Chemical coagulation of greywater: modelling using artificial neural networks

E. V. Vinitha, M. Mansoor Ahammed and Mahesh R. Gadekar

ABSTRACT

In the present study, chemical coagulation with alum and polyaluminium chloride (PACl) was utilized for greywater treatment. More than 140 jar tests on greywater with varying characteristics were conducted in order to determine the optimum coagulant dosage and treated greywater characteristics. The average removal efficiencies of turbidity, chemical oxygen demand (COD) and total suspended solids were obtained as 91, 73 and 83% using alum and 93, 74 and 89% using PACl, respectively. For similar initial turbidity levels, optimum PACl dosages required were significantly less compared to optimum alum dosages. Further, PACl produced treated greywater with lower levels of turbidity compared to alum. Results of the coagulation tests were used to design artificial neural network (ANN) models for the prediction of the optimum coagulant dosage and treated greywater quality parameters. ANN models with initial turbidity, pH, conductivity and alkalinity as the input parameters could predict the optimum coagulant dose and treated greywater quality.
The performance of the models was found to be good, with correlation coefficient values greater than 0.80. Empirical formulas for the prediction of alum and PACl dosages were also derived using the algorithm weights and bias values from the networks eliminating the need for running the ANN software.

Key words | alum, artificial neural network (ANN), chemical coagulation, greywater treatment, polyaluminium chloride

E. V. Vinitha
M. Mansoor Ahammed (corresponding author)
Mahesh R. Gadekar
Civil Engineering Department,
SV National Institute of Technology,
Surat 395 007,
India
E-mail: *mansoorahammed@gmail.com*

INTRODUCTION

Due to population growth, rapid urbanization and high standards of living, fresh water demand is increasing all over the world. Greywater has attracted global attention as an alternative water source over the last few decades (Liu *et al.* 2016). Greywater is the used water collected from clothes washers, bathtubs, showers and sinks, but does not comprise wastewater from toilets (Odeh 2003). Reuse of greywater has great potential due to the low concentration of contaminants in it. Generally, treated greywater is not used for drinking but for toilet flushing, sprinkling irrigation, laundry, car washing, floor washing, or fire extinguishing (Ghunmi *et al.* 2011).

A number of systems varying from low-cost devices to complex treatment systems have been used/studied for greywater treatment. While the low-cost devices divert greywater to direct reuse, complex treatment systems combine treatment processes such as primary treatment, biological treatment and disinfection. Different combinations of chemical, physical and biological processes, such as adsorption, coagulation, sedimentation, filtration, aeration, biodegradation, and disinfection, are used for greywater treatment. The cost and energy requirements of these systems vary depending on the level of treatment. In order to reduce cost, treatment of greywater by natural systems is gaining importance in both developed and developing countries (Li *et al.* 2009). However, these systems require large land areas which limits its application in urban areas.

Greywater does not contain the right nutrients and trace elements required for standard biological treatment. Greywater is generally deficient in macro-nutrients such as nitrogen and phosphorus. The chemical oxygen demand (COD): N: P of greywater has been reported as 1,030: 2.7: 1, and when compared with the ratio of 100: 20: 1 for sewage, greywater is deficient in both nitrogen and phosphorus due to the exclusion of urine and faeces (Jefferson *et al.* 2001; Bodnar *et al.* 2014; Abed & Scholz 2016). The COD: biochemical oxygen demand (BOD) ratio is typically 4: 1 which is much greater than

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values reported for sewage. This limits the application of biological processes for greywater treatment. Further, biological processes would be more suitable for urban areas and public buildings due to the operation and maintenance problems (Antonopoulou *et al.* 2013). For small-scale applications, a robust system with simple operation is necessary.

Although biological processes can achieve higher contaminant removal efficiency, chemical treatment methods are much simpler to implement, especially for small-scale applications. Chemical coagulation is one of the reported pretreatment options for greywater treatment. This pretreatment option is intended to reduce suspended matter, biodegradable organics and nutrients in the feed. Colloidal impurities bearing negative electric charges are more difficult to remove, due to their small size. This negative charge can be neutralized by coagulation and flocculation which enhances the floc formation process and increases the floc size, leading to rapid settling of the suspended and colloidal particles (Ghaitidak & Yadav 2015a). It was reported that substantial removal of microorganisms will also be attained by this pretreatment (Friedler *et al.* 2008). A few studies have been reported on the use of chemical and electrochemical coagulation for greywater treatment (Lin *et al.* 2005; Pidou *et al.* 2008; Friedler & Alfiya 2010; Antonopoulou *et al.* 2013; Ghaitidak & Yadav 2015a; Abed & Scholz 2016), and have shown promise as a pretreatment. Different salts of aluminium and iron have been used as coagulants for greywater treatment; however, few studies compared different coagulants (Antonopoulou *et al.* 2013).

