Energy Consumption Modeling in Activated Sludge Process Using Coupling PCA-ANFIS Approach

Maachou, Radia
Laboratory of Faculty of Chemistry, electrochemistry-corrosion, metallurgy and mineral chemistry, BP 32 El-Allia, PC 16111, USTHB, Algiers, ALGERIA

Lefkir, Abdelouahab*+
ENSTP, Laboratory of TPiTE, Bp 32 Kouba Algiers, ALGERIA

Oulebsir, Rafik
Laboratory of Faculty of civil engineering, Geotechnical and Hydraulic Environment, BP 32 El-Allia, PC 16111, USTHB, Algiers, ALGERIA

Bermad, Adelmalek; Abdelaziz, Soraya
ENP, Ecole Nationale Polytechnique, B.P. 182-16200, El Harrach, Algiers, ALGERIA

ABSTRACT: *The main challenge in Wastewater Treatment Plants (WWTP) by activated sludge process is the reduction of the energy consumption that varies according to the pollutant load of influent. However, this energy is fundamentally used for aerators in biological process. The modeling of energy consumption according to the decision parameters deemed necessary for a good control of the active sludge process namely the removal yields of parameters pollutant such as Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Suspended solids (SS) and Ammoniac ($NH4^+$) that must meet the required standards. To achieve this objective, a coupling of two approaches, the principal components analysis (PCA) method and Adaptatif Neural Fuzzy Inference System (ANFIS) model was envisaged, in the aim to improve the performance of fuzzy reasoning. Indeed, PCA as a factorization tool allowing the reducing of the variable that allows the reduction of the complexity of the studied phenomenon. The neuro-fuzzy learning from the data projected on the principal axes allows the improvement of the model, both in learning and validation periods. The comparative study between ANFIS model, regression PCA model and coupling PCA-ANFIS method applied to the raw data was effected. The results indicate a significant improvement in the validation criteria obtained in the coupling PCA-ANFIS model compared to the other models for the learning and validation periods. The result shows that the coupling PCA-ANFIS can be used to extract information from data and to describe the nonlinearity of complex wastewater treatment processes.*

KEYWORDS: *Wastewater; Activated sludge; ANFIS modeling; PCA.*

INTRODUCTION

The awareness of the environmental problems caused by the discharges from activated sludge process on the hand, and the will to improve and to preserve the quality of the receiving environments on the other hand, has led

* *To whom correspondence should be addressed.*
+ *E-mail: a_lefkir06@yahoo.fr*
1021-9986/2019/6/261-273 6/$/5.06

the adoption of stricter regulatory standards. The respect for the standards of discharge, and consequent overconsumption of energy [1], constitute the main challenge of the wastewater treatment plant operators. Thus, although the main objective of wastewater treatment services is the treatment of effluent discharged into receiving environments, the reduction of energy consumption is gradually becoming a subject of interest. The most important part of the energy consumption is due to the aeration of the basin by agitators. For a large station, the energy consumption of aeration would represent 60% of the consumption [2-5]. In this context, the modeling of biological processes has been the subject of intensive research activities.

The scientific community to model the dynamic biochemical reactions occurring in Activated Sludge Process (ASP) reactors establishes Activated Sludge Models ASM, developed by the International Water Association, as standards. ASM1, ASM3 [6] address carbon and nitrogen degradation under aerobic and anoxic conditions, while ASM2, and ASM2d [7] address the phosphorus removal. These deterministic models are suitable for well-defined systems. *However*, for more complex problems, these models become less efficient. Indeed, the empirical models developed to describe biological processes, have a several limitations and suffer from major challenges i) the large numbers of parameters used, and which are unable to simultaneously process variations on more than one or two key variables of the process [8], ii) the need to measure, analyze and control certain concentrations and characteristic variables of the effluents, and the lack of real-time availability of information on the conditions functioning, iii) the absence of reliable and directly accessible measurements, the inaccuracy of the measurements which lead to difficulties in the choice of the structure of the models, vi) Moreover, these models reflect the mechanism and kinetics of the reactions involved [9] they contain a large number of kinetic and stoichiometric parameters that should be determined by specific laboratory tests and/or process operation, and they may not be practical for plants control [10], especially in developing countries. The accurate description of the system therefore results in highly complex equations which may not be very useful from a practical and operational point of view. To remedy this, we used Artificial Intelligence (AI) models that allow from the input and output history data, of the given process, to extract the required knowledge.

In order to improve the wastewater treatment performance, AI, can overcome the restrictions of the traditional modeling methods and efficiently approximate any nonlinear processes, have been utilized for simulation, prediction and modeling, AI tools are appropriate for a nonlinear processes [8, 11] ; Indeed, Neuro-fuzzy models can provide a human knowledge on the operation of the processes on the basis of which monitoring and control strategies can be developed, taking into account the data available upstream and downstream of the wastewater treatment plant.

