value = 50;
  Pellets.Value = 500;
  WaterspotSimulator.InfluentHeemskerk = 850;
  WaterspotSimulator.Influent = 3150;
if(Run.InitialValue==42||Run.InitialValue==52){
  WaterspotSimulator.ClockFactor = 1;
}
else{
 WaterspotSimulator.ClockFactor = 60;
}
Run_Status.Value=1;
StartTime.Value=CurrentTime;
RunTimeString="0:00:00";
report("Initialized for Run " + Run.InitialValue)
}
else{

RunTime=(CurrentTime-StartTime.Value)/1000;
report("Runtime"+RunTime)
Uren = Math.floor(RunTime/3600);
report("Uren"+Uren)
```

```
Minuten = Math.floor((RunTime-Uren*3600)/60);
report("Minuten"+Minuten)
Seconden = Math.floor(RunTime-Minuten*60-Uren*3600);
report("Seconden"+Seconden)
if(Minuten<10){
 Minuten = "0"+Minuten;
}
if(Seconden<10){
 Seconden = "0"+Seconden;
}
RunTimeString = Uren+":"+Minuten+":"+Seconden;
report(RunTimeString)
report("Runtime: " & RunTime);
report("Run Status = " + Run_Status.Value)
  if(RunTime>5&&(Run.InitialValue==42||Run.InitialValue==52)&&WaterspotSimulator.ClockFactor==60){
  if(RunTime>5&&WaterspotSimulator.ClockFactor==60){
    WaterspotSimulator.ClockFactor = 1;
  }
  if((!(Run.InitialValue==42||Run.InitialValue==52||Run.InitialValue==62)) && Run_Status.Value==1 && RunTime<300){
    WaterspotSimulator.InfluentHeemskerk = 200;
    WaterspotSimulator.Influent = 3800;
  }