Since there is no comprehensive and universally accepted mathematical description of the water and wastewater coagulation process, jar tests are used to determine the optimum coagulant dosages. Although this has been used for determining coagulant dosage for a long time, this technique is not suitable for real-time control when the characteristics of greywater rapidly change. This has led to the development of models for determining the optimum coagulant dosage.

In modelling wastewater treatment processes, the major challenge is to establish the nonlinear relationships between the inputs and outputs of each process. Artificial neural network (ANN) modelling approach is one such tool which is a process control system. ANNs do not require complicated programming, logical inference schemes, or the development of complex algorithms to build a successful model (Liu *et al.* 2015). Application of ANN modelling in the prediction of optimum dosage and effluent characteristics reduces the treatment costs and time consumption in conducting experiments. A number of studies have been reported in the literature on modelling coagulation process using ANN (Maier *et al.* 2004; Wu & Lo 2008; Kennedy *et al.* 2015; Ratnaweera & Fettig 2015). However, no work has been reported on the use of ANN for modelling coagulation of greywater.

The present study compared the performance of two chemical coagulants, namely alum (aluminium sulphate) and polyaluminium chloride (PACl) for treating greywater by conducting jar tests. Performance was evaluated by monitoring water quality parameters such as turbidity, pH, alkalinity, suspended solids, COD and electrical conductivity (EC). These data were used to develop ANN-based models to predict optimum coagulant dosage and treated greywater quality.

MATERIALS AND METHODS

Greywater samples

The greywater samples used in this study were collected from Mother Teresa Bhavan (Hostel-12) located at Sardar Vallabhbhai National Institute of Technology, Surat, India. The source included wastewater from bathroom showers and hand basins and laundry. Greywater was diverted from the greywater collection pipe into a 300 L overhead collecting tank where the greywater was homogenously mixed. Since the peak generation of greywater was found to occur between 7:00–8:30 am and 3:00–5:00 pm, sampling was done at 8.00 am and 4.00 pm so as to get fresh greywater from the collecting tank. A total of 140 greywater samples was collected during the period December 2015–April 2016.

Jar testing

The jar test procedure was used for the determination of optimum coagulant dosage. The test was performed in a jar testing apparatus (DBK instruments, Mumbai, India) equipped with standard rotating blades, and six identical 1-L circular jars. With each greywater sample, two sets of jar tests were conducted employing two coagulants, namely, alum (aluminium sulphate) and PACl. Different doses of coagulant were added to 1-L beakers. Coagulants were added in increments of 10 or 25 mg/L. The treatment conditions were: 1 min flash mixing, 20 min slow mixing and 30 min settling. All the tests were conducted at room temperature (25–28 °C). The turbidity values were measured for the supernatants, and the optimum dosage was selected as that dosage beyond which there was little reduction in supernatant turbidity. Raw and treated greywater samples were analyzed for pH, EC, turbidity, alkalinity, COD, total solids (TS), total dissolved solids (TDS) and total suspended solids (TSS). A total of 140 jar tests each were conducted with alum and PACl as coagulants.

Analytical methods

All the quality parameters were determined following the methods described in *Standard Methods* (APHA 1998). COD was analysed using closed reflux titrimetric method. Turbidity was measured using a turbidimeter (HACH 2100P) and pH was measured using a pH meter (Hanna 209). Total and suspended solids were measured after filtering a sample through Whatman 42 filter paper (pore size 2.5 μm) and dried at 103–105 °C.

Development of ANN models

Two types of ANN models were generated, one for predicting optimum coagulant dose and the other for predicting treated greywater quality (Figure 1). The inputs to the first model for predicting the optimum coagulant dose were the initial greywater characteristics that control the coagulation process (i.e. turbidity, pH, alkalinity and EC) and optimum coagulant dose was the sole model output. The inputs to the second model predicting treated water quality parameters were the initial greywater characteristics and the predicted optimum coagulant dose. The outputs for this model were the treated greywater quality parameters such as pH, turbidity, EC, alkalinity, COD, TS, TDS and TSS.

