Chapter 14

A Survey of Deep Learning Methods for WTP Control and Monitoring

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/intechopen.77196

Abstract

Drinking water is vital for everyday life. We are dependent on water for everything from cooking to sanitation. Without water, it is estimated that the average, healthy human won't live more than 3–5 days. The water is therefore essential for the productivity of our community. The water treatment process (WTP) may vary slightly at different locations, depending on the technology of the plant and the water it needs to process, but the basic principles are largely the same. As the WTP is complex, traditional laboratory methods and mathematical models have limitations to optimize this type of operations. These pose challenges for water-sanitation services and research community. To overcome this matter, deep learning is used as an alternative to provide various solutions in WTP optimization. Compared to traditional machine learning methods and because of its practicability, deep learning has a strong learning ability to better use data sets for data mining and knowledge extraction. The aim of this survey is to review the existing advanced approaches of deep learning and their applications in WTP especially in coagulation control and monitoring. Besides, we also discuss the limitations and prospects of deep learning.

Keywords: artificial neural networks, deep learning, machine learning, coagulation process, water treatment

1. Introduction

1.1. Overview of water treatment process

Water is a unique substance known for its ability to dissolve a variety of substances. When water moves through its hydrological cycle, including precipitation, runoff, infiltration, impounding, use, and evaporation, it comes into contact with different substances that may be more or less dissolved or be suspended in the water. Thus, the type and quantity amount of the dissolved substances, suspended substances, and colloidal substances together determine the overall quality of the water and its fitness for domestic use. Purification and sanitation of water vary as to the source and kinds of water. Municipal waters, for example, consist of surface water and ground water, and their treatment is to be distinguished from that of industrial water supplies. Municipal water supplies are treated by public or private water utilities to make the water potable (safe to drink) and palatable (esthetically pleasing) and to insure an adequate supply of water to meet the needs of the community at a reasonable cost. Except in exceedingly rare instances, the entire supply is treated to drinking water quality for three reasons: it is generally not feasible to supply water of more than one quality; it is difficult to control public access to water not treated to drinking water quality; and a substantial amount of treatment may be required even if the water is not intended for human consumption.

In order to achieve this, a water treatment plant employs many unit treatment processes that are linked in a process train to produce water that is fit for domestic use reliably and consistently from a raw water source at a cost that is reasonable to the consumers. Municipalities are over time facing an increase in population, a decrease in available freshwater supplies, and stricter regulation. The water treatment process may vary slightly at different locations, depending on the technology of the plant and the water it needs to process, but the basic principles are largely the same.

Purification water systems use various methods of water treatment to ensure ongoing water quality, including water quality testing. The testing helps ensure the water treatment process results in a product that meets federal water quality guidelines. Water analysis involves looking for several kinds of contaminants, including unsafe levels of organic, inorganic, microbial, and/or radioactive contaminants. At present, the most common steps in water treatment used by community water systems, mainly surface water treatment [1–3], include:

- Pretreatment: Pumps bring raw (untreated) water, often from lakes or rivers, into the purification plant through screens that exclude fish, weeds, branches, and large pieces of debris. Screening may not be necessary for groundwater. The plant may aerate the water at this point to increase the oxygen content and thus help remove problematic odors and tastes.
- Coagulation and flocculation: Coagulation and flocculation are often the first steps in water treatment. Chemicals with a positive charge are added to the water. The positive charge of these chemicals neutralizes the negative charge of dirt and other dissolved particles in the water. When this occurs, the particles bind with the chemicals and form larger particles called floc.
- Sedimentation: During sedimentation, the heavy floc settles to the bottom of the water supply due to its weight.
- Filtration: Once the floc has settled to the bottom of the water supply, the clear water on top will pass through filters of varying compositions (sand, gravel, and charcoal) and pore sizes, in order to remove dissolved particles, such as dust, parasites, bacteria, viruses, and chemicals.

- Disinfection: After the water has been filtered, a disinfectant (for example, chlorine and chloramine) may be added in order to kill any remaining parasites, bacteria, and viruses and to protect the water from germs when it is piped to homes and businesses.

The main goals of these various operations of water treatment process are to reduce the chemical cost, control the energy consumption required to work the treatment processes, and reduce the water wastes. Many research and studies are performed in order to increase the water treatment plant performances. **Figure 1** presents a schematic overview of these various operations necessary to treat the water. Many measurements of variables recorded by sensors such as turbidity level (TUR), PH, conductivity (COND), dissolved oxygen (DO), and temperature (T) are needed to carry out the jars test in order to determine the optimal dose of the aluminum sulfate.