  else if((!(Run.InitialValue==42||Run.InitialValue==52||Run.InitialValue==62)) && Run_Status.Value==1 && RunTime>300&&
RunTime<600){
    WaterspotSimulator.InfluentHeemskerk = 800;
    WaterspotSimulator.Influent = 3200;
  }
  else if((!(Run.InitialValue==42||Run.InitialValue==52||Run.InitialValue==62)) && Run_Status.Value==1 && RunTime>600&&
RunTime<900){
    WaterspotSimulator.InfluentHeemskerk = 1200;
    WaterspotSimulator.Influent = 2800;
  }
  else if((!(Run.InitialValue==42||Run.InitialValue==52||Run.InitialValue==62)) && Run_Status.Value==1 && RunTime>900&&
RunTime<1200){
    WaterspotSimulator.InfluentHeemskerk = 600;
    WaterspotSimulator.Influent = 3400;
    Run_Status.Value=2;
  }


if(Run.InitialValue==42 && Run_Status.Value==1 && RunTime<600){
if(Run.InitialValue<=42 && Run_Status.Value==1 && RunTime<600){
    WaterspotSimulator.InfluentHeemskerk = 200;
    WaterspotSimulator.Influent = 3800;
}
else if(Run.InitialValue==42 && Run_Status.Value==1 && RunTime>600&& RunTime<1200){
else if(Run.InitialValue<=42 && Run_Status.Value==1 && RunTime>600&& RunTime<1200){
    WaterspotSimulator.InfluentHeemskerk = 1000;
    WaterspotSimulator.Influent = 3000;
    Run_Status.Value=2;
}

if((Run.InitialValue==11||Run.InitialValue==21||Run.InitialValue==31||Run.InitialValue==41||Run.InitialValue==71||Run.Init
