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A Survey of Modelling Techniques and Control Strategies Employed for Coagulation Process in Drinking Water Treatment Plants

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***Abstract*— Modelling techniques and control strategies employed for the coagulation process in the conventional drinking water treatment plants in the last two decades are reviewed in this paper. The contributions of different models and control strategies in the literature to ensure that raw water under treatment is not under-dosed or overdosed with coagulation chemicals are presented. In addition, the possible directions in the future to comply with the strict drinking water regulations are proposed in this paper.**

Keywords—Water Treatment; Coagulation; Modelling; Control; Optimisation

I. INTRODUCTION

One of main processes involved in water treatment plants (WTPs) is coagulation. The role of coagulation is to remove or reduce colour, turbidity and harmful contaminants from the raw water to a satisfactory level through the addition of coagulant and pH adjustment chemicals in conjunction with other unit processes such as flocculation and filtration [21]. Coagulation is a complex and non-linear process that is characterised by physical and chemical activities [35]. However, in combination with other key unit processes, potable water that is not harmful to the public health is guaranteed when the addition of the coagulation chemicals to the raw water are controlled by taking into account changes in quality and quantity of raw water pumped into the water works [24]. The advantages of effective coagulation control among others include reduction in the cost of coagulation chemicals, filter maintenance, and sludge production [1, 58].

Research studies have been carried out to develop empirical models and software modelling tools to determine the optimum amount of coagulant for water coagulation process. These empirical models are applied together with feedforward control strategies to control the addition of coagulation chemicals from the metering pumps into the rapid mixing tank and address the problem of underdosing or overdosing in WTPs [7, 36]. On the other hand, different mechanistic models using the continuous stirred tank reactor (CSTR) modelling concept and first order plus dead time model (FPODT) had been applied to describe the dynamic behaviour of the coagulant dosage system in WTPs. Based on these models, feedback and feedforward–feedback control strategies have been proposed to improve coagulation process in WTPs [8, 61]

In this review, the contributions and applications of different modelling techniques and control strategies proposed by previous studies to ensure that raw water under treatment are not under-dosed or overdosed with coagulation chemicals are presented. The main objective is to present an overview of the merits and limitations of all existing approaches and to identify new possible and promising future research studies in the field of coagulation process in WTPs. The rest of the paper is organised as follows: Section two introduces the coagulation process in WTPs. The modelling techniques are discussed in Section three. Previous studies on control strategies for coagulation process in WTPs are described in Section four. Finally, the concluding remarks are given in the last Section.

II. COAGULATION PROCESS IN WATER TREATMENT PLANTS

Conventional WTPs have a number of unit processes that are linked together to produce potable water for human consumption [5, 59, 65]. One of them is the coagulation process. It involves destabilization and neutralisation of the total surface charge of colloids and suspended solids, algae, natural organic matters and inorganic substances in raw water by addition of optimum amount of coagulation chemicals to the raw water. Coagulation is thus a chemical and physical process that leads to formation of flocs in a coagulation chemical dosing unit [1, 4, 23, 24, 64]. The most commonly used coagulants include aluminium sulphate (alum), polyaluminium chloride (PAC or PAX), ferric chloride, polyaluminium, silicate and sulphate (PASS), Poly organic aluminium magnesium sulphate (PSO-M) and polyelectrolytes or polymers [24]. When coagulants are added to raw water in a rapid mixing tank or pipe at constant feed rate by using metering pump, precipitates or molecular bridges formed are readily adsorbed to colloid particles and neutralize their negative electrical charge leading to coagulation or formation of micro flocs [1].

In WTPs, adjustment of the pH of raw water is an essential requirement for sufficient charge neutralisation and destabilisation of the colloids to take place [4, 23, 76, 82]. Coagulants are acidic salts that consume water alkalinity when they are added to raw water during the treatment process. For low alkalinity water, coagulants addition may consume all the available alkalinity, thereby reducing the pH values too low for effective coagulation to occur. It is therefore necessary to add hydrated lime or caustic soda to raise the pH level and reduce the effect of the acidic nature of the coagulants on the process. Alternatively, high alkalinity water may require dosages of primary coagulant and co-coagulant or acidic solutions to depress the pH values favourable for coagulation to take place. The control of both coagulant and pH adjustment chemical dosages are therefore one of the most critical operational challenges in WTP's operations.