AI models are adapted to the context defined above, with the aim of optimizing energy consumption of aeration basins in ASP that consumption exceeds 70% of total energy consumption. AI is a computing method which mimics the human brain and nervous system. It is a mathematical structure, which is capable of approximating arbitrarily complex nonlinear processes [12] that relate the inputs and output of any system [13]. In contrast to ASM models, the AI models have a dynamic nature and evolutionary, and the most significant advantage is that no precise mathematical model is needed [14], which can well approach any nonlinear continuous function and overcome the shortcomings of traditional control that over depend on accurate mathematical model [15]. AI models are based only on inputs and outputs of the process, without any regard to physical, chemical and biological knowledge of the process. They are therefore of a descriptive nature. These are based on the principle of extracting knowledge from information observed, reflecting the history of human intelligence that gives a powerful predictive ability to describe complex phenomena, such as biological treatment and has real-time solutions to STEP manager.

AI models involved the use of Artificial Neural Networks (ANN), where no priori knowledge for a system is required, and has the ability to learn a relationship between the outputs and the inputs for a system. To develop a process using ANN, it requires suitable network architecture and appropriate data training [16, 17]. Fuzzy inference system (FIS) [13, 18, 19], Genetic Algorithms (GA) use random search for optimization of a fitness function by means of the parameters space coding [10, 20-22].

The Adaptive Neuro-Fuzzy Inference System (ANFIS) model combines the suitable properties and diminishes the disadvantages of the ANN and FIS techniques [10, 18]. The conventional technique neural network is powerful because it can learn to represent data trends are complex and can be used to learn the fuzzy decision rules. Nevertheless, there are limits to the realization of heuristic reasoning problem. However, the use of logical rules is excellent in this area, but is generally weak as regards the acquisition of knowledge and can take into account uncertainty and impreciseness in the data. In this work, to take advantage of both methods, Adaptative Neural and Fuzzy Inference System (ANFIS) techniques were combined to develop a "Neuro-fuzzy" modelin other words neural fuzzy or Adoptive Neuro-Fuzzy Inference Systems (ANFIS) allow overcoming limitations in parameter optimization which offers appealing features. Some research has been carried out on fuzzy neural approach to determine the amount of recycled sludge in the aeration basin while respecting discharge standards with minimal operational costs [23, 24]. Other research developed a neuro-fuzzy model to predict the nitrate concentration in the anoxic zone by controlling the recirculation flow with elimination of the nitrogen in the anoxic phase [25]. The modeling of suspended solids according to the biological and chemical demand for oxygen by fuzzy controller system was carried out[26,27]. Fuzzy logic was used to model the elimination of inorganic matter by minimizing energy consumption [28].

The mastery of the activated sludge treatment process is to determine the optimal values of decision parameters to eliminate the pollution load contained in wastewater (organic and inorganic) respecting the discharge standards required by the environment. In order to improve the performance of these methods, the ANFIS model was applied to determine the energy to deploy especially into the aeration basin. This model determines the aeration profile of the reactor that minimizes energy consumption while respecting the specific constraints (regulatory discharge standards) [1, 29-32]. despite the considerable contribution of the IA in explaining the phenomenon, the problem remains complex because of the large number of inputs and outputs implemented.

The large number of pollution parameters, in a WWTP making their use difficult for modeling purposes. Therefore, having a large number of input parameters can be considered as one of the main common problems for modeling processes using these techniques. To resolve this problem, a Principal Component Analysis (PCA) are used [14, 33]. In order to further reduce the complexity of the phenomenon to model, a factorization of dominant parameters was performed (PCA) that extracts required information from large input vectors through data preprocessing.

A great number of new hybride intelligent techniques have been constructed, such as PCA-ANFIS hybridization was studied by several authors using the PCA as data clustering tool, example includes the work of Huang [14] that used principal component analysis (PCA) to identify model architecture and extract and optimize the fuzzy rule of the network performance, The system includes an ANFIS predictive model and an ANFIS controller in order to improve them by reducing and optimizing the number of rules in other words, the PCA has been used for the projection of individuals on the main axes. Some research is based on reduction of number of variables by PCA then applied to the ANFIS on the reduced variables [10].

The aim of this work is to determine the correlation between input parameters of elimination yields such as BOD, COD, SS, NH4+ and energy consumption as output parameters for an urban WWTP in order to minimize the energy consumption. In this objective, a novel approach basis on coupling PCA-ANFIS that was designed to provide better predictions and to optimize the energy consumption in activated sludge process. ANFIS- PCA coupling consists in modeling the main axis translating most the variable to be explained according to the other main axes consisted of explanatory variables, in other term, projected data matrix on the vectorial space engendered by the raw variables projected in a new orthonormal basis engendered by principal components (PC). in this study, a comparison between three models was effected: the regression model PCA, the ANFIS model and the coupling PCA-ANFIS.

DESCRIPTION OF MODELING TOOLS

Principal Component Analysis (PCA)

The analysis of databases using PCA method is promising for industrial applications because they treat data in a multivariate manner, reduction of many variables, identification of structures that explain the most relevant variance of the data and for clustering analysis. The objective of PCA is to provide simple tools and readable representation of information processed allowing highlighting raw data possible links existing between variables (in term of correlation). PCA can be used to i) Give indications onto the nature, the strength and the relevance of these links, to facilitate their interpretation and discover what are the dominant tendencies of the data set; ii) Reduce effectively the number of dimensions studied [34] (thus to simplify the problem), by seeking to express the most faithfully possible the original data detected through relationships between variables.