The ANN architecture consisted of a multilayer perceptron (MLP). Optimization of ANN topology is one of the most important steps in the development of a model (Salari *et al.* 2009). Topology of an ANN is determined by the number of its layers, number of nodes in each layer and the nature of transfer functions which were found by trial and error. The approximate number of neurons to the hidden layer was calculated by $(I + O) \times 0.5$, where I and O are the number of model inputs and outputs, respectively. This method is not technical because factors to affect the networks' structure are the number of samples in a training set (Yuan *et al.* 2003). Three-layered feed forward back propagation neural network with topology 4:6:1 was used for modelling of optimum coagulant dosage and topology 5:20:8 for modelling of treated greywater parameters (Figure 1).

The models were trained using the back propagation algorithm, as it has already been used successfully for the prediction of coagulant doses in previous studies (Piuleac *et al.* 2013). The training function used was Levenberg-Marquardt (LM) and this algorithm locates the minimum of a multivariate function that can be conveyed as the sum of squares of non-linear real-valued functions. It implies an iterative principle that works in such a way that root mean squared error (RMSE) value will always be reduced in each iteration of the algorithm. This makes 'trainlm' the fastest training algorithm for networks.

The range of variables studied is summarized in Table 1. A total of 140 data points each were used in the present study for alum and PACl models. The available data points were divided into three subsets, namely (i) a training set (60%) for adjusting the connection weights, (ii) a testing set (20%) for resolving when to stop training and optimize

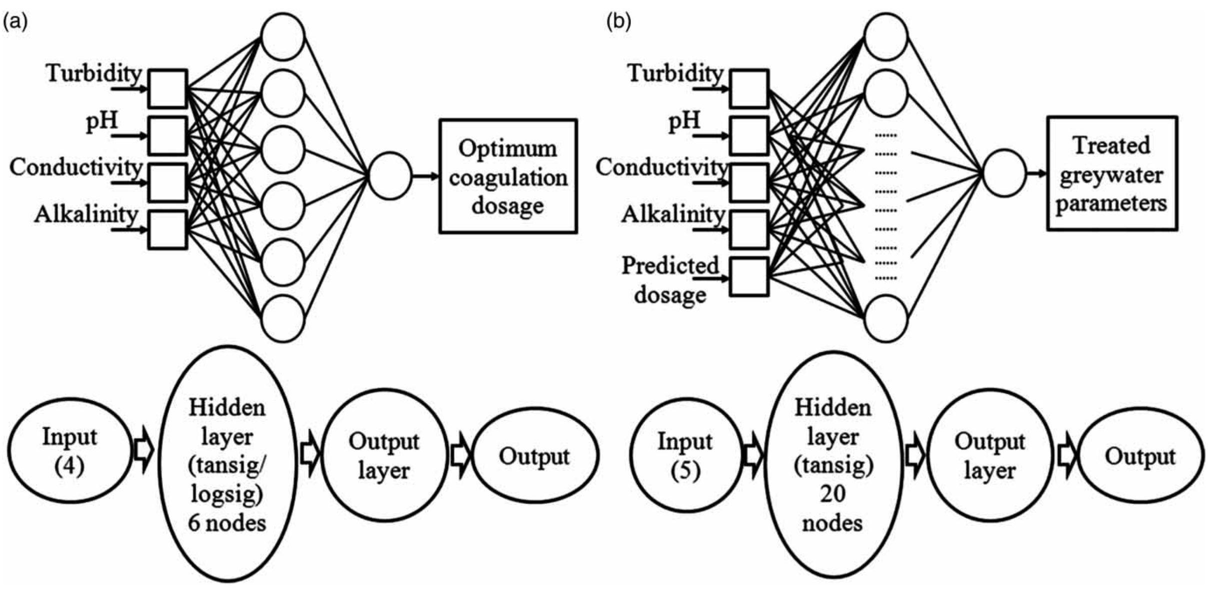

Figure 1 | Neural network topology for (a) coagulant dosage model and (b) treated greywater quality model.