Jar test is a routine laboratory experiment that is performed to determine the optimum quantity of coagulants and pH adjustment chemicals required to reduce the level of contaminants in raw water as part of the treatment process. It is used to determine the set points for the controller of the coagulant dosage system. Due to rapid changes in the raw water characteristics especially the surface water, the Jar test cannot respond adequately to such variations. Based on this disadvantage, it is therefore not suitable for online or automatic control of water treatment process. For application of automatic control to coagulation process, a good model that would give better description of the process is required for excellent controller performance [59, 67, 68].

The test is an example of one-factor-at-a-time (OFAT) method. It involves finding how the dependent variable or response is affected by varying each factor when other factors are held constant. In other to overcome the limitations of the OFAT method, other approaches such as partial or full factorial design, response surface methodology (RSM) and the Taguchi approach have been proposed as alternative to it. In particular, RSM has been commonly used to determine the influence of several independent variables or factors in the dependent variables. RSM is a collection of mathematical and statistical techniques that are used to model and analyse problems in which response(s) of interest are influenced by several factors or variables with an explicit objective of optimising this response even in the presence of complex interaction [73]. The application of RSM or central composite design to jar tests was studied in [84] to optimise coagulation condition at the Sri-Gading WTP, Malaysia. The study showed that the RSM jar test produced lower optimum alum and polymer dosages than the traditional jar test and was able to produce water of comparably quality. However, the number of experimental runs involved in the RSM jar tests was higher than the conventional jar test.

III. Modelling Techniques for Coagulation

A. *Emperical Modelling*

Empirical or data-based modelling methods involve establishing a relationship between the input and output dataset from a system under consideration under normal or test operating conditions using mathematical representations especially where there is poor understanding of the process [68]. Statistical and intelligent modelling tools are commonly used for modelling the non-linear relationship between raw water quality parameters (input variables) and coagulant dosages, raw and/or treated water quality indices (output variables). References [7] and [65] have detailed discussions on the raw water quality and operational parameters that are usually considered for empirical modelling of the coagulation process. Researchers have used various empirical modelling tools to develop models for predicting the optimum coagulant dosage for water treatment process at different locations.

The statistical techniques that are commonly used for coagulation process modelling include linear and multiple regression models. They are static models for quick estimation of an output variable from input variables. For instance, in [76], the authors proposed a series of regression models to predict alum dosages for both coagulation (turbidity and colour removal) and enhanced coagulation (natural organic matter) processes. The validity of these models were confirmed by [69] when the authors applied them to estimate the initial coagulant dosages in a coagulation assessment and optimisation study.

Other studies that developed statistical regression models to predict optimum coagulant dosage are reported in [16] and, [23]. The study by [72] proposed quadratic regression models based on RSM to optimize the coagulation process in WTPs. The model had turbidity and total organic carbon has the dependent variables while the alum dose and coagulation pH were the two factors. The evaluation of the developed models using statistical indices showed that the model was adequate and its predicted response was very close to the experimental data. However, these statistical models do not describe the dynamic response of the system and may not be the best option for automatic coagulation control in WTPs.

Artificial neural networks (ANNs) have also been extensively applied to model the coagulant dosage prediction system and to facilitate the application of process control and automation in WTPs [6, 19]. A detailed description of the operational principles, architecture and algorithms of ANNs can be found in [7, 34, 46, 47, 83] and other related references. For instance, in [29], annual and seasonal ANN models were developed and implemented in a WTP with significant reduction in coagulation chemical usage.

Further studies carried out in references [7, 26, 30, 31, 41, 43, 54, 55 63, 68, 80, 81] on applications of ANNs to model coagulation process showed that the ANNs were capable of identifying usable relationships between the inputs and desired output variables in terms of water quality and WTP operational parameters. The ANN models could thus supplement the bench scale jar test for determining optimal operating characteristics of the plant.