The modeling of water treatment processes is challenging because of its complexity, nonlinearity, and numerous contributory variables, but it is of particular importance since water of low quality causes health-related and economic problems which have a considerable impact on people's daily lives. In most research works, linear and nonlinear modeling methods are used to model for example residual aluminum, turbidity, and coagulant dose in treated water, using both laboratory and process data as input variables. The approach includes variable selection to find the most important factors affecting the quality parameters.

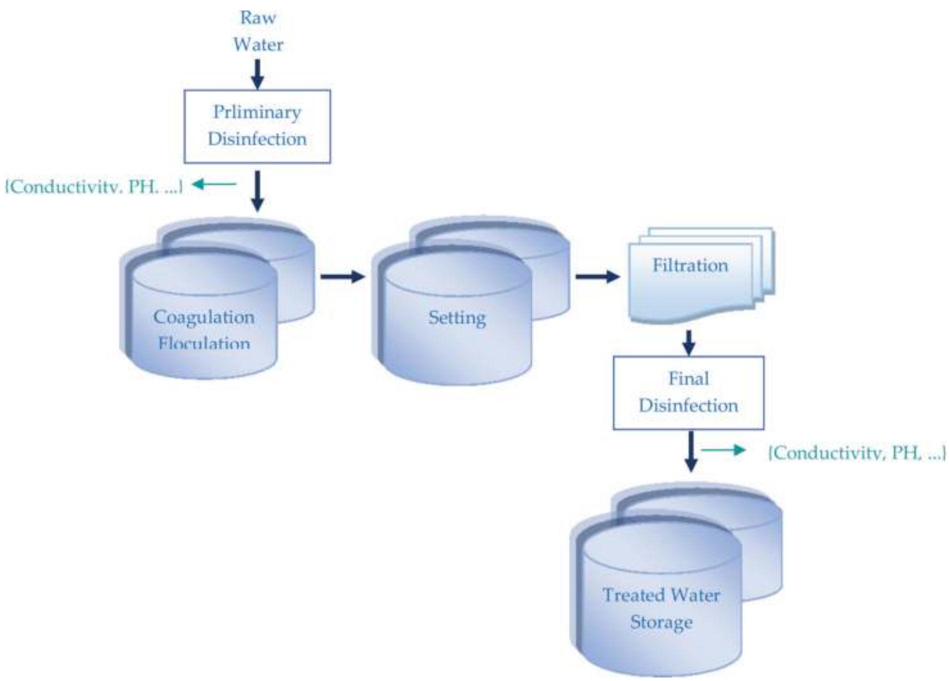

Figure 1. Simplified synopsis of the water treatment plant.

In the following, we review some techniques used for purifying raw water and the control strategies proposed so far trying to supply drinking water in a reliable manner. This control problem is very complex due to the variable quality of raw water, the seasonal changes that temperature and PH have on disinfection capabilities, the transport delays associated with the transport time of water from one point to another, and the multiple-input, multiple-output nature of the issue in question. In this chapter, we focus on one of main aspects related to the optimization of water treatment plants, which is the control and monitoring of coagulant dose, in which we have experience. There are two families of approaches that are described in this chapter: the first one covers the classical applications dedicated to understand and establish relationships between raw water characteristics and the coagulant reagent destabilizing the colloidal matter in suspension. The second family deals the leading applications carried out in machine learning, especially those using deep neural networks for automatic control of coagulation process.

1.2. Coagulant control and monitoring

Purification of drinking of drinking water is a very important problem in environmental engineering. Stricter drinking water quality standards demand improvement of control systems for water treatment. The efficient operation of a water plant depends upon the success of the clarification stage. Generally, the regulation of chlorination in drinking water systems is based on open-loop control. The application of feedback control in drinking water purification systems has been delayed due to the lack of sensors for measuring chlorine concentration in a reliable fashion. Although chlorine concentration sensors have been used in large drinking water systems, these sensors are typically used for monitoring purposes mostly for coagulation control. Various closed-loop controllers have been proposed. In [4], a feedback control scheme is implemented using color and turbidity sensors and variable speed pumps. The sensors are used to determine the current characteristics (i.e., color and turbidity) of the raw water, and the pumps are used to dose a coagulant into the raw water, which achieves clarification of the water. A third measurement, a conductivity sensor, has been considered in to suppress errors obtained from the color sensor (i.e., color sensor measurements are considerable higher than laboratory results), when the turbidity of the water is high.