Table 1 | Summary of experimental results with alum and PACl

	Raw greywater		Coagulated greywater with alum			Coagulated greywater with PACl		
Parameter	**Range**	**Mean ± SD**	**Range**	**Mean ± SD**	**Average removal (%)**	**Range**	**Mean ± SD**	**Average removal (%)**
pH	6.54–9.30	7.68 ± 0.26	6.46–7.54	6.90 ± 0.21	–	6.4–7.34	6.88 ± 0.20	–
Turbidity (NTU)	19–287	83 ± 50	2–12	6 ± 2	91.4	1–10	4 ± 2	93.4
EC (μS/cm)	420–1296	769 ± 165	456–1697	865 ± 206	−11.9	450–1369	819 ± 174	−6.9
Temperature (°C)	22.6–30.4	26.5 ± 2.2	22.9–29.1	25.4 ± 2	–	23.0–29.7	25.9 ± 2.0	–
Akalinity (mg/L)	128–332	214 ± 34	64–188	138 ± 20	35.0	64–190	133 ± 24	35.6
COD (mg/L)	66–354	134 ± 71	3–157	45 ± 34	73.2	3–152	42 ± 32	74.2
TS (mg/L)	320–1050	575 ± 144	272–783	474 ± 98	16.3	271–800	474 ± 114	17.4
TDS (mg/L)	230–726	415 ± 97	252–784	452 ± 98	−8.40	240–742	438 ± 102	−5.8
TSS (mg/L)	60–580	160 ± 85	4–70	32 ± 16	82.6	4–290	27 ± 43	88.6
Coagulant dose (mg/L)			70–400	199 ± 66	–	70–240	142 ± 42	–

network architecture and internal model parameters and (iii) a validation set (20%) for testing the generalization capability of the model over the range of the data used for calibration. This division was done randomly by the network. Distribution of the calibration data into training and testing subsets is needed to avoid overfitting of data to ensure that the validation data are not used as part of the model development process in any capacity (Maier *et al.* 2004). All the data points were normalized into the (-1)-1 range, using 'mapminmax' function of MATLAB. During the training process, weights and bias values were added to the connection between neurons in a random way. The weights were modified until the error between the predicted and experimental values were minimized and it is desired that this error should be as small as possible. Correlation coefficient (R) and RMSE and mean absolute error (MAE) were the different model performance measures used in the study (Equations (1)–(3)) (Guclu & Dursun 2010). The network was trained repeatedly until the RMSE value of the model was very low and R value was close to 1.

$$\mathrm{R} = \left[1 - \frac{\sum_{i=1}^{n}(Pi - Oi)^2}{\sum_{i=1}^{n} Oi^2 - \frac{\sum_{i=1}^{n} Pi^2}{n}}\right]^{1/2} \quad (1)$$

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{n}(Pi - Oi)^2}{n}\right]^{1/2} \quad (2)$$

$$\mathrm{MAE} = \frac{\left[\sum_{i=1}^{n}|Pi - Oi|\right]}{n} \quad (3)$$

where n is the number of data, Pi is the predicted value and Oi is the observed value.

RESULTS AND DISCUSSION

Efficiency of coagulation

Table 1 presents the mean characteristics of raw greywater and greywater treated with alum and PACl. It can be seen that the characteristics of the greywater vary widely, and in the present study, all the tests were conducted with real greywater without adjusting any of its characteristics. Turbidity of raw greywater ranged from 19 to 287 NTU, pH from 6.54 to 9.30 and COD from 66 to 354 mg/L. The pH values, turbidity, COD and TSS of raw greywater found in this study were consistent with values reported in the literature (Li *et al.* 2009; Ghaitidak & Yadav 2015a). The optimum coagulant dosage ranged between 70–400 mg/L and 70–240 mg/L for alum and PACl, respectively.

