Neural networks and genetic algorithms in membrane technology modelling

S. Strugholtz, S. Panglisch, J. Gebhardt and R. Gimbel

ABSTRACT

For the operation of many drinking water treatment processes influences of raw water quality and operational settings on process performance are unknown. Therefore black box models such as neural networks are a promising way to model drinking water treatment processes. The combination of neural networks with genetic algorithms also enables fast process optimization. The application of neural networks and genetic algorithms in drinking water treatment will be shown for a ceramic membrane microfiltration plant. First, neural networks were applied for prediction of the course of transmembrane pressure (TMP) over several cycles with high precision. In a second step these models were applied for operational costs optimization by genetic algorithms. Based on Darwin's idea of the survival of the fittest, settings for filtration time, flux and aluminium dosage were optimized, leading to minimized operational costs with a costs reduction of about 15%. The study proved the effectiveness of genetic algorithms and the applicability for online optimization being planned for further studies.

Key words | ceramic membranes, drinking water, genetic algorithms, neural networks, optimization

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INTRODUCTION

Drinking water treatment plants have to provide good water quality and at the same time low operational costs. Owing to various physical, chemical and biological interactions drinking water treatment processes are often difficult to handle and reliable predictions for the course of processes are difficult to obtain. Therefore great importance is attached to the application of neural networks as black box models in a wide field of drinking water treatment facilities (Baxter *et al.* 2001). To improve profitability appropriate optimization potentialities have to be implied for which genetic algorithms on the basis of neural network models are a powerful combination. In this article the application of neural networks and genetic algorithms is shown for membrane microfiltration with ceramic membranes which is a process gaining more and more attention over traditional polymeric membrane filtration.

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In recent years the use of membrane technology has become an economic alternative to conventional processes. However, before realization of large-scale plants, extensive and time-consuming studies at the bench scale or pilot plant scale are usually necessary to adapt the plant to the on-site conditions. This is not only necessary for the membrane step itself but also for possible pre-treatment facilities such as coagulation/flocculation. Up to now these studies have been performed using a mixture of 'trial and error' and operators' experiences from other sites. Additionally, membrane plants in dead-end mode are often operated based on fixed time schedules instead of relating operational parameters to transmembrane pressure (TMP) development or incoming changing water conditions.

Due to the lack of knowledge about influencing parameters, neural networks as black box models are

capable of modelling fouling (Delgrange 1998; Shetty & Chellam 2003) as well as on-site performance prediction (Teodosiu *et al.* 2000; Oh *et al.* 2004; Veerapaneni *et al.* 2004) from operational and water quality data derived by online data logging and laboratory measurements during pilot or bench-scale testing.

In surface water treatment coagulation is a common pre-treatment step for micro- and ultrafiltration (MF/UF) processes. Neural network approaches also exist for modelling coagulant dosage (Gagnon *et al.* 1997; Maier *et al.* 2004) but so far not in combination with a membrane treatment step. Additionally, in dead-end membrane processes chemically enhanced backwashes (CEB) at defined intervals are necessary to improve process stability. Veerapaneni *et al.* (2004) included backwash frequencies for CEB in their networks but without detailed examination of single cycles.

In a further step existing neural models can be used for process control; for example to avoid irreversible fouling and improve productivity (Cabassud *et al.* 2002). For existing models many optimization approaches can be applied: for example, conjugate gradient methods, Newton's method or quadratic programming. All these methods have the drawback that only one solution per iteration is generated which may be located in a local optimum. This limitation can be avoided by using genetic algorithms where a variety of settings in the form of chromosomes is presented to the model over several generations. The optimization is gained by the principle of Darwin's survival of the fittest. Genetic algorithms have already been used for membrane processes optimization on the basis of mathematical models (Yuen *et al.* 2000; Murthy & Vengal 2006). In MF/UF drinking water treatment processes up to now no reliable mathematical model exists to describe permeate flow or transmembrane pressure. Therefore the combination of neural network modelling and genetic optimization is a promising way to increase membrane process productivity (Chen & Seidel 2002).

Within this study neural networks were trained for predicting the TMP at cycle start as well as the TMP at cycle end, considering process parameters and water quality parameters as well as coagulation and CEB parameters. A sensitivity analysis of the neural network shows the influence of different input parameters on the targets which may also contain hints on mechanisms in membrane filtration. With a reliable prediction quality genetic algorithms can be applied to the models for the purpose of finding the optimal combination of control variables (e.g. coagulant dose, filtration flux and time, backwash frequency, chemical demand). By this means the productivity can be optimized and chemically enhanced backwashes (CEB) can be initiated by necessity instead of a rigid time schedule leading to reduced operational costs.

METHODS

Neural networks

For this study commercially available software (Neuro Model, Atlan-tec, Germany) was used for neural network modelling. It works with the backpropagation algorithm containing special methods for convergence which are based on the method of conjugate gradients. The network structure consists of an input layer, one hidden layer and an output layer. The number of neurons and training settings are fixed by an expert system of the software. Further information on neural networks can be found in Bishop (1995).

Before network training typical data are generated from the raw data by hierarchical data clustering, assuring that all settings, also non-stationary, are equally presented to the network as training data.