Coagulation process is one of the critical processes performed in the water treatment of surface waters, involving many biological, physical, and chemical phenomena [1–3]. The control and monitoring of a good coagulation are essential for maintenance of satisfactory treated water quality and economic plant operation. Basically, colloidal particles are separated by means of a chemical coagulation process that consists to destabilize charge of the suspended particles by adding coagulant. The coagulant generally used in the drinking water industry is aluminum sulfate because of its effectiveness, accessibility, and low price. Some studies have been carried out to improve the effectiveness of the aluminum sulfate or to replace this coagulant by another natural, available, and cheaper. Mukheled [5] used Date seeds and Pollen Sheath as coagulant to treat different levels of turbidity (75, 150 and 300 NTU). Ali et al. [6] tried *Moringa oleifera* seed in the coagulation process to treat low turbid water in Malaysia. However, Aho et al. [7] highly recommended the use of this natural coagulant in the domestic turbid water purification in Nigeria. Other natural coagulants are proposed as an important alternative in the water treatment plant. The coagulants are from plant origin such as nirmali seed and maize [8], *Cassia angustifolia* seed [9], mesquite bean and cactus latifaria [10], chestnut and acorn [11], Cocciniaindica fruit mucilage [12], and from different leguminous species [13]. Those natural products have coagulating activity in the treatment of turbid water and can be used as coagulant or as coagulant aid with other synthetic and industrial coagulants (aluminum sulfate…) in order to reduce the coagulant consumption in the water treatment plant [14].

Coagulant dosage is chosen empirically by operators based on their past experience, laboratory jar-testing, and various information on water quality parameters. The jar-test apparatus simulates mixing, flocculation, setting, and a single test may take about 1 hour to be performed. Jar-test involves taking a raw water samples and applying different quantities of coagulant to each sample [15]. After a short period of time, each sample is assessed for water quality and the dosage that produces the optimal result used a set point. This operation should be repeated by the operators each time when the quality of raw water changes. The aluminum sulfate is the compound likely to be mathematically modeled, and therefore, its value can be estimated according to the data available in the treatment plant. Disadvantages associated with jar-testing are that regular samples have to be taken requiring manual intervention and operators can make manually in raw water quality. Both manual and automatic methods are used to predict optimum coagulant dose [15, 16]. Automatic method is ensured by streaming current detectors [17–19]. The streaming current detector (SCD) is an instrument used to measure coagulated particle stability for the feedback control of coagulant dosage. Muzi Sibiya [20] reports the results of the online control of polymeric coagulant dosage at rapid mixing step in water treatment. The results show that the SCD reading increases as the polymeric coagulant dosage increases. The supplier recommended cationic polymer concentration for an SCD calibration standard of 100 mg/l was found suitable for SCD calibration purposes. The streaming current reading of the coagulated water at optimum coagulant dose was not significantly affected by raw water turbidity.

There is no mechanistic model describing the coagulant dosage related to the different variables affecting the process and also by using cheapest products. An interesting alternative to elaborate models is the use of deep neural networks often used in machine learning. Process data can be used directly to represent input-output process relationships. Artificial neural networks (ANN) proved to be extremely flexible in representing complex nonlinear relationships between many different process variables [21]. They do not require any a priori precise knowledge on the relationships of the process variables. Various applications were performed in order to develop a neural model for the online estimation of optimal coagulant dosage from raw water characteristics. Previous researches [22–26] show the efficiency of such approach using neural networks.