Figure 2 presents the effect of initial turbidity on optimum coagulant dosage and turbidity of treated greywater using alum and PACl. In order to aid discussion, the results are presented in terms of different initial turbidity ranges. It is clear that when the initial turbidity was high, the coagulant dosage required was also high for both alum and PACl. It is known that adequate coagulant must be added to destabilize suspended colloids or to generate a good settling floc (Pernitsky & Edzwald 2006). Particle interactions are one of the driving forces that determine

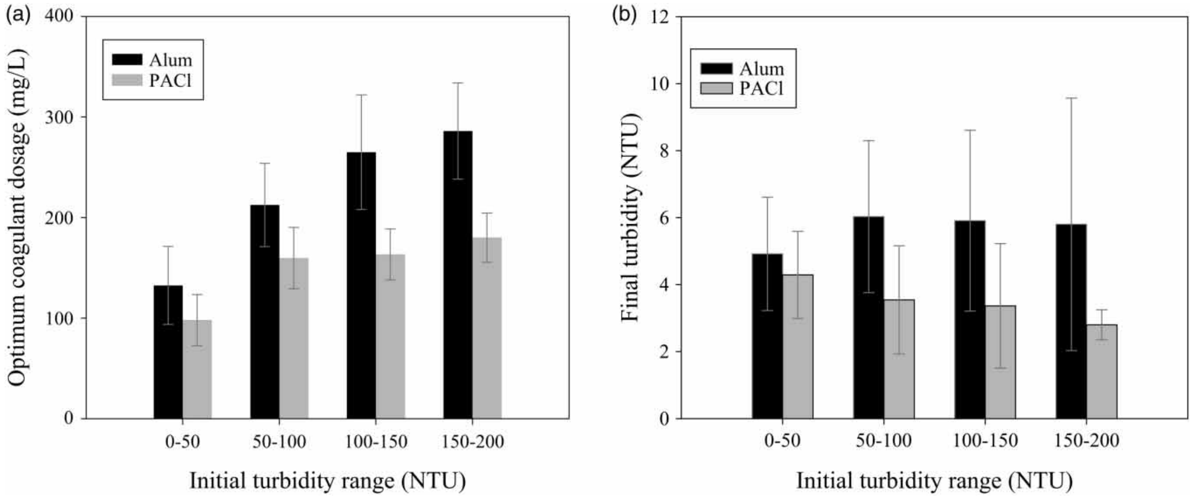

Figure 2 | Influence of initial turbidity on (a) optimum coagulant dosage and (b) final turbidity of alum and PACl.

coagulation efficiency. Mechanisms for destabilization comprise compression of the electric double layer, adsorption and charge neutralization, adsorption and inter-particle bridging, and enmeshment. Compared to alum, the optimum coagulant dosage for PACl was significantly less for similar initial turbidity levels (Figure 2(a)). Further, for similar initial turbidity ranges, in spite of higher optimum dosages for alum, the final turbidity were significantly lower for PACl when compared to alum (Figure 2(b)). This may be due to the several limitations of alum such as requirement of fast mixing to proper functioning, inferior performance at lower temperatures and poor efficiency for attracting organic suspended solids. Non-optimum pH also leads to excessive dosage requirements and optimum pH should be between 5.5 and 7.5 (Pernitsky & Edzwald 2006). Very few studies compared the performance of alum and PACl for greywater treatment. Ghaitidak & Yadav (2015a) compared PACl and alum, and they reported that PACl resulted in higher turbidity removal when compared to alum. Antonopoulou *et al.* (2013) observed higher suspended solids and COD removal efficiency with alum when compared to $FeCl_3$. However, the dose of alum required was much higher (100–800 mg/L) compared to that of $FeCl_3$ (20–80 mg/L). Pernitsky & Edzwald (2006) compared the performance of alum and PACl for treating different waters, and reported that natural organic matter was the most important factor affecting the coagulant dose. Raw water alkalinity was also found to be important for choosing the coagulants.

Figure 3 shows the effect of initial pH on optimum coagulant dosage and pH reduction during coagulation. It is evident from Figure 3(a) that as the initial pH increased