To use neural networks for optimization and control, information on the prediction security is needed. Therefore a SecurityNet is integrated (Froese 1997). This patented method as shown in Figure 1 works with five parallel trained networks with different initializations from which the obtained errors are evaluated. The evaluation of these errors provides prediction accuracy in every point of the parameter range. Generally, better prediction quality is

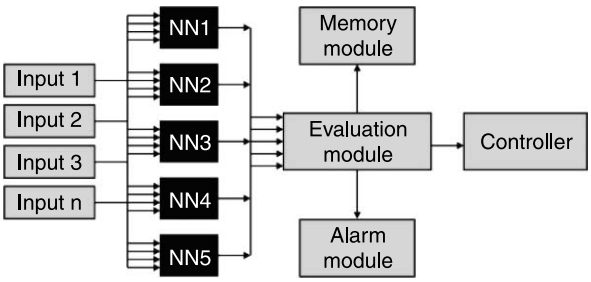

Figure 1 | SecurityNet to evaluate prediction accuracy.

attainable in regions with high concentration of data sets. For optimization and control only parameter settings within the defined prediction accuracy can be used. This system can also be applied for the design of experiments in regions where the prediction quality is low.

Genetic algorithms

Genetic algorithms are inspired by Darwin's evolutionary theory that in nature always the fittest individuals are more likely to survive. By transferring possible process settings to binary coded chromosomes, lots of possible operating points can be tested at the same time, seeking the fittest chromosome; that is, striving for the global maximum of the parameter range. In this way several manipulable variables can be optimized at the same time at a comparably low computational complexity.

From an initial population the fittest solution of the optimization problem (e.g. in the case of this study the minimization of operational costs) is searched over a defined number of generations. From generation to generation in each case the fitness of two chromosomes is compared and the one with the higher fitness is selected for the next generation. Additionally the selected chromosomes undergo genetic operations, namely crossover and mutation, gaining new chromosomes for the offspring. A scheme of the process is shown in Figure 2.

Using neural networks as a model for genetic optimization, the input parameters are divided into constants or disturbance variables and into manipulable variables which are those to be optimized for the given optimization problem. The manipulable variables provide a data range in which they may be varied. This should be selected within the area of training parameters, assuring that no extrapolation is possible. Additionally, the output variable of the network must be inside a defined range of the SecurityNet value obtained from network training, so that each solution is near a solution that was already present in the training dataset. If there are other logic or operational barriers to be taken care of these must also be implemented as barriers for the search area. For optimization a target function including the manipulable variables is defined. Each time a better fitness is generated the chromosomes are decoded back to the original values.

Ceramic membrane microfiltration

Owing to mechanical robustness and chemical resistance, the application of ceramic membranes offers operational advantages over polymeric membranes which are currently dominant on the water treatment market. In Japan a new membrane system with a high packing density was introduced by NGK Insulators Ltd, Japan, allowing economic, large-scale applications. This membrane system was tested by IWW Water Centre, Mülheim, Germany on behalf of NGK in a pilot plant study to investigate the technological and economic performance of a hybrid surface water treatment process with coagulation pretreatment over one year. In the plant, which is shown in Figure 3, up to six test modules with a membrane surface of 0.4 m^2 each could be operated in parallel. The membranes have a nominal pore size of 0.1 μm, the diameter of the feed channels is 2.5 mm. The coagulant was first dosed into a mixing tank; after 6 months coagulation was changed to in-line coagulation. The pilot plant was fully automated and connected to a data logger. Besides the operational parameters flux and pressure, the water quality parameters turbidity, coagulation pH and temperature were measured online. Additional information on plant design and operational/economic results can be found in Lerch *et al.* (2005) and Loi-Brügger *et al.* (2006).

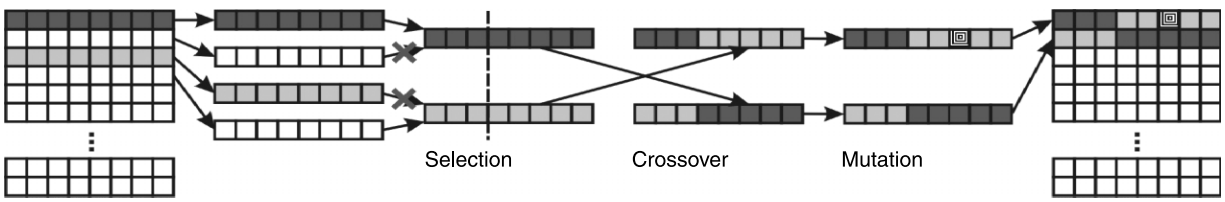

Figure 2 | Selection and Mutation of genetic algorithms.

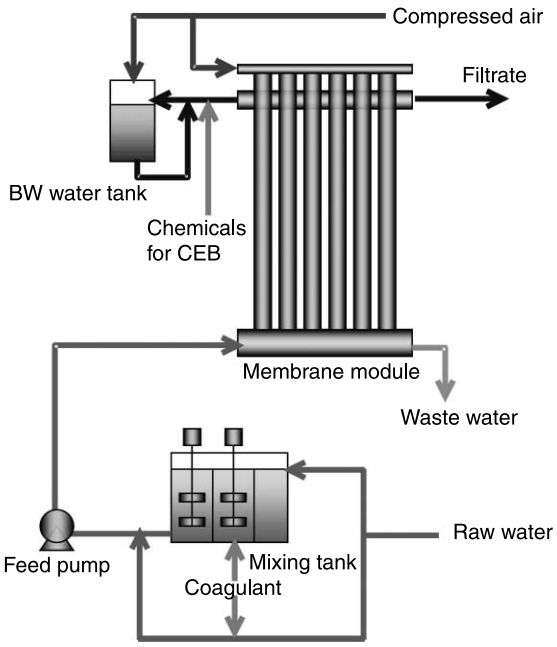

Figure 3 | Ceramic membrane microfiltration pilot plant.