ialValue==81) && Run_Status.Value==2 && RunTime>900){
  Run_Status.Value=3;
    Run.InitialValue=Run.InitialValue + 1;
  }

  if((Run.InitialValue==12||Run.InitialValue==22||Run.InitialValue==32||Run.InitialValue==42||Run.InitialValue==52) &&
Run_Status.Value==2 && RunTime>1200){
    Run_Status.Value=3;
    Run.InitialValue=Run.InitialValue+10;
    if(Run.InitialValue==51||Run.InitialValue==61){
      Run.InitialValue=Run.InitialValue+1;
    }
  }
  if(Run.InitialValue==62 && RunTime>2400){
    Run_Status.Value=3;
    Run.InitialValue=Run.InitialValue+10;
  }
  if(Run_Status.Value==3){
    WaterspotSimulator.DesiredState=5;
  }
}
```

2.6

Plots of the experiment runs

Plots of the experiment runs (raw data)

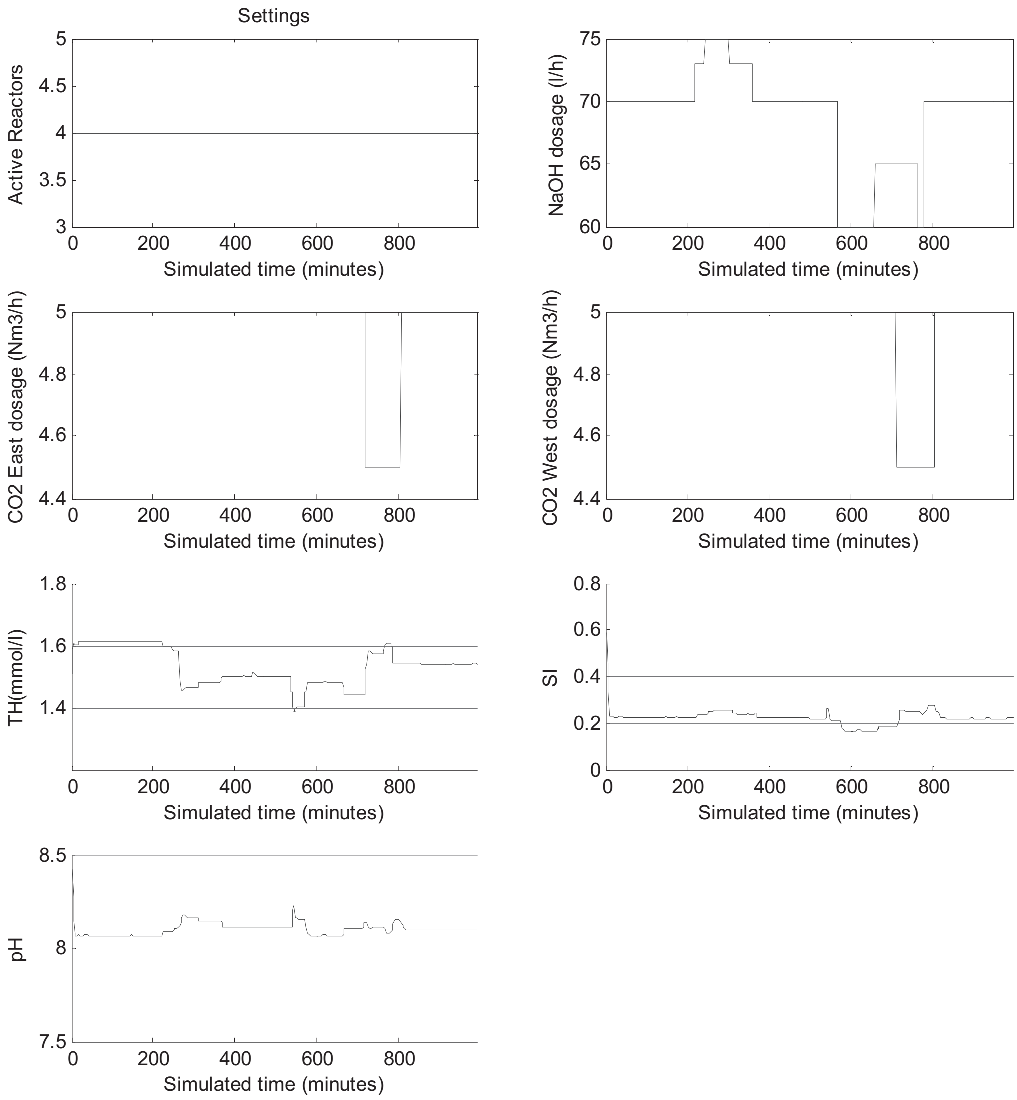


Figure 1. Experienced Operator number 1, training run 1

Plots of the experiment runs (raw data)

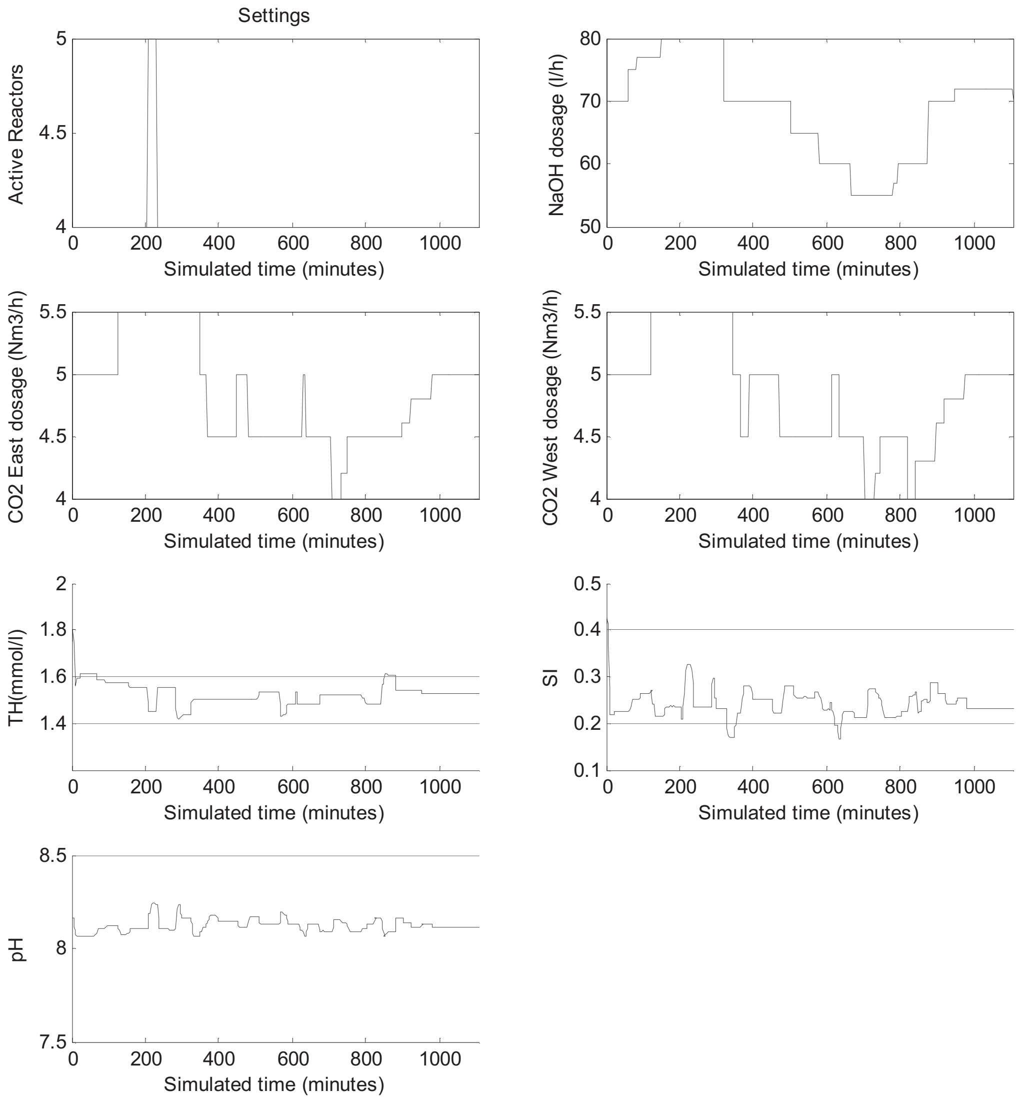


Figure 2. Experienced Operator number 1, training run 2

Plots of the experiment runs (raw data)

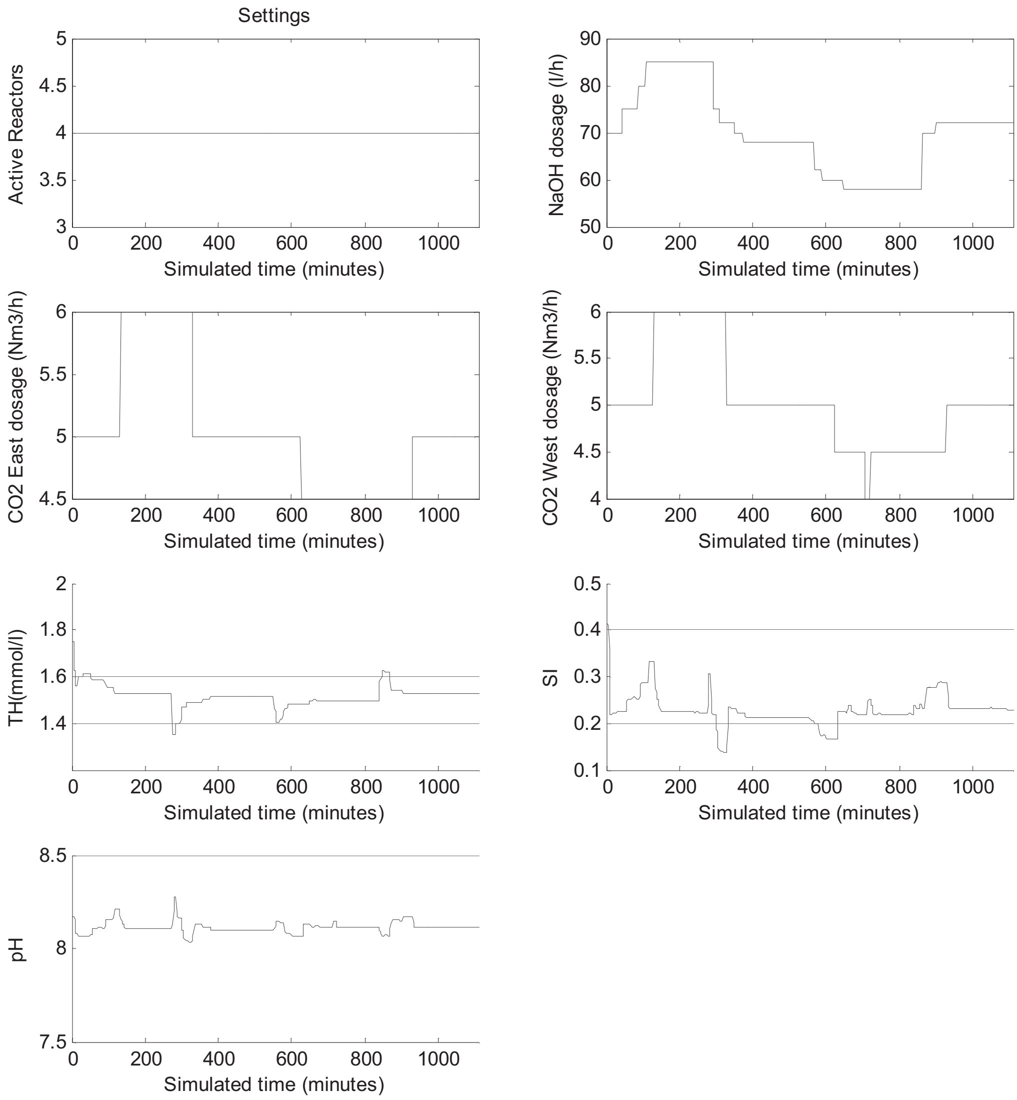


Figure 3. Experienced Operator number 1, training run 3

Plots of the experiment runs (raw data)

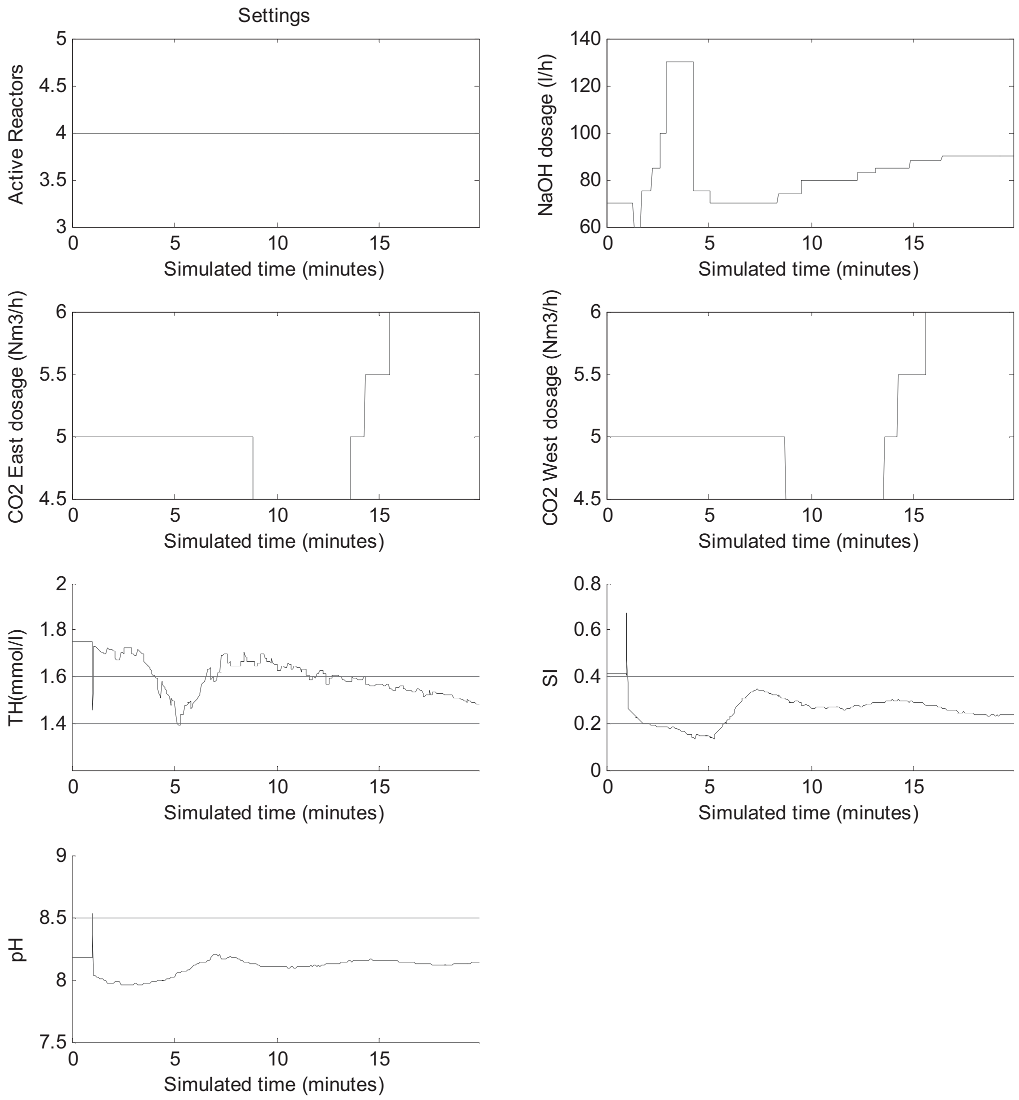


Figure 4. Experienced Operator number 1, transfer run 1

Plots of the experiment runs (raw data)

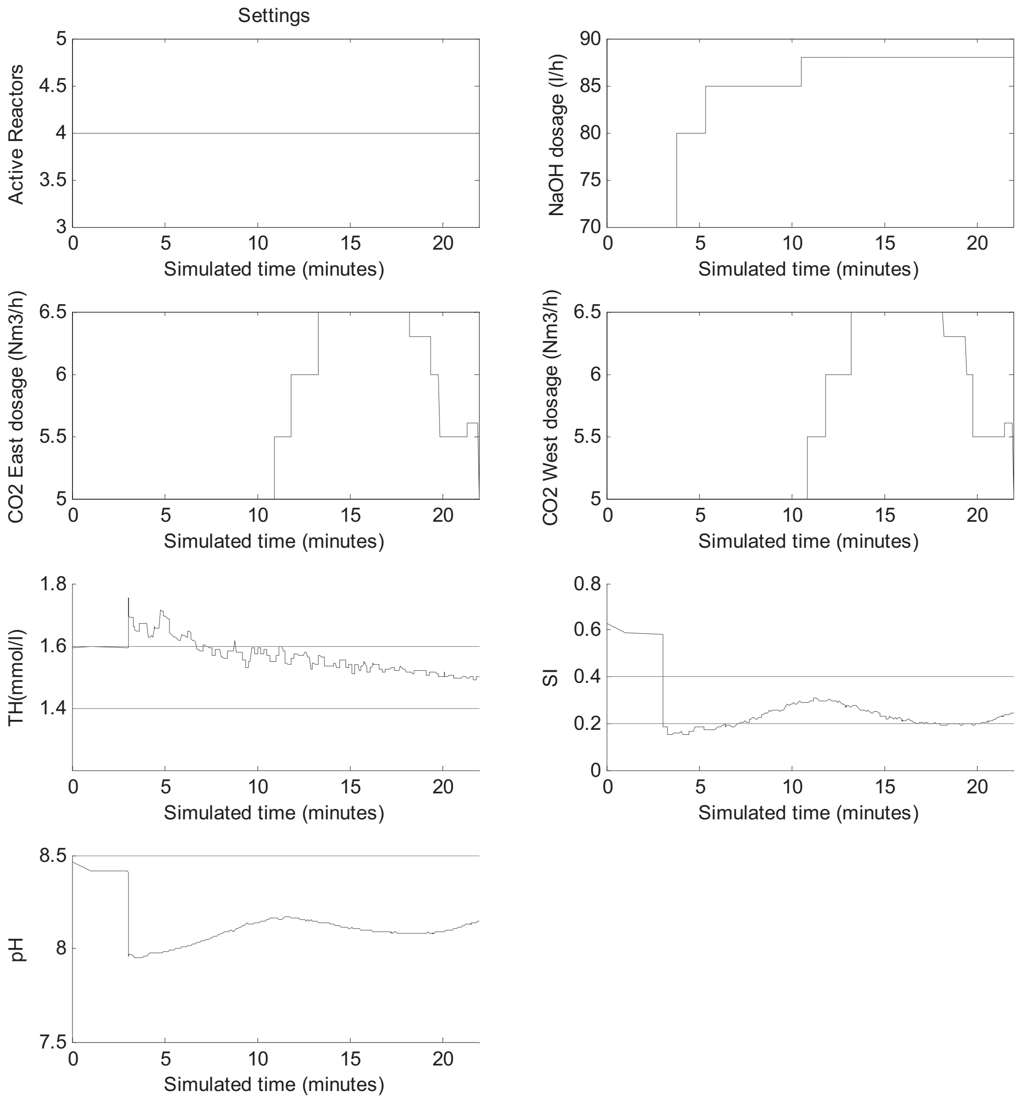