Moreover, studies have been carried to ensure that reliable and good data are obtained from WTPs database to train, test and validate ANN models in order to have better results. In this regards, [74] proposed a single-parameter validation scheme and self-organising map (SOM) model to reconstruct invalid sensors' data. This study was extended in [75] by proposing a hybrid system made of SOM to reconstruct missing data and multilayer perceptron (MLP) to model the coagulation process in a WTP. The study indicated that the prediction capability of the hybrid system was better than a linear regression model. Reference [50] investigated the application of unsupervised learning approach based on the SOM algorithm to detect invalid raw water quality data, rebuild and validate them in order to provide reliable inputs to the automatic coagulation control system.

Other variants of ANN have been applied to the coagulation process due to its ability to represent complex and nonlinear processes that are difficult to model mathematically. A study by [49] focused on a neural soft sensor to model the coagulant dosage prediction system using factorial analysis on a set of raw water quality and operational parameters.

Similarly, [38] proposed a neural software sensor for online prediction of optimum amount of aluminium sulphate dosage. The performances of these soft sensors with real data were satisfactory. The generalized regression neural network (GRNN) and the radial-basis function neural network (RBFNN) techniques were studied in [35] to predict optimum coagulant dosage for WTPs. The simulation results showed that the trained GRNN model outperformed the corresponding RBFNN model.

The ANN models were combined together with other intelligent methods to model the coagulation process in WTPs. In one of the previous studies, a combination of fuzzy model for normal condition and ANN model for abnormal condition was developed in [33] to predict the optimum coagulant dosage for a WTP in South Korea. The results showed that their proposed model (prediction error of 0.8) performed better than the regression method (prediction error of 5.2). Other intelligent models such as expert system in conjunction with ANNs (ESNN) was proposed by [86] to determine the optimum chemical dosage rate for a drinking WTP in China. The results showed reduction in the chemical coagulant dosage by 21% compared to previous years when conventional jar test was in use. The concept of data mining was applied to estimate three different coagulant dosage in a study by [5]. The decision tree and ANN are combined to develop the selection and prediction model. Their proposed models showed reasonable results to estimate the coagulant volume.

Apart from ANNs, adaptive neuro-fuzzy inference systems (ANFIS) have been studied and used also to model the coagulant dosage prediction system. Comprehensive discussions on the ANFIS can be found in [40, 87] and other references in these papers. An instance of applying ANFIS to model a coagulant prediction system was discussed in [18]. The study proposed ANFIS based on Conditional Fuzzy c-means (CFCM) and Fuzzy Equalization (FE) method to estimate the coagulant dosage for WTPs. The results of the proposed model was compared with the ANN, linear regression, zero-order and first-order ANFIS models. The training and validation root mean squared error (RMSE) of the proposed method (1.12 and 1.85 respectively) were found lower than the RMSE of others models (above 1.9). In [79], the coagulant dosage prediction system was modelled using both ANN and ANFIS tools. The results of the comparative study showed that the ANN model was better than the ANFIS model when the raw water had high turbidity due to storm water. On the other hand, the optimal self-prediction model developed using ANFIS tool made a better prediction of the coagulant dosage than the ANN model when there were no information on raw water quality indices.

In another related study, [36] used ANFIS to develop a coagulant dosage model for a WTP. The authors proposed fuzzy inference systems based on grid partition (ANFIS-GRID) and subtractive clustering (ANFIS-SUB) for the process modelling. The outcome of the study indicated that the ANFIS-SUB outperformed the ANFIS-GRID due to its simplicity in parameter selection. In [48], the ANFIS and ANN models were developed for estimation of the optimum coagulant dosage. Simulation results performed on a laboratory based WTP indicated that ANFIS model (training and validation RMSE values were 0.11 and 0.0781 respectively) had better prediction ability than ANN model (training and validation RMSE values were 0.3215 and 0.1706 respectively). Reference [37] applied dynamic evolving neuro-fuzzy inference system on-line (DENFIS-ON) and off line (DEFIS-OFF) schemes to model the coagulant dosage for a water treatment plant. The results of the simulation studies between the two schemes showed that DENFIS-ON gave better prediction accuracy than DENFIS-OFF.