MODELLING AND OPTIMIZATION

In addition to the general advantage of black box modelling with neural networks on the basis of measured data there is further benefit for operators of water treatment plants as well as scientists in using a model with proper accuracy (Figure 4).

The operator can use the model for parameter prediction to gain information on process development in advance. This gives the operator the chance to react to changing conditions and to check new settings without laboratory testing. Also a training simulator could be developed to train new operators.

For scientists the design of experiments based on the prediction quality of the neural network may be effective in reducing the effort required in pilot plant testing. In particular, intensive analysis of networks can help to provide information on the impact of influencing parameters on the process (e.g. raw water quality). This may help to supply additional process knowledge without intensive laboratory testing which at best can be helpful for a mechanistic understanding of water treatment processes.

Optimization (Figure 5) gives the operator the possibility of finding optimal process settings to react in time to changing conditions, such as raw water quality. This will help to reduce the costs not only for the process operation itself but also for chemical demand or laboratory tests. Neural networks in combination with genetic algorithms can be applied online for process control and automation.

The prediction of parameters in drinking water treatment is shown here with the example of a membrane treatment process. Genetic optimization to find new optimal settings on the basis of predicted data is usually an online application as, with new settings, process conditions are changed. Therefore the optimization will be shown as a feasibility study for a short period of time where the prediction accuracy is very high.

Neural network modelling

To describe the membrane process, detailed knowledge on each point of filtration is not necessary as during the filtration step TMP rises linearly and in the case of this ceramic membrane process the backwash step follows the same procedure each time but with various CEB intervals. Therefore characteristic fingerprints were calculated for each filtration cycle consisting of (i) backwash (neutral or CEB) and (ii) filtration as shown in Figure 6. The slope of TMP increase (*mTMP*) is obtained by linear regression from TMP data logged every minute. From slope and filtration time *TMPs* at cycle start and *TMPe* at cycle end can be determined. As the pH of CEB was not continuously measured, a pH value was set constant for neutral (pH7), alkaline (pH10.5) and acidic (pH2) conditions, giving the network a parameter for differentiation between the different programs. Also the coagulant dosing had to be set constant as it was not measured online, but the error from this is quite low as a high precision dosing pump was used.

Important parameters to describe the backwash process are:

- the backwash efficiency coefficient (BEC)
- the difference between two following *TMPs* (*DTMPs*) to describe fouling or cleaning benefit from one cycle to the other
- the irreversible fouling *TMPirr* as the difference between *TMPs* and the constant start TMP (*TMPo*) after an intensive cleaning in place (CIP) or installation of new modules.

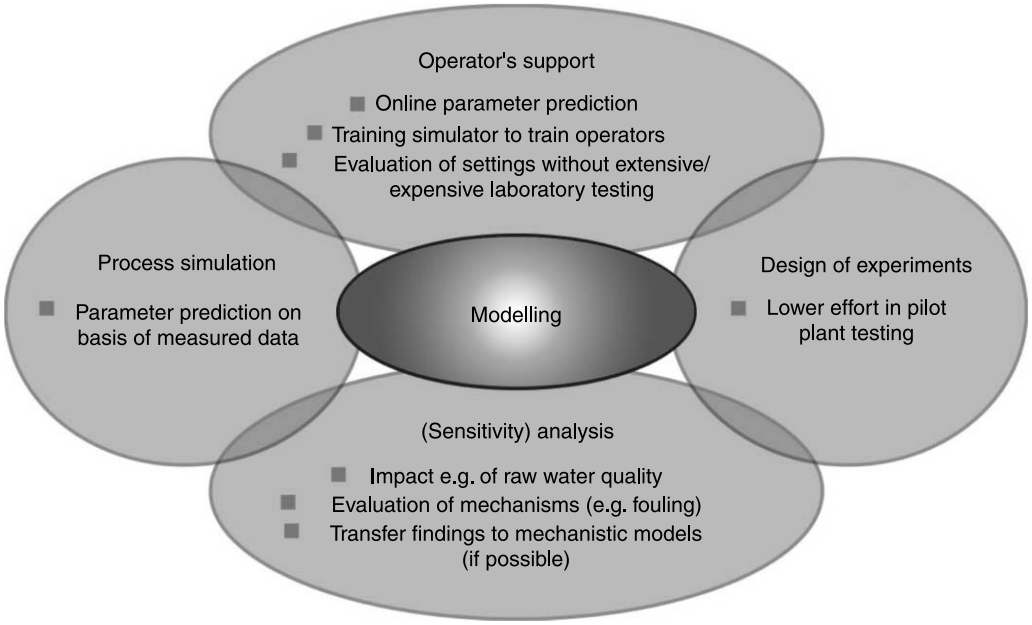

Figure 4 | Potentials of neural network modeling.