2. Deep neural networks for coagulation control and monitoring

2.1. Overview of artificial neural networks and deep learning

Since their origin in 1943 [27], artificial neural networks (ANNs) have been used to provide the best solutions to large various nonlinear problems. The ANNs have generated a lot of motivation of machine learning research and industry, thanks to many progress results in robotic processing [28], object recognition [29], speech and handwriting recognition [30], and even real time sign-language translation [31]. Overall, an artificial neural network can be described by three main parts: (1) Input nodes that provide information from the external source (signals, features, image, and measurements) to the network. Each input has an associated weight, which is assigned on the basis of its relative importance to other nodes. These input nodes are usually normalized via the activation functions, which perform a certain fixed mathematical operation. (2) Hidden nodes responsible for extracting patterns associated with the process or system are being analyzed. These layers perform most of the internal processing from a network. (3) Output nodes are collectively responsible for computations (processing performed by the neurons in the previous layers) and producing the final network outputs. Depending on the arrangement of neurons and their interconnection via the processing layers, the main architectures of artificial neural networks can be divided as follows: single-layer feedforward network (as example, perceptron and the ADALINE), multilayer feedforward networks (multilayer perceptron (MLP) and the radial basis function (RBF)), recurrent networks, and mesh networks (The Self-Organizing Map the main representative of mesh architectures).

Despite the idea that deeper architectures would provide better results compared that are shallower already used, empirical tests with deep networks had found similar or even worse results when compared to networks with only one or two layers [32, 33]. Training was also found to be difficult and often inefficient [33]. Finally, this concept started to change with the proposal of greedy layer-wise unsupervised learning [34], which allowed for the fast learning of deep belief networks and solving the vanishing gradients problem. Thus, since 2006, deep learning's revolutionary advances in speech recognition, image analysis, and natural language processing have gained significant attention. With the ever-growing volume, complexity, and dynamicity of online information, deep learning approach has been an effective key solution to overcome such information overload. Recent studies also demonstrate its effectiveness in anomaly detection and prediction tasks. Deep learning is a sub research field of machine learning. It learns multiple levels of representations and abstractions from data, which can solve both supervised and unsupervised learning tasks [35]. In this subsection, we briefly review the key array of deep learning concepts using some of the sources included in the annotated section of the bibliography [36–38]:

- Multilayer perceptron (MLP) is a deep artificial neural network with hidden layers (one/or multiple layers) between input layer and output layer that makes a decision or prediction about input. An MLP can be viewed as a logistic regression classifier where input is first transformed using a nonlinear transformation to project the input data into a space linearly separable. A single hidden layer is sufficient to consider MLP a universal approximator. Since 2006, scientific researchers have shown that there are considerable benefits to using many such hidden layers, e.g., the very premise of deep learning.
- Recurrent neural network (RNN) performs the same task for every element of a sequence, with the output being depended on the previous computations. In a traditional neural network (feedforward neural network), all inputs and outputs are independent of each other. The idea behind RNN is to employ sequential information in order to capture information

about what has been calculated so far. We can say that RNNs have a "memory". Long short term memory (LSTM) and gated recurrent unit (GRU) network are two variants generally chosen to solve the vanishing gradient problem.

- Convolutional neural network (ConvNet) is a special kind of feedforward neural network with convolution layers and pooling operations. Each neuron receives some inputs, performs a dot product, and optionally follows it with a nonlinearity. ConvNet architecture posits an explicit assumption that the inputs are images, which provide (encode) certain properties into the architecture. These then allow to perform two things: easily and efficiently implement the forward function and vastly reduce the amount of parameters in the network.

- Restricted Boltzmann machine (RBM) is a parameterized generative model representing a probability distribution. Boltzmann machine consist of two types of layers, so called visible and hidden neurons. The visible layer corresponds to the components of an observation. The hidden layer models dependencies between the components of observations (for a digital input image, one visible unit for each pixel). Restricted means that there are no intra-layer communications in visible layer or hidden layer.

- Auto-encoder (AE) is an unsupervised model pretraining that has three layers: an input layer, an encoding (hidden) layer, and a decoding layer. The AE model is trained to reconstruct its inputs, which forces the hidden layer to try to learn good representations of the inputs. The learned representation of auto-encoder can be used for dimensionality reduction and can be used as a feature for another task. There are many variants of auto-encoders such as denoising auto-encoder, marginalized denoising auto-encoder, sparse auto-encoder, contractive auto-encoder, and variational auto-encoder (VAE).

- Deep semantic similarity model (DSSM) has developed for representing text strings (sentences, queries, predicates, entity mentions, etc.) in a common low-dimensional semantic space and measuring their semantic similarities. DSSM is frequently used in various applications including information retrieval and Web search ranking, contextual entity search and interestingness, image captioning, etc.

- Neural autoregressive distribution estimation (NADE) is an unsupervised neural network which is inspired by RBM but uses feed-forward neural network and the framework of auto-regression for modeling the probability and density distribution of binary variables in high-dimensional vectors.