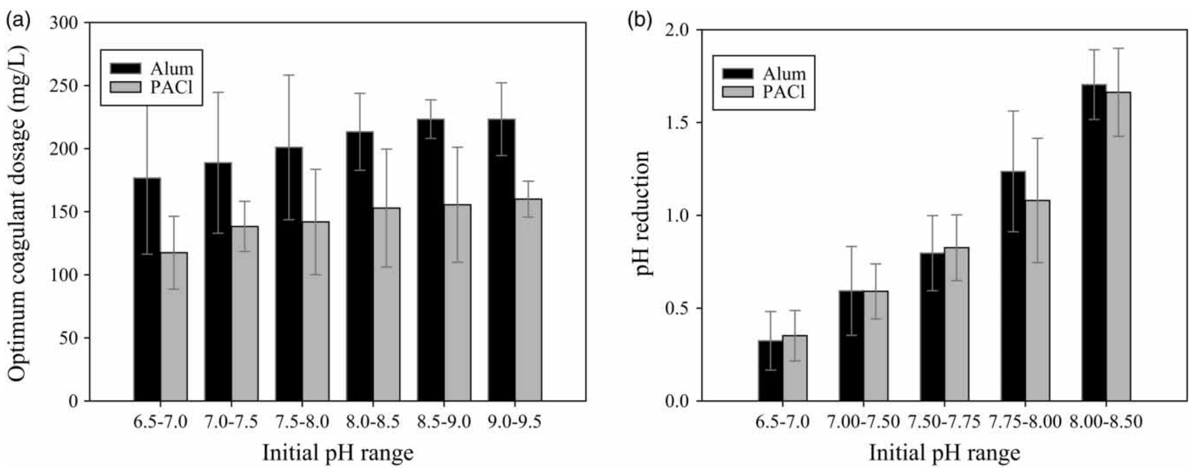

Figure 3 | Effect of initial pH on (a) optimum coagulant dosage and (b) pH reduction.

optimum dosage also increased. The average optimum coagulant dosage increased from 175 to 225 mg/L and from 117 to 160 mg/L for alum and PACl, respectively, as the initial pH range increased from 6.5 to 9.5. Addition of coagulants resulted in a reduction in pH. It is seen that as the initial pH increased, the pH reduction also increased (Figure 3(b)). This is because of the requirement of higher coagulant doses at higher initial pH values, which led to larger pH reduction. It can be seen that an almost similar reduction was observed for alum and PACl in the lower pH ranges, whereas in the higher pH values, alum dosed samples exhibited larger drops in pH value compared to PACl dosed sample. In alum coagulation processes for greywater treatment, initial pH is very important because aluminum species solubility is pH dependent. PACl is much less sensitive to pH, operating within a range of pH 4.5–9.5. Pidou et al. (2008) observed optimum alum dose increasing with an increase in pH in the pH range of 4.5–7.0. Ghaitidak & Yadav (2015a) also reported a similar observation in the pH range of 5.5–8.4. However, they used pH-adjusted greywater, whereas in the present study all the tests were conducted with greywater with its original pH in the range of 6.54–9.30.

EC is an alternate measure for TDS, which provides a measure of the dissolved salt content. In the present study, EC of greywater was in the range 420–1,296 μS/cm. It was found that the conductivity of the treated greywater was closely correlated with the initial conductivity of greywater. Coagulation resulted in an increase in conductivity of greywater which might be due to the addition of dissolved ions in the form of alum or PACl dosages. As the alum and PACl dosage increased, the conductivity increment rate increased due to a larger addition of ions. With alum, conductivity increment was higher as the dosage was high compared to PACl.

The initial alkalinity of the greywater was between 100 and 330 mg/L, while the final alkalinity was in the range 64–188 mg/L and 64–190 mg/L for alum and PACl, respectively. Alkalinity is a measure of the acid-neutralizing capacity of water and serves as a buffer against changes in pH. If the initial alkalinity of the raw water source is too low to buffer the decreasing pH due to coagulant additions, additional alkalinity will have to be added. In this study, the levels of alkalinity were sufficient to buffer the water and prevent the pH from reaching below 6.0, even with the largest alum doses. Figure 4 illustrates the effect of optimum coagulant dosage on alkalinity reduction with alum and PACl. The coagulant addition not only decreased pH but also diminished alkalinity, as expected. It is clear that with

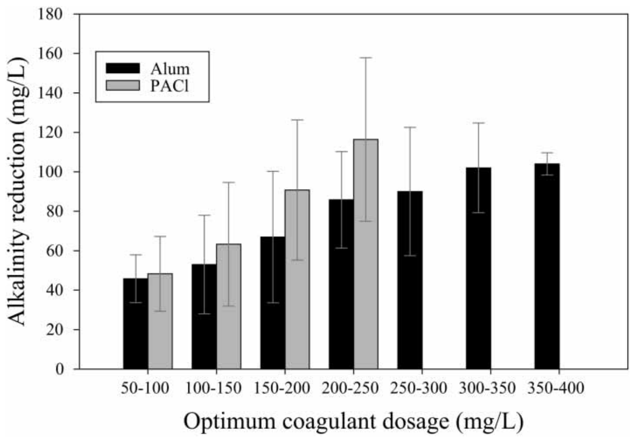

Figure 4 | Effect of optimum coagulant dosage on alkalinity reduction.

increase in coagulant dosage, alkalinity reduction increased for both alum and PACl. It is known that chemical coagulants consume alkalinity. It has been reported that alkalinity can affect the hydrolysis processes of many coagulants and have deep influences on coagulation efficiency (Ye et al. 2007).