All parameters with description, calculation and minimum and maximum values are given in Table 1. From the data logged every minute, collected over one year of operation about 3,850 characteristic datasets were calculated as described above. Training was conducted with about 3,250 of these datasets. Before training about 600 datasets from different times of operation with different settings for filtration time, flux, backwashing program and aluminium dose were separated for testing and parameter prediction with untrained data. The model deviation is

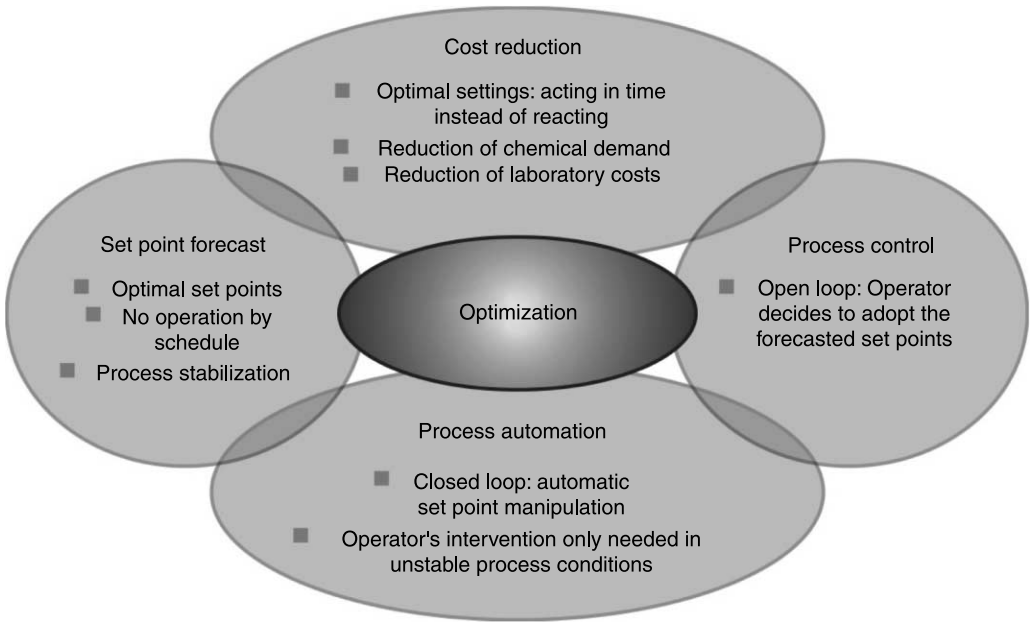

Figure 5 | Potentials of optimization with genetic algorithms on the basis of neural networks.

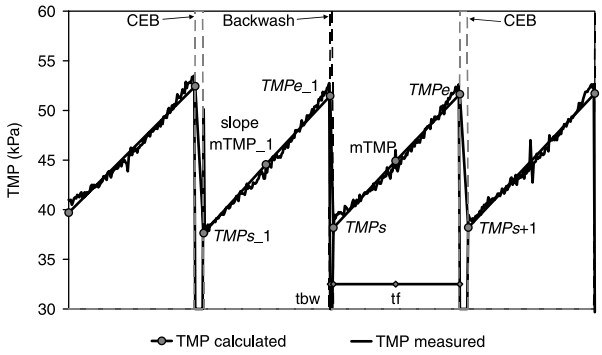

Figure 6 | Calculation of characteristic points.

calculated by:

$$Deviation = \frac{predicted\ value - measured\ value}{maximum\ measured\ value - minimum\ measured\ value} \quad (1)$$

Modelling settings can be seen in Table 1. For modelling of a complete filtration cycle the characteristic points *TMPs* at the beginning of a filtration step and *TMPe* at the end of filtration are modelled in two separate networks. As filtration time and backwash duration are set parameters and are therefore known the development of a whole cycle is completely predictable. *TMPs* and *TMPe* were trained in separate networks as they are dependent on different influencing parameters and to a different extent. First, model training was conducted with all possible input parameters. Next, the input parameters were reduced to the necessary ones in such a way that prediction quality of independent test data was not reduced in comparison with the model with all possible input parameters. In the following, the models are called *TMPs_red* for prediction of *TMPs* and *TMPe_red* for prediction of *TMPe*. Figures 7 and 8 show the prediction of *TMPs* and *TMPe*, respectively, from one cycle to the next. After 6 months of pilot plant studies coagulation was changed to inline coagulation. For this process change no specific parameter was included as an input parameter but, as Figures 7 and 8 show, prediction quality after dataset 300 (those for inline coagulation) is as good as that up to dataset 300. So the neural networks are independent of the coagulation procedure.

The deviation between the predicted and measured *TMPs* and *TMPe*, respectively, is also shown in Figures 7 and 8. Obviously, the prediction by the model is very good as the deviation is about 1.1% on average for both parameters and generally lower than 5% for each dataset.

The other advantage of using two separated models to predict *TMPs* and *TMPe* is that with this method it is possible not only to predict the next filtration cycle but also to use the networks for prediction of several cycles in the future. For parameter prediction in online application only input parameters already measured can be passed to the network model. Therefore, the neural networks for prediction were trained in a way that *TMPs* was predicted from the values measured one cycle before (model called *TMPs_red*) and with this prediction, *TMPe* was predicted from *TMPs* and from input parameters of the cycle before (model called *TMPe_red*). *TMPe* was then the new input for the next prediction of *TMPs* + 1. As Figure 9 shows, prediction over several cycles is possible by assuming constant water quality parameters and process settings. This method is patented by Ondeo Services (Vincent *et al.* 2004).

For *TMP* prediction to further cycles it is of interest to evaluate the addition of errors for stringing together the networks for prediction of *TMPs* and *TMPe* to find out how many cycles can be predicted by assuming constant conditions with sufficient accuracy. Therefore the networks were strung together as explained above. As this involved working with historical data, measured parameters were also available to compare with the predicted data. The deviations that arose are shown in Figure 10. The deviation was about 1.1% at the first cycle (cycle 0) and increased with further following cycles. After the second predicted cycle (cycle + 1) the deviation increased further for *TMPs* but even after 10 cycles (cycle + 9) prediction was possible with a mean absolute deviation below 3.5%. Prediction of 10 cycles into the future means a time span of 7.5 h to 20 h, depending on the filtration time applied.