Different intelligent data-based modelling tools such as linguistic equation (LE) and rough set decision rules had been used also to model coagulant dosage prediction systems from a set of historical water quality data [44, 70]. Simulation results showed that the proposed models were promising but further improvement was recommended. The support vector machine regression techniques using two different kernel functions (radial basis function (RBF) and polynomial function), and K-Nearest Neighbours (KNN) were investigated in [85] to predict coagulant dosage in WTPs. The results indicated that KNN has better predictive capabilities than the support vector machine regression techniques.

Furthermore, the application of evolutionary computational techniques to coagulation process modelling had been proposed though few studies had been reported. For instance, genetic programming (GP) was proposed by [57] to develop a model for the coagulant dosage prediction system as part of a decision support system for a full scale WTP. Results of the validation tests showed that the proposed method would be helpful for the economic operation of WTPs. In a related study, [77] proposed minimum cluster volume fuzzy algorithm (MCV) based on genetic algorithm to develop a coagulant dosage prediction model. The proposed model showed better results when compared to a linear regression model.

From all the studies reviewed, it is obvious that empirical modelling techniques have been proposed and studied extensively for coagulation control in WTPs. However, the limitation of these empirical models is that these models are only effective when the available online data from the process are accurate and reliable [42]. In addition, these empirical models only show the input and output relationship between the water quality parameters with little or limited information about the dynamic behaviour of the system. They depend solely on past operational or historical data from the plant's database for training and validation. When these data are not available or inadequate, the prediction models will provide unsatisfactory results. Another drawback to these techniques is the huge amount of data involved and complexity of the knowledge governing the process which may be difficult for the plants' operators to assimilate especially considering that the models need to be trained periodically to produce reliable results.

B. Software Modelling

Some relevant software packages for modelling water treatment processes including coagulation are identified in [22, 60, 78]. Each of these software packages has its own merits and demerits especially in that they are specific to a limited number of applications. For instance, Stimela modelling software and its key features are discussed in [61]. It was developed to improve the operation of drinking water treatment processes. The author applied the software to model different aspects of WTPs in Netherlands and made useful contributions towards the improvement of these

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operations. In [78], the authors observed that EPAnet software library lacked elements to describe the hydraulic properties of drinking WTP units. Consequently, they innovatively used the EPAnet software to build hydraulic models for a WTP at Harderbroek, Netherlands. Their results emphasized that the model could be used to support plant personnel in their daily operations when calibrated and validated with historical data.

Further study carried out by [22] on software modelling techniques showed that most of the existing water treatment simulators had issues that should be addressed for effective utilisations in WTPs. The major limitation of the modelling software is the amount of data and effort required to re-calibrate the software models to produce satisfactory results when applied outside the domain of their initial calibrations. Based on this, [22] proposed integration of the essential features of OTTER and Stimela to develop a simulator that would address the deficiencies of the existing modelling environments. The details of the proposed modelling platform for water treatment process are fully discussed in [60].

C. Physical/Mechanistic modelling

The mechanistic models are derived from the underlying principles and theories governing the process under consideration. They could be generalised for different domains but may not be adequate to represent the system accurately [3]. Majority of the models for the coagulation process are based on empirical techniques as earlier presented. This may be associated with the complex physicochemical processes involved in coagulation, limited understanding and poor quantification of the relationship between the inputs and outputs of the process [2, 7, 36, 68]. Therefore, few studies and limited progress have been reported on the application of mechanistic techniques to address the problem of coagulation control in drinking WTPs.