COD removal efficiency of the coagulation was also monitored. For alum, at lower dosages (50–100 mg/L) COD removal efficiency was 66% and at higher dosages (300–350 mg/L), the removal efficiency was improved to 82%. For PACl also, COD removal increased from 70 to 84% when the dosage was increased from 50 mg/L to 200–250 mg/L range. This is similar to the removal efficiency reported in the literature. Pidou et al. (2008) obtained an optimum COD removal efficiency of 64% at an aluminium dose of 24 mg/L with alum. In spite of a lower dosage, the COD removals were always higher with PACl when compared to alum for the same greywater samples. It should be noted that while chemical coagulation would result in substantial removal of contaminants, it cannot meet most of the reuse standards set by different agencies, and in order to meet these standards further treatment such as granular filtration or disinfection would be required.

Modelling with ANN

Feed-forward back propagation neural network models were built for alum and PACl coagulation treatment. The neural network for prediction of coagulant dosage had five input neurons including the four process input variables (pH, turbidity, alkalinity and EC) and the bias. The output neuron consisted of optimum coagulant dosage. The hidden layer had six neurons including the bias. The neural network for prediction of treated greywater parameters had six input neurons to include the five process input variables (pH, turbidity, alkalinity, EC and predicted optimum dose) and the bias. It had eight output neurons for the prediction of treated greywater parameters such as pH, turbidity, EC, alkalinity, COD, TS, TDS and TSS. The hidden layer had 20 neurons, including the bias. Hidden neurons were added to the network during the training process in the software (Yuan *et al.* 2003). In this study, the tan-sigmoid and log-sigmoid transfer functions were used in the hidden layer. Various trials for different numbers of neurons, network inputs, training function and transfer function were tried until the network was able to make good predictions, and optimum parameters were fixed for ANN models (Table S1, Supplementary Material, available with the online version of this paper).

Table 2 summarizes the results obtained from the models and the graphical representation of the same is presented in Figure S1 (Supplementary Material, available online). The correlation coefficient (R) values for the models on training and test data sets were close to each other, which means that models generalize well and are likely to make actual predictions. The values of R for predicting alum dose and PACl dose were 0.90 which show a good correlation, while the values of R for greywater quality parameters were 0.99 for both alum and PACl models which depicts the accuracy of these models. The RMSE values obtained for the ANN models for the prediction of dosage was 26 and 15.9 mg/L for alum and PACl, respectively. A low RMSE indicates more accurate evaluation (Joo *et al.* 2000). However, in these models, RMSE values were not close to zero because the coagulants were added in increments of 10 or 25 mg/L during jar tests and this is reflected in the models. The models can be improved by obtaining the optimum coagulant dosage by conducting jar tests with narrower coagulant dosages. The regression plots (Figure S1) for alum and PACl models demonstrate that the models performances are, in general, accurate in training phase, where all data points roughly fall onto the line of agreement. PACl models were superior to alum models in the validation phase.

Table 2 | Performance of the ANN models

Model		RMSE	Correlation coefficient (R) Training	Testing	Validation	All
1 a)	Prediction of optimum alum dosage	26	0.92	0.90	0.80	0.90
1 b)	Prediction of treated greywater parameters by alum	9.6	0.99	0.97	0.98	0.99
2 a)	Prediction of optimum PACl dosage	15.9	0.93	0.89	0.86	0.90
2 b)	Prediction of treated greywater parameters by PACl	10.4	0.99	0.97	0.98	0.99

The accuracy in prediction of individual parameters which were evaluated by calculating coefficient of determination (R^2) and MAE and is presented in Table S2. The scatter plots of actual and predicted values of each parameter by ANN models for alum and PACl were also created (Figures S2 and S3). It was seen that R^2 values for optimum dosage and final EC were above 0.80 which showed good relationship between actual and predicted values (Kennedy *et al.* 2015). The MAE values indicate the variation of the predicted values from the actual values of the parameters. Results confirm that neural network model reproduces the results, within experimental ranges adopted in the fitting model. (Table S2 and Figures S2 and S3 are available online.)