Figure 5. Experienced Operator number 1, transfer run 2

Plots of the experiment runs (raw data)

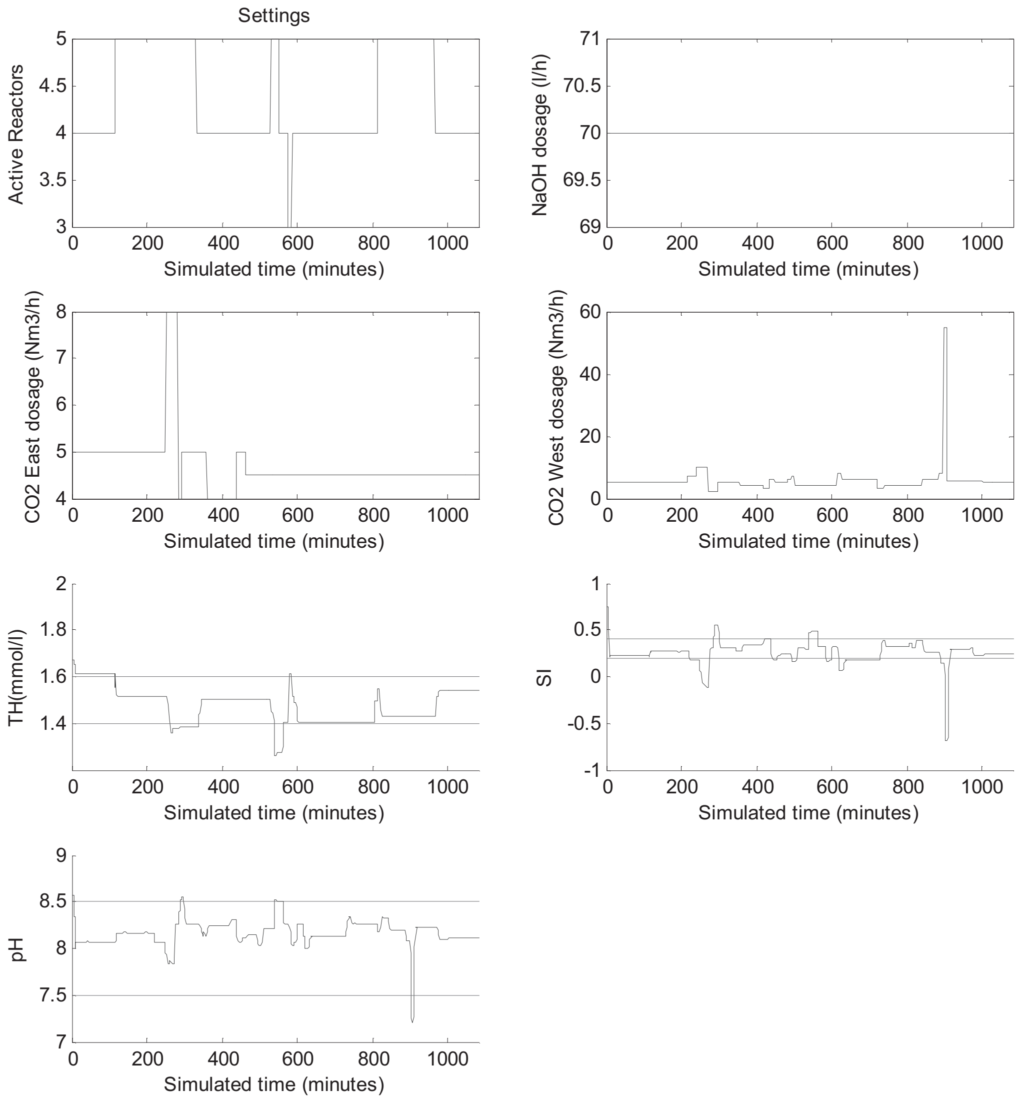


Figure 6. Layman 60x number 1, trainings run 1

Plots of the experiment runs (raw data)

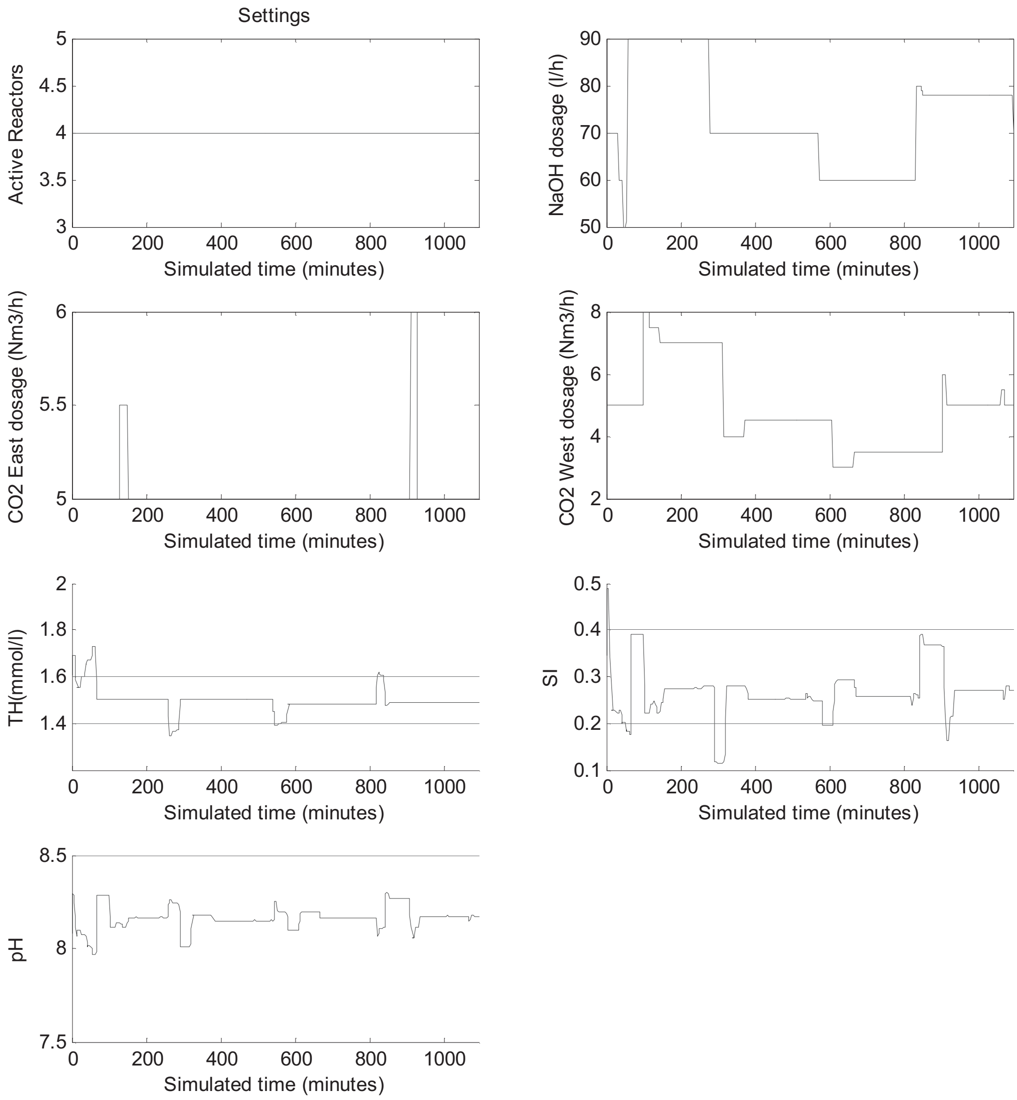


Figure 7. Layman 60x number 1, trainings run 2

Plots of the experiment runs (raw data)

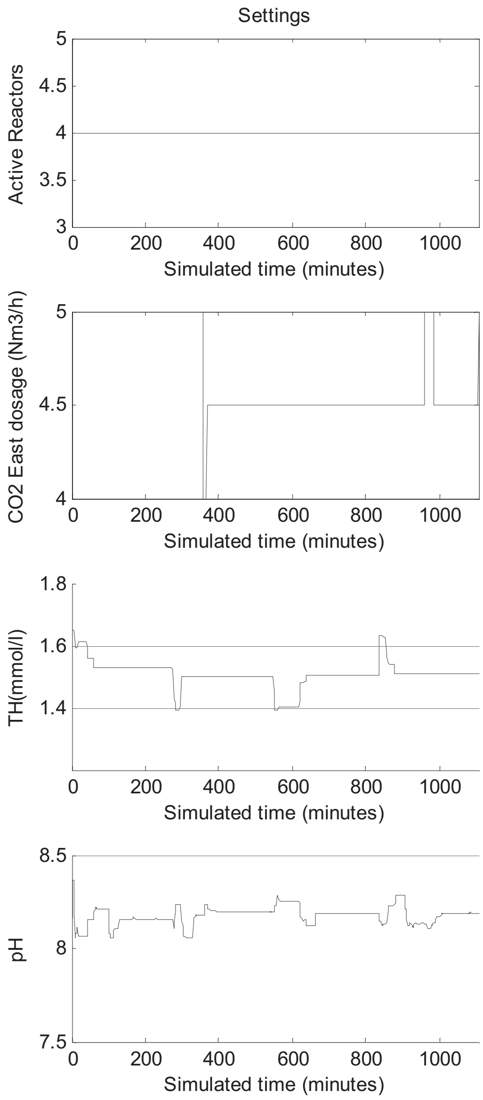


Figure 8. Layman 60x number 1, trainings run 3

Plots of the experiment runs (raw data)

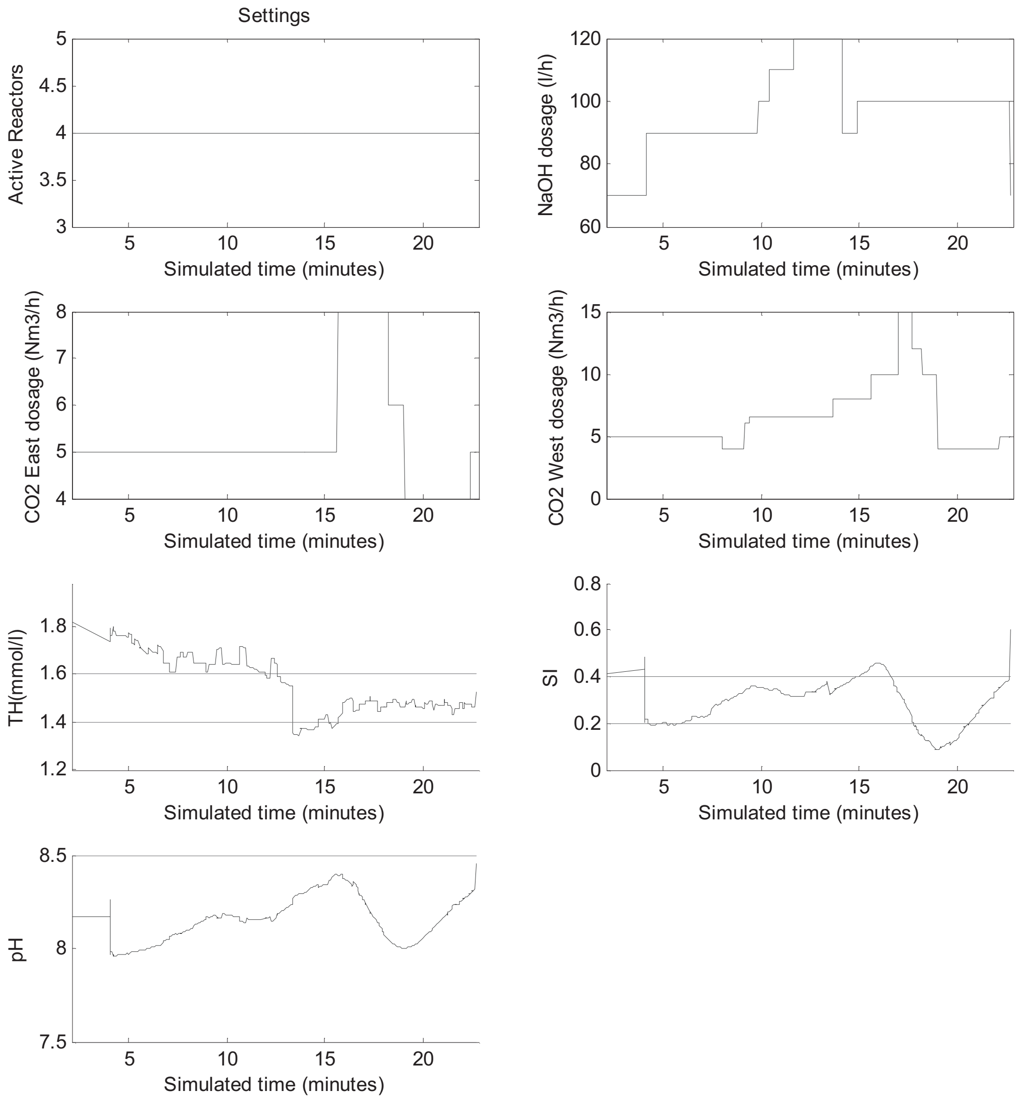


Figure 9. Layman 60x number 1, transfer run 1

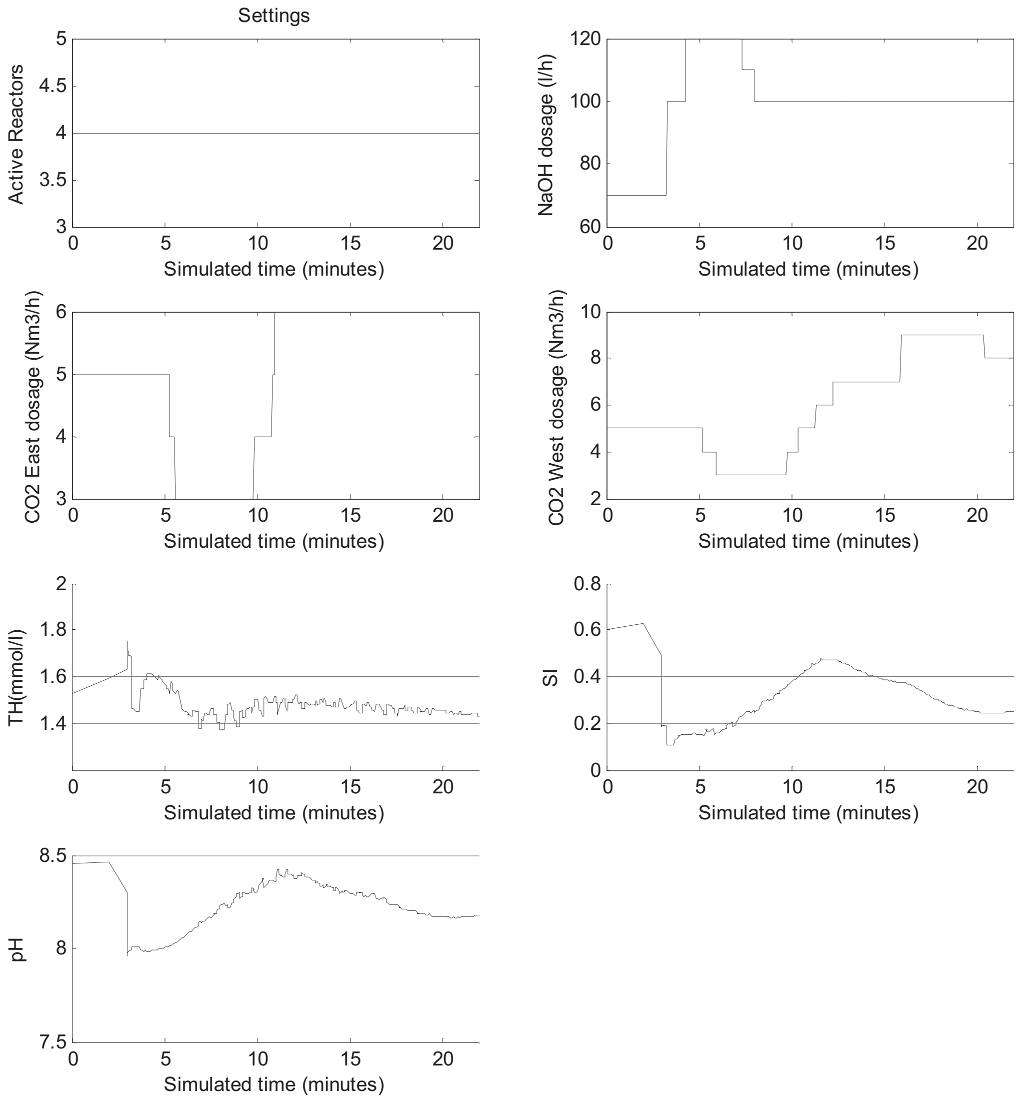


Figure 10. Layman 60x number 1, transfer run 2