Genetic algorithm optimization of operational costs

For optimization a new network for the prediction of the optimum transmembrane pressure at the end of a filtration cycle, *TMPe*, was trained (model called *TMPe_opt*). For optimization the input parameters were separated into manipulable variables and disturbance values that cannot

Table 1 | Model parameters with minimum and maximum values and their usage as network input parameters

Description	Abbreviation	Unit	min	max	Measure	*TMPs*_all	*TMPs*_red	*TMPe*_all	*TMPe*_red	*TMPe*_opt
Water quality parameters						*Network input parameters*				
Temperature	Feed_T	°C	2	25	online	_1	_1	_1	_1	0
Turbidity	Feed_Tur	FNU	0.5	100	online	_1	X	_1	_1	0
Load with aluminium c(AI) * Flux * tf	Load_AI	mg m^{-2}	235	1,575	calculated	_1	_1	_1	_1	_1
Load with turbidity Feed Tur * Flux * tf	Load_Tur	FNU m^{-2}	80	30,000	calculated	_1	_1	_1	X	X
Process parameters										
Flocculation pH	Feed_pH	–	6.8	7.5	online	_1	X	_1	X	_1
Feed pressure	Feed_P	kPa	20	175	online	_1	_1	_1	_1	_1
TMP cycle start	TMPs	kPa	8	110	calculated	_1	_1	1.0	1.0	1.0
TMP cycle end	TMPe	kPa	8	205	calculated	_1	_1	_1	_1	_1
TMP cycle slope	mTMP	kPa min^{-1}	0.005	2	calculated	1	1	1	1	1
*TMPs-TMPs*_1	DTMPs	kPa	−15	15	calculated	_1	_1	_1	_1	_1
Irreversible fouling *TMPs-TMPo*	TMPirr	kPa	−5	90	calculated	_1	_1	_1	_1	_1
Backwash time	tbw	min	2	19	calculated	_1	X	_1	X	X
Backwash pH	bw_pH	–	2	10.5	set	_1	_1	_1	_1	_1
Last backwash with the same pH	t_same_pH	min	47	7,000	calculated	_1	_1	_1	_1	_1
Backwash efficiency (*TMPs-TMPe*_1)/(*TMPs*_1-*TMPe* 1)	BEC	–	0.4	9	calculated	_1	_1	_1	_1	_1
Manipulable variables										
Flux	Flux	lm^{-2} h^{-1}	80	300	online	_1	_1	_1	_1	0
Filtration time	tf	min	45	120	calculated	_1	X	_1	X	0
Al-concentration	Al	mg l^{-1}	1.5	3.5	set	_1	_1	_1	_1	0

_1: input parameter from the cycle before the present one
0: input parameter from the present cycle
x: parameter not used for modelling

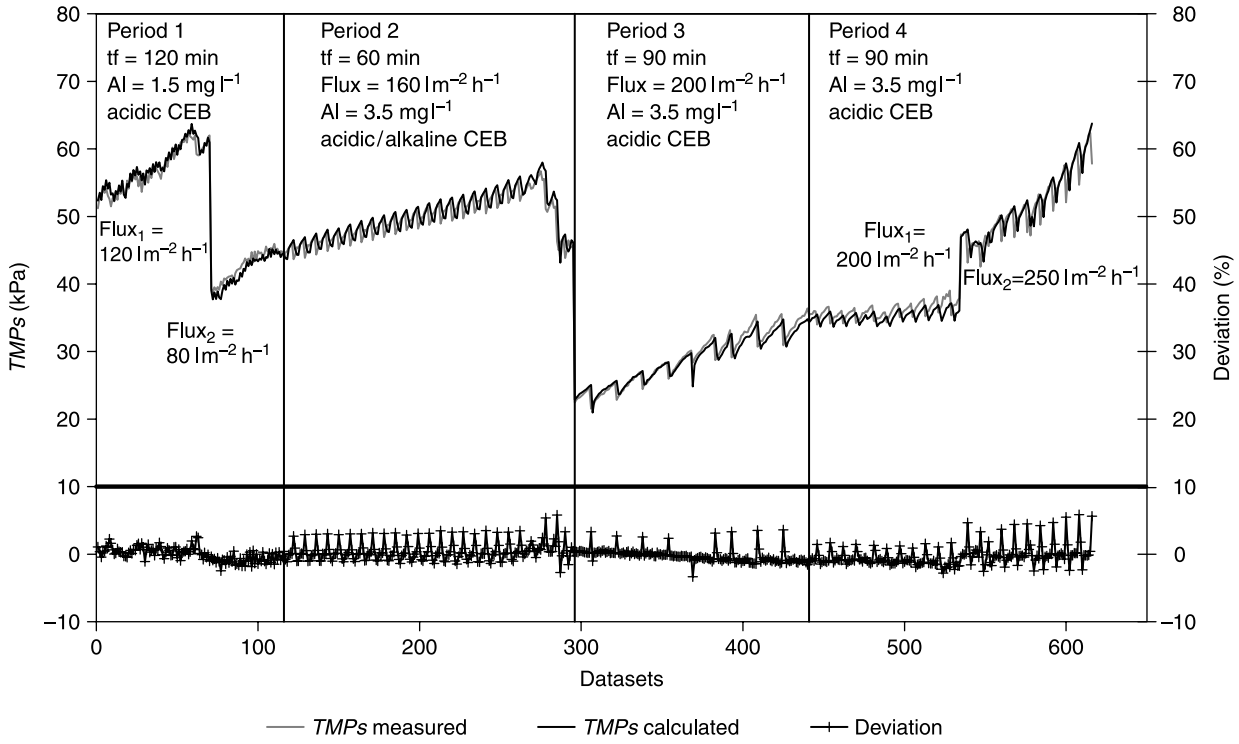

Figure 7 | Prediction of *TMPs* over one cycle.