In a study by [2], the authors developed a mechanistic model for the coagulant dosage system based on experiments from a twin pilot WTP. The proposed model was a simplified model without any mathematical derivation. The simulation model showed unstable results when tested in the presence of disturbances. Therefore, the model required modification and improvement. In [53], the authors carried out residence time distribution (RTD) experiments to develop the hydrodynamic models for surface water treatment pilot plant equipment in Romania based on tracer concentration measurements. A comparison of results between the simulation model using Cholette-Cloutier (CC) models and the RTD experiment indicated that the pilot plant could be well approximated by a combination of the simple CC models used in their research work.

Furthermore, a study reported by [56] used the second-order, discrete-time transfer function to represent a coagulant dosage system to facilitate the application of feedback control to the system. In another attempt to model the coagulation process in a WTP, a nonlinear mathematical model was proposed in [32] that described the relationship between the inlet and outlet concentration of the coagulant and colloidal particles in a mixing tank using the concept of continuous stirred tank reactor (CSTR) model. The outcomes of the model simulation showed promising results. However, the authors suggested further investigations to improve the overall model of the system.

Having identified the need to develop a model that describes the physicochemical and dynamic nature of a coagulant dosage system, [8, 9] proposed a mechanistic model for a hypothetical system from the first principles. In [10, 11], a dynamic model of coagulant dosage system or coagulation chemical dosing unit (CCDU) for Rietvlei WTP, South Africa was proposed. Validation results from the real data collected from the plant showed that the proposed model was a good representation of the dosing unit.

All of these previous works on mechanistic models showed that there are limited number of studies in this regard. There is thus a need to improve the existing models or develop novel dynamic model to achieve adequate control and optimisation of the coagulation process in WTPs taking into considerations the effects of input variations and disturbances on the system.

IV. CONTROL STRATEGIES FOR COAGULATION

An effective control strategies is needed to obtain the desired response from the operations of a plant [66]. Most modern and new WTPs are built to be fully automated. This is possible due to the application of computer algorithms to facilitate control functions in the plant's operations. A detailed description and application of modern control systems to WTPs and coagulation process in particular can be found in [28]. A good number of dosing control strategies have been proposed in the literature. They could be broadly classified as feedforward, feedback and feedforward-feedback (two-degree of freedom) control strategies [1, 43]. Feedforward control measures one or more process input parameters and computes the appropriate actuator setting based on these values. However, a feedback controller adjusts the actuators continuously to decrease the size of the error between the desired reference signal or set point and the output variable.

A. Feedforward control

Feedforward or predictive control involves adjusting the levels of coagulation chemicals added to a process stream as a result of sensory information from the raw water variable(s). Basically, this is achieved by changing the feed rate of the metering pumps according to the measured flow rate of the raw water [1, 51, 58]. This approach however becomes inappropriate, when the flow rates vary rapidly and there are large changes in other water quality variables. The coagulant dosage controller therefore exhibit low performance and instability.

To address these problems in feedforward control strategy shown in Fig. 1a, several models such as multilinear regression equation, artificial neural networks and fuzzy inference system algorithms have been proposed to predict the required amount of coagulant under varied conditions to replace the flowmeter response. The models have capabilities to handle either a few or several water variables provided there is availability of accurate data relating to them. In a previous study, a feedforward control based on a fuzzy and ANN models, and PID control was proposed by [33] for a coagulant dosage system with satisfactory results after field tests were carried out.

Another study on feedforward controller based on adaptive neuro-fuzzy network was proposed by [25] for a WTP. The new controller demonstrated better results over the

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process controller used in the plant. In [7], the integration of ANN models with the supervisory control and data acquisition (SCADA) system to optimise the chemical costs and doses online in real-time was presented. Reference [27] proposed a feedforward control was developed using models based on nonlinear transformation of variables, multilayer perceptron (MLP) and radial basis function (RBF) to improve the system in conjunction with a proportional controller. A feedforward control strategy based on the pulse width modulation (PWM) controller and ANFIS prediction model was proposed by [48] to control the flow rate of the alum dosing pump for a laboratory based WTP. The result of the real time implementation of the intelligent steady state controller was satisfactory. The findings of these research works on feedforward control were positive however they rely on the availability of an accurate empirical or data-based model for effective performance.