Plots of the experiment runs (raw data)

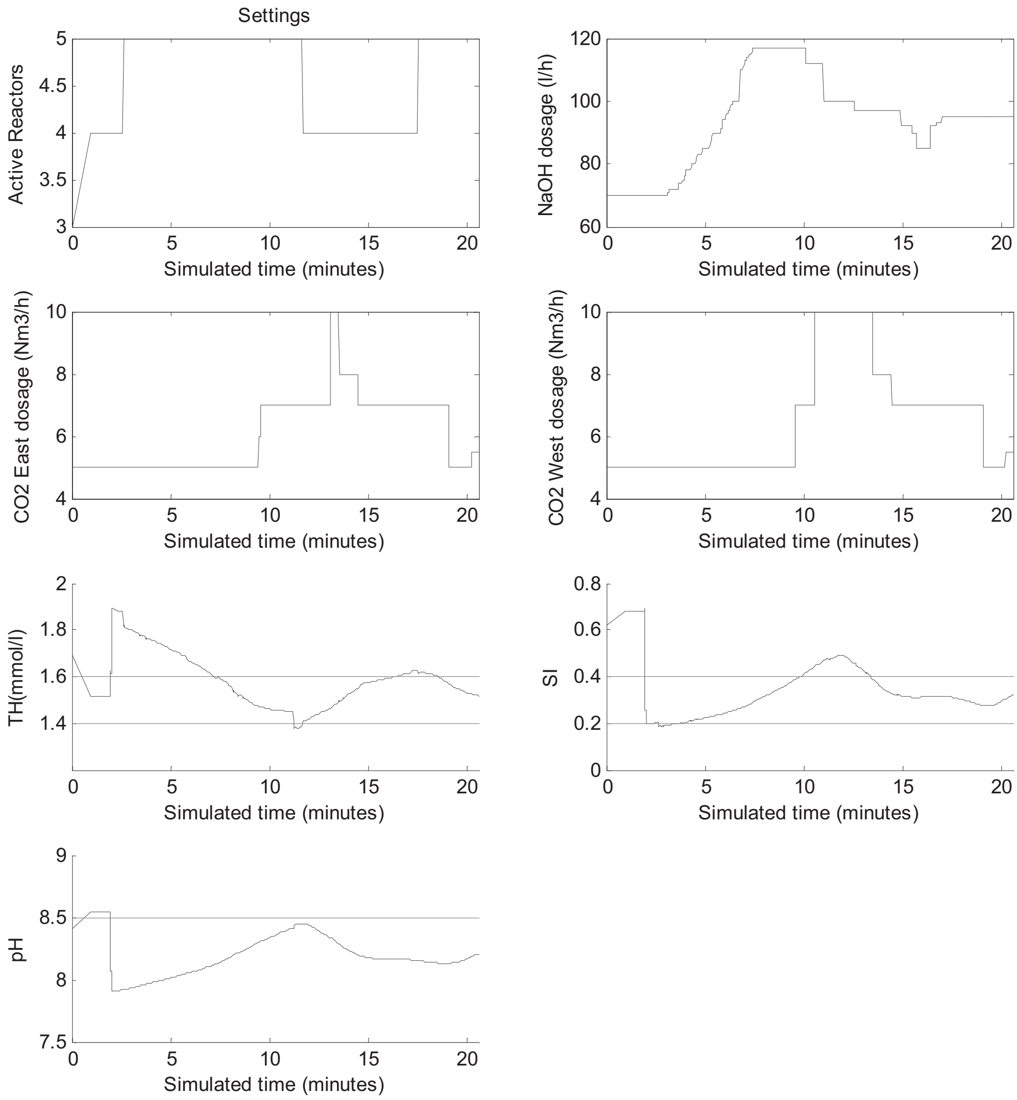


Figure 11. Layman 1x number 1, trainings run 1

Plots of the experiment runs (raw data)

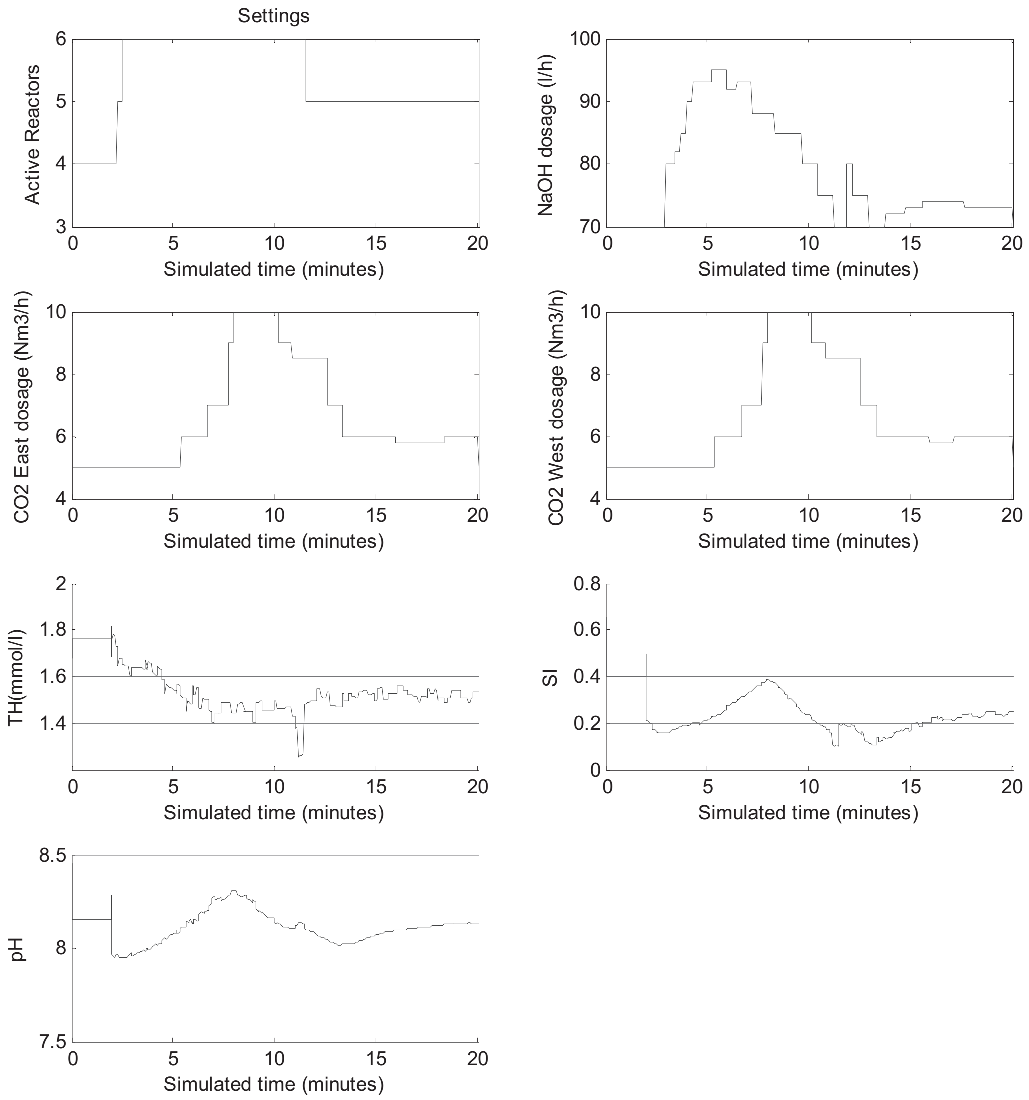


Figure 12. Layman 1x number 1, trainings run 2

Plots of the experiment runs (raw data)

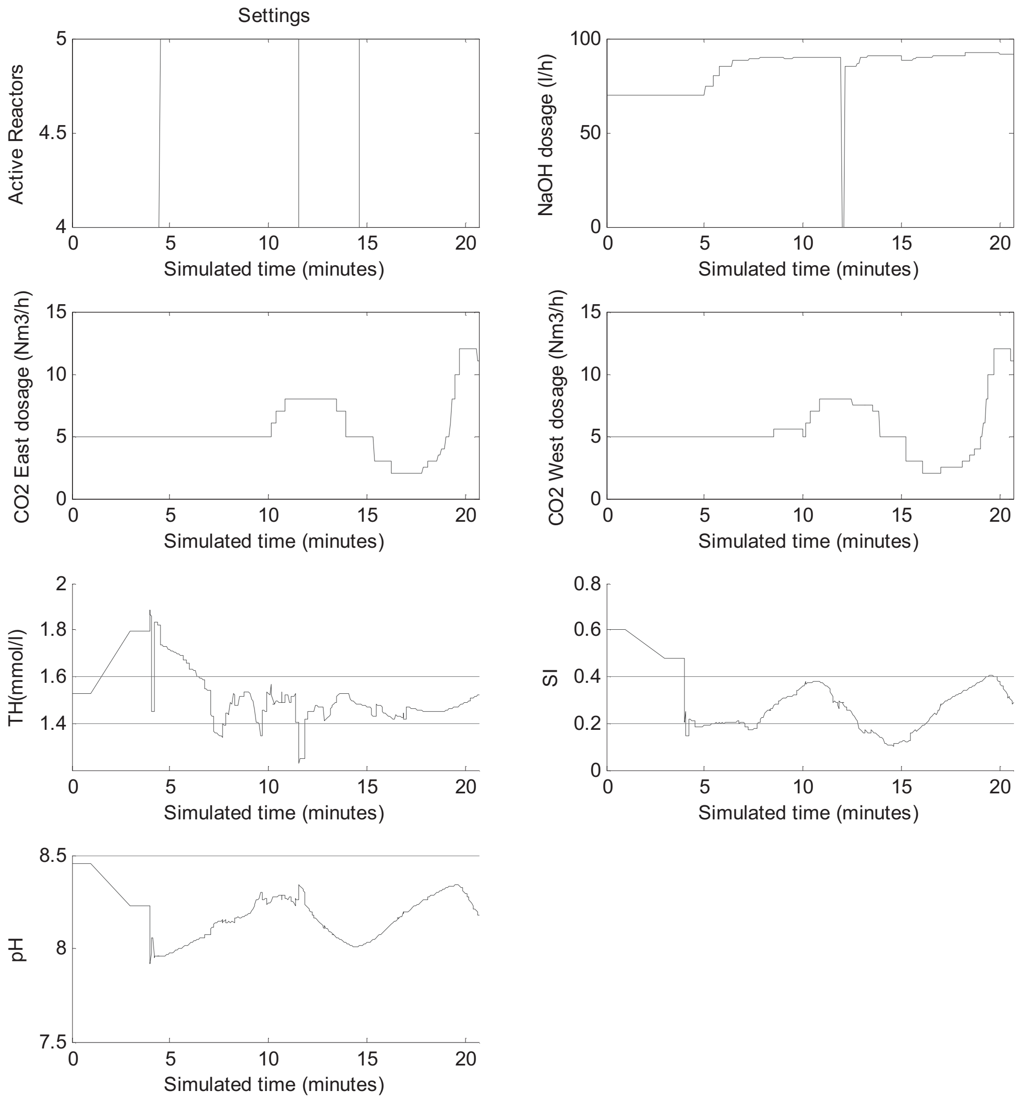


Figure 13. Layman 1x number 1, trainings run 3

Plots of the experiment runs (raw data)

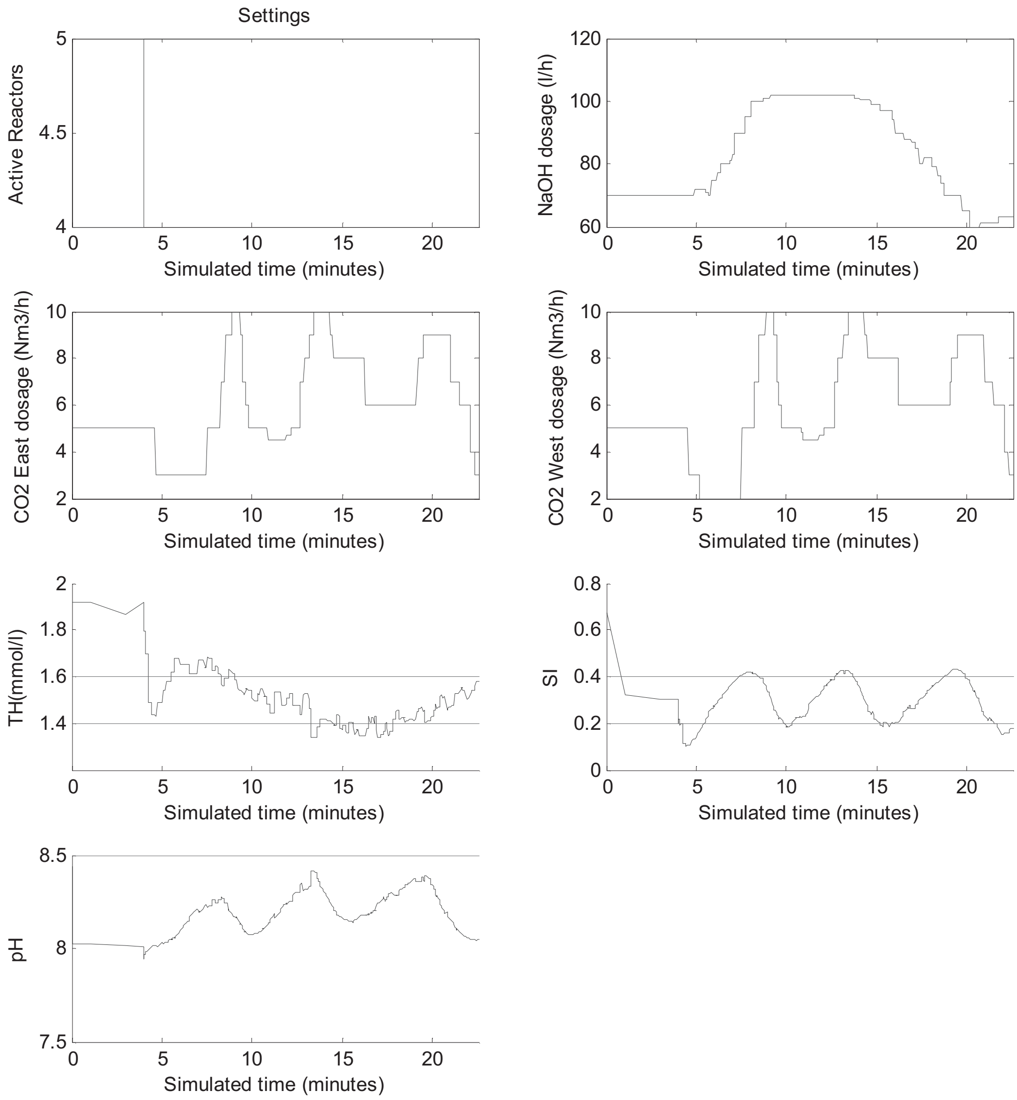


Figure 14. Layman 1x number 1, transfer run 1

Plots of the experiment runs (raw data)

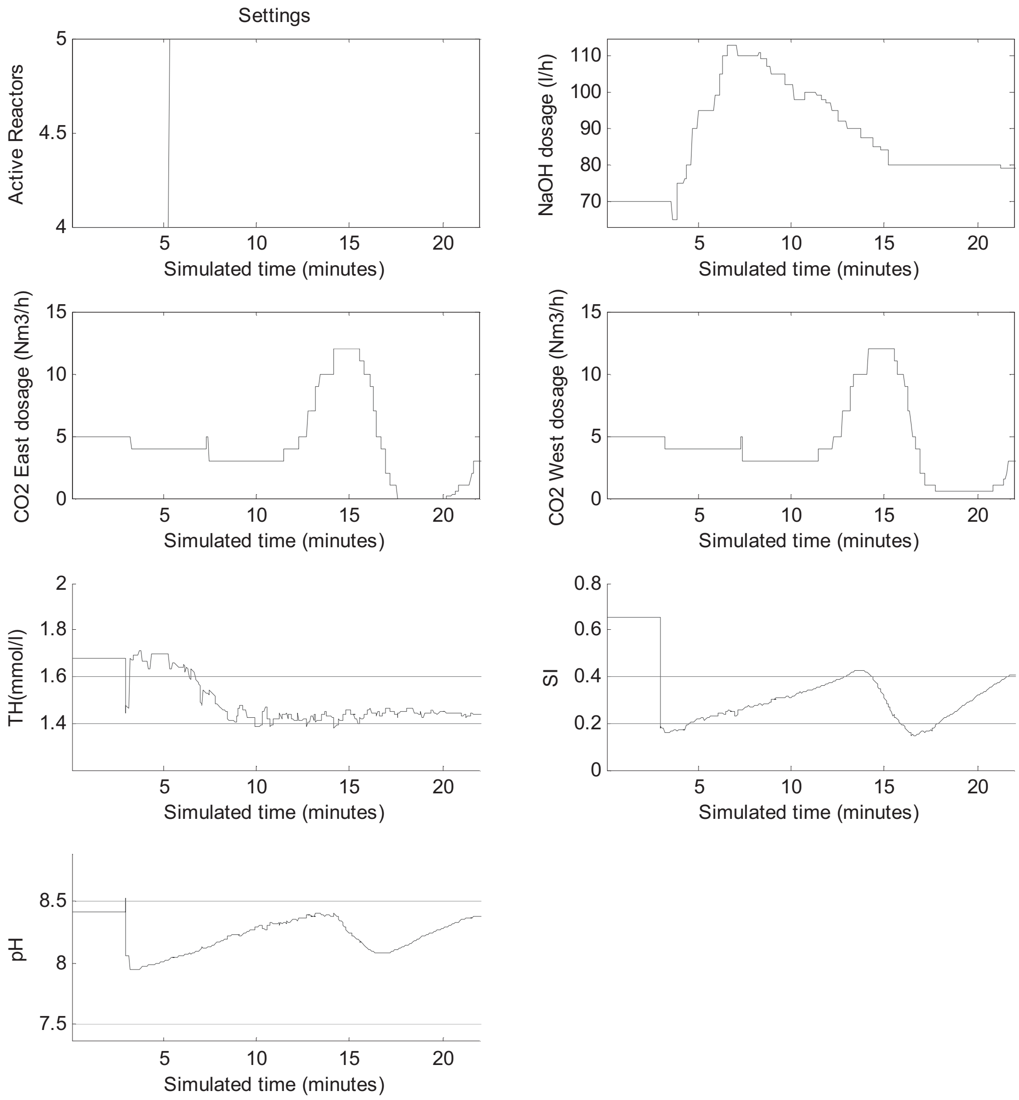


Figure 15. Layman 1x number 1, transfer run 2