- Generative adversarial network (GAN) is a generative neural network comprised of two nets: a discriminator and a generator, pitting one against the other, e.g., the two neural networks are trained simultaneously by competing with each other in a minimax game framework.

In the article, Zhang et al. [38] provide a comprehensive review of recent research efforts on deep learning–based recommender systems toward fostering innovations of recommender system research. A taxonomy of deep learning–based recommendation models is presented and used to categorize the surveyed articles. Wide and deep learning (WDL) is one of the models presented in this paper. This model can improve the accuracy, as well as the diversity of recommendation. The WDL (shown in **Figure 2**) can solve both problems, regression and

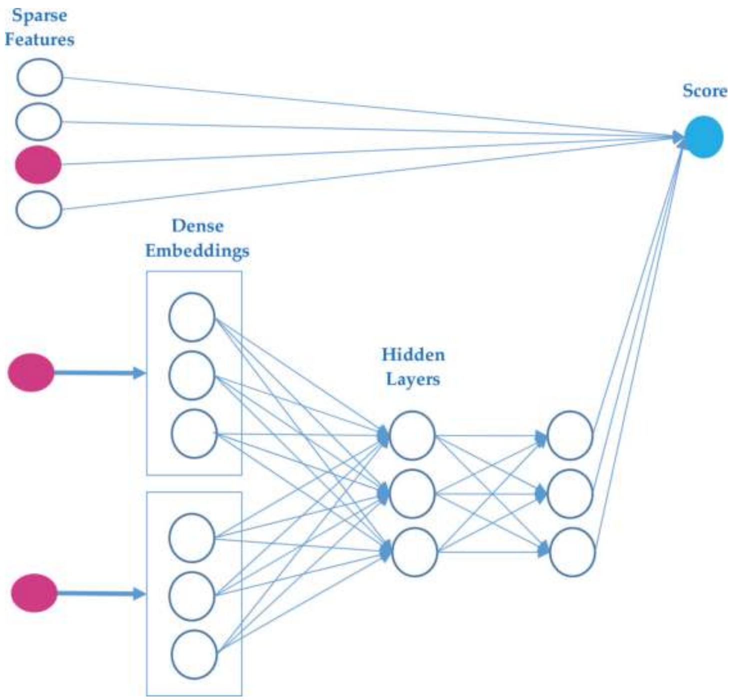

Figure 2. Illustration of a wide and deep learning.

classification, by combining two learning techniques: the wide learning component (single-layer perceptron) and deep learning (multilayer perceptron). The aim searched from combining these two learning techniques is that it enables the recommender system to capture both tasks: (1) memorization, which is the capability of catching the direct features from historical data, and (2) generalization by producing more general and abstract representations.

For different fields, suitable applications vary depending on the nature, type, and purpose of the data. While scientific researchers can be interested in searching for anomalies in the sleep patterns of a patient, economists and industrials may be more interested in forecasting the next prices some stocks of interest will assume. These kinds of problems are addressed in the literature by a range of different approaches used to perform tasks such as classification, segmentation, anomaly detection, and prediction. Applying deep neural network techniques also into treatment water process [25, 39–46] has been gaining momentum due to its state-of-the-art performances and high-quality recommendations. In contrast to traditional recommendation models, deep learning provides a better understanding of user's demands, item's characteristics, and historical interactions between them.

2.2. Neural software sensors for coagulation automatic control

Several works [25, 39–42] have already shown the potential of these techniques for modeling the coagulation process. All these studies propose to relate the coagulant dose to different

http://dx.doi.org/10.5772/intechopen.77196

descriptors parameters of the quality of raw water, such as turbidity, pH, conductivity, etc., using a neural network. The learning base is constructed using a jar-test test history to model the optimal coagulant dose. Agdar et al. [39] propose to use the color, conductivity, and turbidity of raw water to predict the dose of coagulant. The results obtained on a pilot site [39] seem encouraging. However, the lack of input descriptor parameters does not allow to take into account all variations in the quality of the raw water. Another study [40] proposes to use many more input parameters of the RNA model. Mirsepassi et al. [41] also propose to use a history of these different parameters, that is, to consider the value of the parameters at times $\{t-1, t-2, \ldots, t-6\}$ (t represents the current day). Gagnon et al. [25] show the interest of building seasonal models. They use four descriptors parameters of the raw water quality: pH, turbidity, conductivity, and temperature. This study compares the accuracy of an annual year-round model with four seasonal patterns. Nevertheless, the determination of the four periods of application of each model seems difficult. Valentin et al. [42] have developed an alternative to the jar-test and SCD methods allowing for the automatic determination of optimal coagulant dose from raw water characteristics, using a self-organizing map and MLP approaches to validate the sensor measurements before coagulant dose estimation.