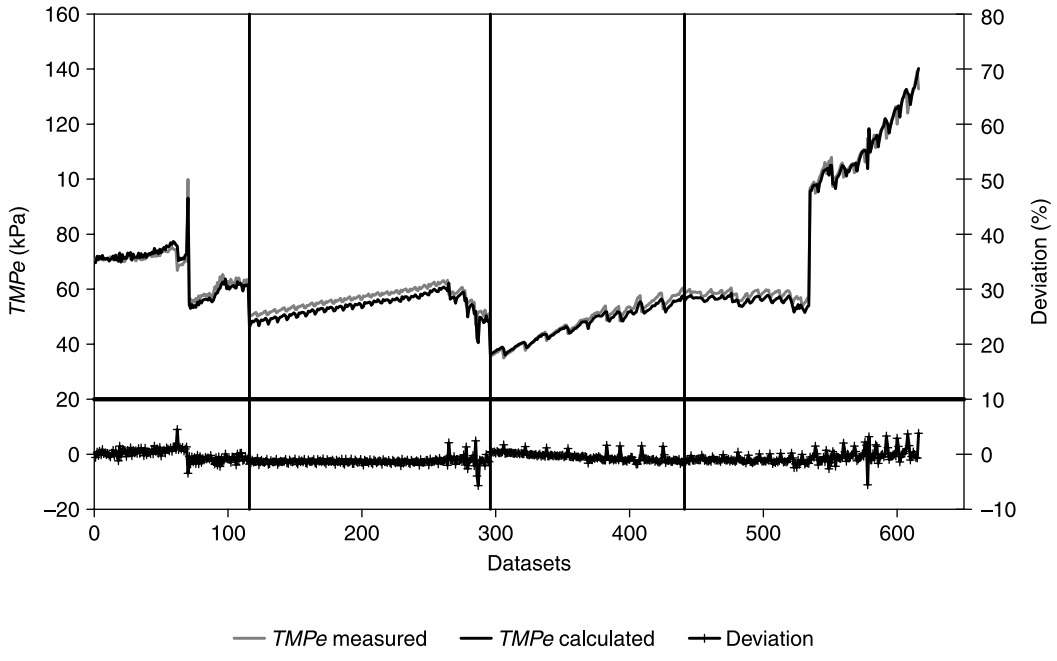

Figure 8 | Prediction of *TMPe* over one cycle.

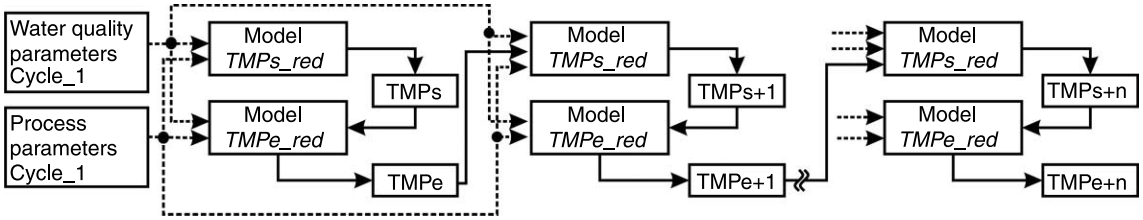

Figure 9 | Prediction of *TMPs* and *TMPe*.

be influenced. The model *TMPe_opt* had to contain the manipulable variables of the actual cycle (filtration time *tf*, flux *Flux*, coagulant concentration *Al*) that were to be optimized and the actual measurable water quality parameters (feed temperature *Feed_T*, feed turbidity *Feed_Tur*). As *TMPs* is the first parameter of the optimized filtration step of the actual cycle, *TMPs* was still predicted by the parameters measured one cycle before (model called *TMPs_red*). After prediction *TMPs* was passed to the model *TMPe_opt* which was used as a model for the genetic optimizer (GenOpt, Atlantec, Germany). In this tool a cost function was defined in order to optimize the manipulable variables to result in minimal operational costs. With these optimized manipulable variables *TMPe* could be predicted. The results of the modified process parameters from the optimizer were given back to the model *TMPs_red* with a time delay of one simulation step or one filtration step. The procedure is shown in Figure 11.

It is important for the optimization that the manipulated variables and the predicted *TMPe* stay in a range that is covered with sufficient prediction accuracy. This is assured by the SecurityNet described in the introduction which checks the prediction accuracy for each prediction of *TMPe*. If the SecurityNet value or prediction accuracy exceeded a value that can be set for the model output in the optimizer (here *TMPe*), the manipulable variables that were proposed to gain minimal operational costs were not considered. Also the manipulable variables are restricted to their value range: the minimum and maximum value covered by the training data.