B. Feedback control

The previous studies on the applications of feedback control strategies include the use of sensors such as a streaming current detector, zeta meter, dispersion analysers (PDA) and pH meter to measure the controlled variables $(Y(s))$ after the coagulation process, comparing the measured values with the set point $(R(s))$ and adjusting the metering pumps accordingly $(U(s))$ to correct any deviation from the expected results $(E(s))$ as shown in Fig. 1b.

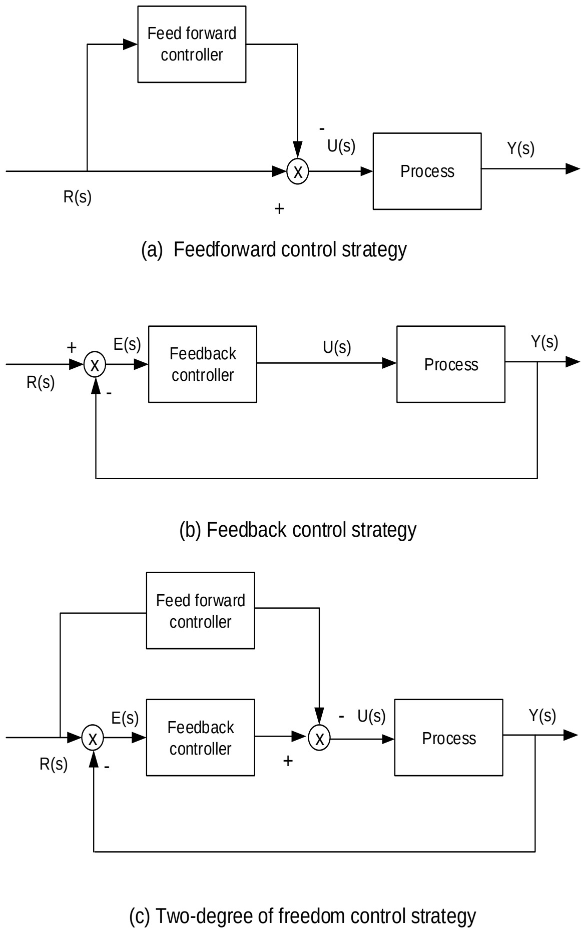

Figure 1. Control strategies for coagulation process

Detailed descriptions of a streaming current detector can be found in [20], pH sensor in [17], zeta meter in [59], PDA in [58] and other related references in these literature. Other parameters which are seldom measured are aluminium residuals, floc size, floc image, UV-absorbance 254 and total organic carbon (TOC) using appropriate online sensors. Due to cost of online sensors, the use of software sensors is being proposed to replace these expensive online sensors [58].

Conventional Proportional-Integral-Derivative (PID) control algorithms are the most commonly used and well established class of controllers in water treatment processes. However, the use of PID control and a streaming current detector for coagulation had been found to have a number of limitations such as an inaccurate dynamic system model to describe the behaviour of the system, slow response of the PID controller to longer system delay or dead time, daily and seasonal variations in water quality parameters and loop interaction effects within the system [68].

For instance, in a study performed by [2], the authors investigated the application of feedback Proportional-Integral (PI) control on the coagulation process in a twin pilot plant to improve the existing manually flow-proportioned control system. A new decoupling control scheme was proposed that reduced the loop interaction between the pH and coagulant dosage loops. The new control strategy was found to be less susceptible to disturbances when compared with the separate feedback control loops. Moreover, in a study on a feedback control strategy by [56], the author compared the performances of PID and linear model predictive control (MPC) scheme for a coagulant dosage system in WTPs. Simulation results showed that the linear MPC had a better response to disturbances than the PID controller. However, the study did not consider the effect of pH variations on the coagulation control. Thus, further studies were required to overcome these challenges.