Given the strong evolution of the raw water characteristics, an important property for such system is indeed the robustness with regard to the sensors failings or to the unexpected raw water characteristics, owing to accidental pollution for example. Coagulation process is one of the critical processes performed in the drinking water treatment, involving many biological, physical, and chemical phenomena. As we have already mentioned, the control of a good coagulation is essential for maintenance of satisfactory treated water quality and economic plant operation. Thus, an over-dosage can lead both to an increase in the operating costs and to public health concerns. While an underdosage can cause failure to meet the water quality targets, the coagulation has a strong impact on the clarification step. In addition to these developments on the coagulation automatic control, we have developed a software sensor based on a hybrid system [44–47], including a Self-Organizing Map (SOM) for measurements validation and missing data reconstruction [45], a multilayer perceptron (MLP) for coagulant dose prediction [47], and a neuro-fuzzy method to identify functional states of treatment plant [44, 45]. The main objective of our works conducted was to validate and rebuild the measurements of characteristics raw water so as to provide reliable inputs to the automatic coagulation control system.

In many anomaly detection applications, abnormal (negative) samples are not available at the training stage. For instance, in a computer security application, it is difficult to have information about all possible attacks. In the machine learning approaches, the lack of samples from the abnormal class causes difficulty in the application of supervised techniques. Therefore, the obvious machine-learning solution is to use an unsupervised algorithm. For this, we adopted an unsupervised learning approach based on the self-organizing map algorithm introduced by Kohonen [48]. Self-organizing map is one of the most popular neural network models. It belongs to the category of competitive learning networks. The SOM method is based on unsupervised learning, which means that no human intervention is needed during the learning and that little needs to be known about the characteristics of the input data. We could, for example, use the SOM for clustering data without knowing the class memberships of the input data. The SOM can be used to detect features inherent to the problem and thus has also been called SOFM (self-organizing feature map).

For coagulant dosage prediction, the MLP architecture (inputs, number of hidden layers, and number of neurons) has been fixed a priori. To define relevant descriptors of raw water quality affecting the coagulant dosage, a principal components analysis (PCA) is used within this framework. The number of neurons in the hidden layer has been optimized with a pruning method "weight-decay" [49, 50] in combination with the "Levenberg–Marquardt" algorithm [51], allowing the weak weights to be penalized (the connections with weak weight are eliminated). In this framework, the weights and biases of the network are assumed to be random variables with specified distributions. The regularization parameters are related to the unknown variances associated with these distributions. To take into account the uncertainly bound to the size limited of the learning set, the "Bootstrap" sampling [52] has been used to generate confidence interval for the model outputs. The results confrontation with test data of treatment plant located in Morocco [45, 46] shows that it is possible to determine online and in a very satisfactory way the optimal coagulant dose and this in various phases of functioning.

To assure a good monitoring and contribute to a good operation of this process, it would be necessary to exploit all process information, such as the measurements of raw water characteristics and their evolutions resulting for example from unforeseen abnormalities, as well as the expert knowledge. For these reasons, we chose to carry the behavior monitoring of this process by using a neuro-fuzzy method, called "LAMDA" (Learning Algorithm for Multivariate Data Analysis) classification technique [53, 54], which allows aggregating this information for informing the operator by specific situations. The classification idea is the evaluation of the significant system signals (raw water quality measurements + neural coagulant dose) to recognize the factors related to such or such other situation and to help the operator to make a decision during the failure appearance. This approach was a first application that shows the utility of classification techniques in the monitoring and the surveillance of this process type. It is clear that the final objective was to spread this monitoring to other treatment processes in order to detect at the earliest a drift functioning or to identify a failure on an upstream unit (**Figure 3**).