As the process is run with constant flux ($m^3\,m^{-2}s^{-1}$) the hydraulic power P_{hydr} ($W\,m^{-2}$) is proportional to TMP (Pa).

$$P_{hydr} = TMP \cdot Flux \tag{2}$$

The applied specific energy E_{hydr} ($J\,m^{-2}$) is given by integration of P_{hydr} over filtration time. Assuming a linear TMP increase from *TMPs* to *TMPe* the applied hydraulic energy is:

$$E_{hydr} = 0.7 \cdot \frac{TMPe - TMPs}{2} \cdot Flux \cdot tf \tag{3}$$

assuming a constant efficiency factor of 0.7. Energy costs can be specified as €0.08 per kWh.

Costs for aluminium dosing are given by the aluminium load *Load_Al* ($kg\,m^{-2}$) which is a function of coagulant concentration *Al* ($kg\,m^{-3}$), flux *Flux* ($m^3\,m^{-2}s^{-1}$) and filtration time *tf* (s). The coagulant has a price of €0.30 kg^{-1}.

$$load\_Al = Al \cdot Flux \cdot tf$$

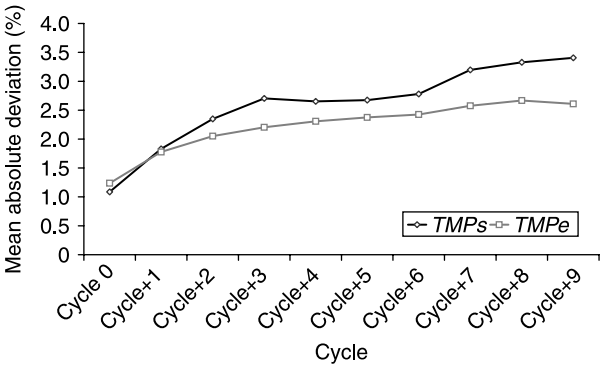

Figure 10 | Deviation increase for parameter prediction over 10 cycles.

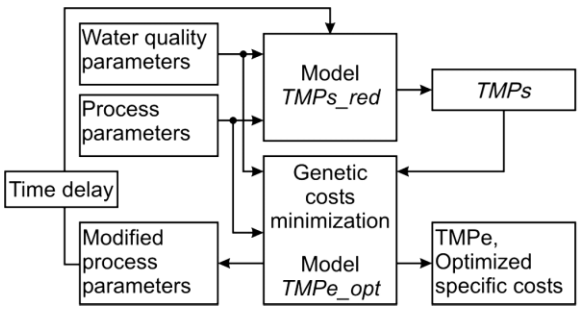

Figure 11 | Procedure of costs minimization with genetic algorithms.

As backwashing always follows the same procedure, constant mean costs of €0.012 m^{-2} membrane surface can be assumed for effluent and chemical costs.

Produced amount of water Q_{prod} (m^3 m^{-2}) within one filtration cycle with filtration time *tf* and flux *Flux* is given by:

$$Q_{prod} = Flux \cdot tf \tag{4}$$

and process efficiency is given by the time slice of production t_{prod} (−); i.e. filtration time *tf* is related to full cycle running time consisting of filtration time *tf* and backwash time *tbw* (s).

$$t_{prod} = \frac{tf}{tf + tbw} \tag{5}$$

This gives the specific cost function *Costs* (€ m^{-3}) for the operational costs per produced amount of water:

$$Costs = \frac{0.012€/m^2 + 0.08 \cdot 2.8 \cdot 10^{-7} €/Ws \cdot E_{hydr} + 0.3€/kg \cdot Load\_Al}{Q_{prod}} \cdot t_{prod} \tag{6}$$

For optimization first a precisely predicted dataset should be found. Therefore the models for prediction of *TMPs*, *TMPs_red*, and *TMPe*, *TMPe_opt*, were strung together as for parameter prediction with the difference that the input parameters were always the actual ones or those of the cycle before the trained one. Figure 12 shows the result for prediction of 10 cycles in the future for *TMPs* with a reduced number of datasets for faster calculation performance. A mean average error of 1.8% for *TMPs_red* and of 1.5% for *TMPe_opt* arose for prediction of 10 cycles into the future. For optimization datasets 120 to 129 were chosen as they showed very low deviation.

Genetic algorithms generate optimal settings for minimal costs without regard to the prediction quality of the neural network. As these optimal settings may be extrapolations (i.e. settings that are not patterns in the training dataset of the neural network), the result for the genetic algorithm must be in a range where the neural network gives a prediction with low deviation. This can be guaranteed by the SecurityNet introduced above as it gives a prediction accuracy at each point of the neural network. Acceptable