In view of the above, further investigations into the application of multivariable control strategies to coagulation process were performed in [12]. A nonlinear model predictive control (NMPC) was proposed to control the surface charge and pH values of the chemically dosed water from the coagulation chemical dosing unit (CCDU) at the Rietvlei WTP by regulating the three flow rates of the coagulation chemicals in order to satisfy the control objectives of the plant. Subsequently, a fuzzy model predictive control (FMPC) scheme was proposed for the dosing unit. The proposed control scheme demonstrated superior ability when compared with the NMPC scheme (Bello et al., 2014e). The study by [14, 15] further investigated the implication of a CCDU operating at different operating regions. To solve the control problem associated with it, a switching multiple model predictive control (SMMPC) for the CCDU was proposed. Satisfactory results were obtained from the simulation tests. This work was extended by proposing a fuzzy weighting model predictive control (FWMMPC) scheme for the CCDU. The computer simulation tests of FWMMPC scheme showed better performance when compared with the switching and weighting MMPC schemes.

C. Feedforward-feedback control

Fig. 1c shows the combination of feedforward and feedback control strategies to correct the predicted effect of changes due to input variables on the system, and errors

$(E(s))$ between the set points $(R(s))$ and measured variables $(Y(s))$ through the control variable, $(U(s))$. In a study to illustrate the application of feedforward-feedback control strategy to the coagulation process, [23] discussed a combination of feedforward control algorithm integrated in a programmable logic control (PLC) to compute the optimal doses of coagulant and pH adjustment chemical based on the UV absorbance-254 and turbidity of the raw water and a feedback control for the pH loop. However, the proposed technique did not have provision for any feedback mechanism to measure the surface charge or determine if the charge neutralization of colloids was adequate for optimum coagulation to take place.

In another study, [a practical feedforward control system with fuzzy feedback trim to control the coagulant dosage system at a WTP was discussed in [16]. Reference [39] discussed the feasibility of applying a feedforward fuzzy logic controller and feedback controller to determine the optimum chemical dosage and control the performance of a coagulant dosage system. A series of tests performed on the system at a WTP over a period of one month showed the practical viability of the control algorithm programmed in a small-scale PLC unit. However, in spite of the attractive nature of fuzzy logic control, some difficulties such as knowledge acquisition from experienced operators, and a large set of rules involved in developing the rule base, were identified as limitations of the approach in these studies. Generally, the number of studies performed on the control strategies for coagulation process is still very limited in spite of wide range of emerging and available advanced control algorithms. Therefore, there are future studies that could be carried out to address and improve the challenging problem of coagulation control in WTPs.

V. FUTURE DIRECTION AND CONCLUSIONS

In this paper, a general overview of modelling and control strategies for coagulation process in WTPs in the literature in the last two decades has been discussed and examined. Due to the global importance attached to the provision of safe and potable water, there is a need for continuous investigation on coagulation process modelling and control in order to meet the industry regulators' standards, optimise coagulation chemical usage and reduce operational cost. Future studies that should be considered based on the review in this paper are summarised in this section.

Firstly, it is proposed that more studies should be carried out to use intelligent data-based modelling techniques to estimate the coagulation chemical dosages from the water quality parameters. In this regards, a combination of evolutionary computational techniques such ant colony optimisation, evolutionary algorithm, genetic algorithm, particle swarm optimisation, simulated annealing and swarm intelligence with fuzzy systems and artificial neural networks should be considered to develop more effective and reliable coagulant dosage prediction models.

Based on these models, the development of intelligent and adaptive feedforward controllers that would respond adequately to changes in raw water quality parameters and adapt to changes in the system operational conditions should be studied and implemented accordingly. More research studies should also be directed toward the development of mechanistic models based on distributed parameter system and plug flow reactor to achieve the objective of removing colloidal particles and harmful contaminants from raw water. In addition, the use of hybrid models developed using both the mechanistic and empirical methods to estimate the parameters of the process from the measured data of the system should be investigated and explored by researchers.

The advanced and emerging control algorithms in the areas of nonlinear, adaptive, robust, intelligent and model predictive control schemes should be proposed for the process and evaluated in terms of their servo and regulatory response performances. This should facilitate further studies on the application of feedforward-feedback control strategies using the existing or newly developed models to ensure that adequate and high quality drinking water is available for the public consumption.

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