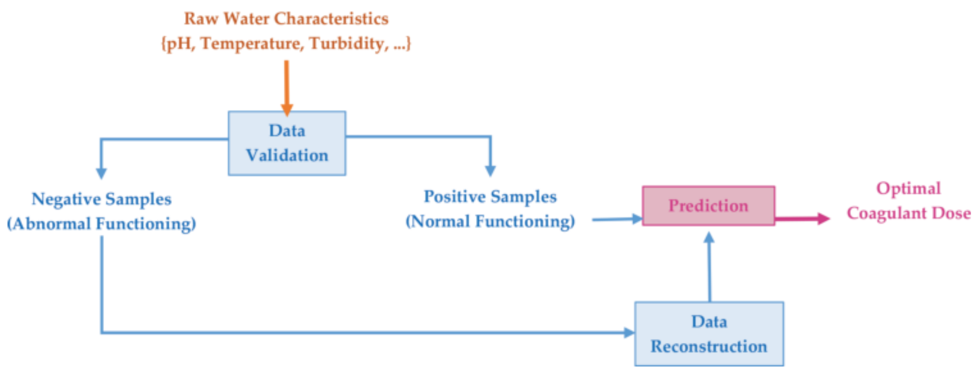

Figure 3. Hybrid system proposed for coagulation control and monitoring.

3. Other propositions to purification water processes control

An expert system for a water purification system that performs supervisory control of water quantity, and automatic filter basin control, is developed in [55]. The sand bed filters can be in four possible states: waiting for filtering, filtering, waiting for scouring, and scouring. The filter basins in a water purification system are usually divided into groups connected in parallel. Online data are gathered from distributed control systems throughout the water purification system. In [56], filter basin control is based on control of filter scouring basin and control of the number of filter basins in operation. Filter scouring occurs when the water flow falls below a preset minimum value. The number of filters in operation is controlled to match the plant processing flow to total filtering flow. A different approach is presented in [56], where the proposed chlorination control system for water treatment is a double cascade PI loop for controlling the hypochlorite dosed in the system by means of free chlorine measurements taken at two sample points of the disinfection system. Denitrification of drinking water has been also proposed in several studies. In [57], SISO and MIMO robust variable structure controls for fixed bed bioreactors are developed. A SISO variable structure control is used to control the total concentration of nitrates and nitrites by changing either the inlet flow rate or the ethanol concentration. A MIMO variable structure control is needed to optimally regulate the ethanol concentration of drinking water. In [58], drinkable water is also treated by a fixed bed bioreactor. A multiinput and multioutput sliding control law of a distributed parameter bio-filter is designed to improve the quality of the water in order to control the harmful component concentration at the outlet of the bioreactor and to optimize the addition of carbon source. However, to our knowledge, it is certainly regrettable that no specific model based on deep neural networks is performed on this type of process.

4. Conclusions

Water resources systems management practice, include drinking water treatment process, around the world is challenged by serious problems. Climate change and land use change are increasingly recognized as having the major impact on hydrologic variables and therefore on management of water resources. Certainly, the profession has been slow to acknowledge these changes, and that fundamentally new approaches will be required to address them. Evolutionary algorithms are becoming more prominent in the water treatment processes field. Significant advantages of evolutionary algorithms include: (1) no need for an initial solution; (2) ease of application to nonlinear problems and to complex systems; (3) production of acceptable results over longer time horizons; and (4) generation of several solutions that are very close to the optimum (and that give added flexibility to a water manager). Special attention is given to evolutionary optimization by deep neural networks to predict and capture anomalies in coagulation process, regarded as a complex and critical process. The use of deep neural networks for process modeling and control in the drinking water treatment is currently on the rise and is considered to be a key area of research. With regard to previous works, the neural approach offers the advantage of very short computational times and to be able intrinsically to describe some nonlinear relations between inputs and outputs system. In this chapter, we provided an extensive review of the most notable works to date on coagulation control and monitoring. Both classical methods and deep neural networks are ongoing hot research topics in the recent decades. There are a large number of new developing techniques and emerging models each year; here, we provide an inclusive framework for comprehensive understanding toward the key aspects of this field, clarify the most notable advancements and shed some light on future studies to promote lines of action for the work on this issue: developing intelligent systems for water process managing and optimization.

When applying deep learning, one seeks to stack several independent neural network layers that, working together, produce better results than the already existing shallow structures. In this paper, we have reviewed some of these modules, as well the recent work that has been done by using them, found in the literature. Employing deep learning to data analysis and forecasting has yielded results in these cases that are better than the previously existing techniques, which is an evidence that this is a promising field for improvement in order to propose and develop online reliable systems to WTP monitoring and automatic control.

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