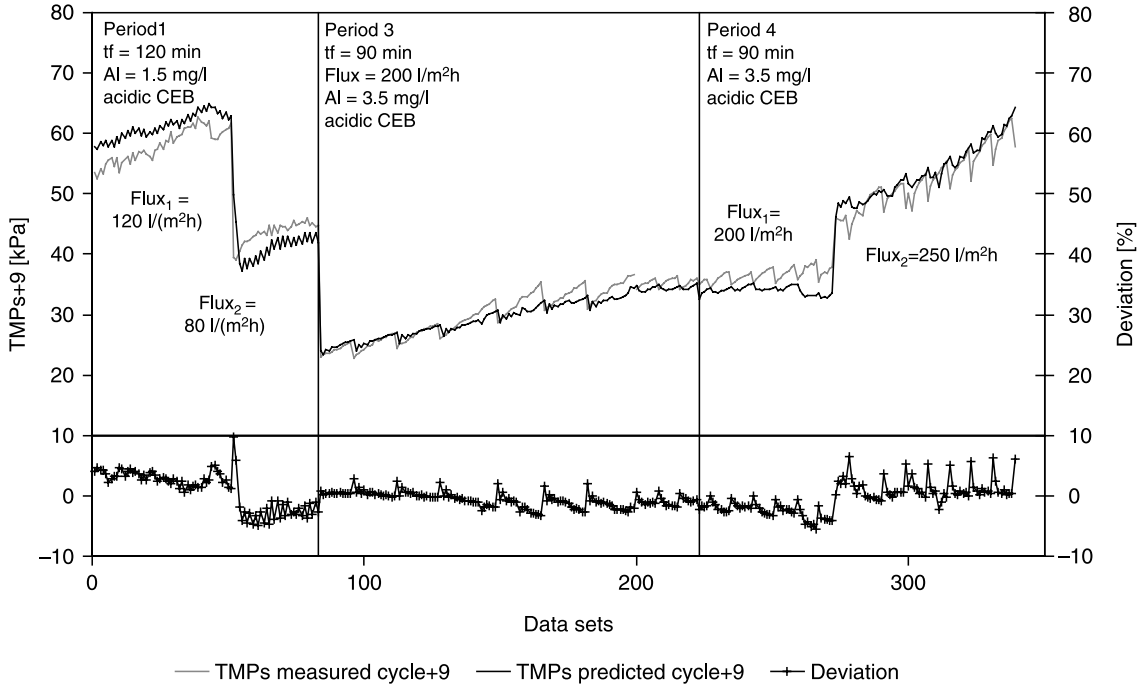

Figure 12 | Prediction of 10 cycles to the future.

extrapolated settings delivered by the genetic algorithm therefore have to be restricted to an allowed prediction accuracy of the neural network of +/− 0.5kPa. Additionally, the range within which the genetic algorithm is allowed to search for the optimum should be restricted to a range where secure prediction is possible. Therefore, the manipulable parameters were limited to the minimum and maximum of the experimentally tested settings. Flux was restricted to 250 l m^{-2} h^{-1} as a flux of 300 l m^{-2} h^{-1} was only tested for a very short period of time so that the model predictions are not secure enough in this area.

In Figure 13 *TMPs* and *TMPe* before and after optimization are compared. Additionally, the estimated savings are shown. The mean operational costs calculated from experimental results within this period amounted to €0.045 m^{-3} produced water. As Figure 13 shows, with optimization, savings could be 15% on average.

Initial parameters for optimization were a flux of 200 l m^{-2} h^{-1}, a filtration time of 90 min and an aluminium concentration of 3.5 mg l^{-1}. First, cost savings were obtained by reduction of energy costs by lower flux of 180 l m^{-2} h^{-1} but higher productivity due to higher filtration time of 120 min. By increasing productivity with linearly rising flux up to 200 l $m^{-2}h^{-1}$ at constant filtration time of 120 min, costs could be further reduced up to 20% despite higher energy consumption. Optimal aluminium concentration was found to be nearly equal to the experimental dosage and therefore did not affect the costs.

The results are transferable to other data ranges. The genetic optimizer is usually used for online optimization.

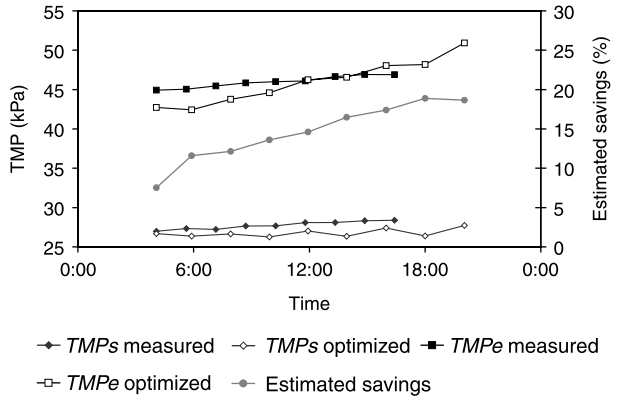

Figure 13 | Costs optimization and development of process parameters.

As only historical data were available this study shows the effectiveness of these genetic algorithms. For further studies the genetic optimizer will be applied online.

In this study CEB intervals were not considered for optimization. This has to be done in a further step in order to reduce irreversible fouling to a minimum.

CONCLUSIONS

Owing to the highly complex nature of drinking water treatment processes, models are useful for parameter prediction to obtain insight into the mechanisms and for process optimization. The most promising direction for modelling is in the application of neural networks. For optimization a new approach of the combination of neural networks with genetic algorithms was used. Genetic algorithms are a fast and powerful tool to find the optimum solution for a multi-dimensional optimization problem by an algorithm related to Darwin's survival of the fittest.

In this study neural networks were used for prediction of transmembrane pressure (TMP) of a membrane pilot plant with coagulation pretreatment over a time horizon of 7.5 to 20 hours with high accuracy. For this, characteristic values were calculated to describe a cycle consisting of backwash and following filtration. The data were derived from a 1-year pilot plant study of ceramic membrane microfiltration. For this process, models for TMP prediction at filtration start and end could be trained, which also considered the influences of coagulation pretreatment and chemically enhanced backwash (CEB).

The experimental results have shown ceramic membranes to be an economical alternative to the more common polymer membranes. By application of genetic algorithms it was shown that a reduction of operational costs is possible. Up to now membrane processes have been operated with constant process adjustments. With genetic algorithms it is possible to find optimal values for manipulable variables which in case of this study were filtration time, flux and aluminium dosage. For the presented optimization problem it has been shown that operation with maximum filtration time and flux was possible. This results in increased productivity and, thus, in considerable reduction of operational costs.

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