Sensitivity analysis

The neural net weight matrix was used to assess the relative importance of the various input variables on the output variables. Based on the partitioning of connection weights, an equation was proposed (Salari *et al.* 2009):

$$\mathrm{Ij} = \frac{\sum_{m=1}^{m=Nh}\left(\left(\left|W_{jm}^{ih}\right| / \sum_{k=1}^{Ni}\left|W_{km}^{ih}\right|\right) \times \left|W_{mn}^{ho}\right|\right)}{\sum_{k=1}^{k=Ni}\left\{\sum_{m=1}^{m=Nh}\left(\left|W_{km}^{ih}\right| / W_{km}^{ih}\right) \times \left|W_{mn}^{ho}\right|\right\}} \tag{4}$$

where Ij is the relative importance of the jth input variable on the output variable, Ni and Nh are the numbers of input and hidden neurons, respectively, Ws are connection weights, the superscripts 'i', 'h' and 'o' refer to input, hidden and output layers, respectively, and subscripts 'k', 'm' and 'n' refer to input, hidden and output neurons, respectively. The relative importance of input variables on the optimum coagulant dose efficiency as calculated by Equation (4) is given in Table S3 (available online), and it was found that all the variables (turbidity, pH, EC and alkalinity) have strong effects on the optimum coagulant dose. Therefore, none of the variables studied in this work could have been neglected in the present analysis.

Derivation of empirical formula

Empirical formula can be derived to correlate operating parameters with the optimum coagulant dosage. This will eliminate the need for running the ANN software. According to the optimized network training, empirical formula for the prediction of the coagulant dosage for alum and PACl were derived using the algorithm weights in Equations (5) and (6), respectively. The transfer function used was tansig and logsig for alum and PACl, respectively.

$$\text{Optimum dose for alum} = (2.9956 \times \text{F1}) + (0.41074 \times \text{F2}) - (0.45749 \times \text{F3}) + (0.33505 \times \text{F4}) + (0.20251 \times \text{F5}) + (0.09729 \times \text{F6}) + 2.5393 \quad (5)$$

$$\text{Optimum dose for PACl} = (-2.0516 \times \text{F1}) + (-0.4174 \times \text{F2}) - (-0.5070 \times \text{F3}) + (-0.3023 \times \text{F4}) + (-0.5137 \times \text{F5}) + (-0.0570 \times \text{F6}) + 1.1035 \quad (6)$$

Fi values are the tansig and logsig transfer functions (Nasr *et al.* 2016), which were used in the hidden layer given by:

$$\text{Fi} = \frac{2}{(1 + \exp(-2 \times Ei))} - 1; \;\; \text{i} = 1{:}6 \quad (7)$$

$$\text{Fi} = \frac{1}{(1 + \exp(-\text{Ei}))} - 1; \;\; \text{i} = 1{:}6 \quad (8)$$

respectively for alum and PACl where Ei is the weighted sum of the input and is defined as follows:

$$\text{Ei} = \text{Wi1} \times \text{turbidity} + \text{Wi2} \times \text{pH} + \text{Wi3} \times \text{conductivity} + \text{Wi4} \times \text{alkalinity} + \text{bi} \quad (9)$$

Connection weights (W) and bias (bi) values are given in Table S4 (available online).

CONCLUSIONS

The effectiveness of chemical coagulation for greywater treatment using alum and polyaluminium chloride (PACl) was assessed and attempts were made for developing models with artificial neural networks for predicting optimum coagulant dosage and treated greywater quality. The results of the study indicated that for similar initial turbidity levels, PACl dosage required was significantly less compared to alum. Coagulation resulted in an increase in EC of greywater due to the addition of dissolved ions in the form of coagulants and conductivity increment was high for alum. COD removal efficiency obtained was 66 to 82% for alum and 70 to 84% for PACl when the coagulant dose was in the range 70–350 mg/L and 70–240 mg/L, respectively, for alum and PACl. The ANN models with initial turbidity, pH, EC and alkalinity as input parameters could predict the optimum coagulant dose and treated greywater quality with correlation coefficients in the range of 0.90–0.99.

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