Multivariate statistical methods are capable of handling collinearities among large numbers of variables and, at the same time, they compress the information of many variables into a few uncorrelated principal components or latent variables [35].

The PCA is a statistical method analysis that reduces the size of a data matrix. Indeed, it transforms the first set of data in the second set in smaller size compound of new variables, which are linear combinations of the original variables. The purpose of the PCA is to identify linear relationships among the different variables of the system, using the input and output data of the system.

In computational terms, the principal components are found by calculating the eigenvectors and eigenvalues of the data covariance matrix. This process is equivalent to finding the axis system in which the covariance matrix is diagonal. The eigenvector with the largest eigenvalue is the direction of greatest variation; the one with the second largest eigenvalue is the (orthogonal) direction with the next highest variation and so on [33].

The PCA considers "P" variables for which we arrange of "N" individuals. The individual "i" is described by the vector belonging to R^P.

$$X_i = \left\{ X_{ij} / j = 1 \text{ to } P \right\} \tag{1}$$

The term X_{ij} is a real number that represents the measurement of the variable X_j on individual i. On an individual, there are a number of variables. The variable "j" is described by the vector R^n:

$$Xj = \left\{ X_{ij} / i = 1 \text{ to } N \right\} \tag{2}$$

The matrix [X] resulting of the crossing " NxP " constitutes the matrix of data.

The covariance matrix between X_j and $X_k$variables is given by:

$$\mathrm{Cov}\left(X_j, X_k\right) = \frac{1}{N}\sum_{i=1}^{N}\left(X_{ij} - \overline{X_{ij}}\right)\times\left(X_{ik} - \overline{X_{ik}}\right) \tag{3}$$

$$j = 1, P \quad ; \quad K = 1, P$$

The initial variables undergo, sometimes, a change in reduced centered variables in order to reduce the distortion of valuable scales and to make dimensionless variables on the other hand. The matrix of covariance, in this case, describes the matrix of correlation between variables X_j and X_k and it is given by:

$$\mathrm{Cor}\left(X_j, X_k\right) = \frac{\mathrm{Cov}\left(X_j, X_k\right)}{S_j S_k} = \tag{4}$$

$$\frac{\sum_{i=1}^{N}\left(X_{ij} - \overline{X_j}\right)\times\left(X_{ik} - \overline{X_k}\right)}{\left[\sum_{i=1}^{N}\left(X_{ij} - \overline{X_j}\right)^2 \times \sum_{i=1}^{N}\left(X_{ik} - \overline{X_k}\right)^2\right]} \qquad j=1,P \quad ; \quad k=1,P$$

We note that:

$$\left[A\right] = \left\{\mathrm{Cor}\left(X_j, X_k\right),\ j = 1, P\ ;\ k = 1, P\right\} \tag{5}$$

Note that the correlation matrix [A] is a symmetric matrix definite positive, it is, therefore, diagonalizable. The correlation matrix is replaced by a diagonal matrix noted [D] by reducing the number of variables necessary to describe individuals with a minimal loss of information [33].

The [D] matrix is obtained after resolution of the following polynomial equation:

$$\mathrm{Det}\left(A - \lambda_I I\right) = 0 \tag{6}$$

Where:

[I]: is the Identity Matrix with (PxP) dimension.

λ_I: are called the eigenvalues and represent the diagonal values of the diagonal matrix [D].

These new variables are called principal components (PCs). PCs, Ratter F_j, represented as a linear combination of the X_j variables, which are calculated from the eigenvectors of the correlation matrix:

$$\left(A - \lambda_I I\right)F_j = 0 \tag{7}$$

ANFIS model

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a multilayer feed-forward network, which uses theneural network and fuzzy reasoning to map inputs into an output. It is a fuzzy inference system (FIS) implemented in the framework of adaptive neural networks [25]. It represents a useful neural network approach for the solution of function approximation problems. Data-driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. Since their introduction, ANFIS networks, have been successfully applied to classification tasks, rule-based process controls, pattern recognition problems [18].

The fuzzy inference system is composed of fuzzy rules, based on a fuzzification of the input and output parameters followed by a supervised learning of these rules, using the neural networks that allows a weighting of these rules:

a) A clustering technique (K-means) was used for the fuzzification of input and output parameters for the determination of the number of clusters (low, medium, high ...).

b) To optimize the number of rules to be considered, a weighting of fuzzy rules resulting from fuzzy classification is performed by supervised learning using the single-layer neural networks.

Since the model is dynamic, any new information introduced will affect the fuzzy reasoning and may change the weighting of the rules.

Coupling PCA -ANFIS

The prediction capability of AI techniques strongly depends on the status of the training data. If there are noise and uncertainty in the training data, a problem of over-fitting often arises. Since AI techniques use only input and output data observed from the target system, it is necessary to extract required information from large and noisy input vectors through data preprocessing.

The PCA can be considered as a statistical model. A static model derived from a statistical analysis by PCA alone for the reproduction of the variable to explain, the energy to consume, to express in the form of a linear combination of the main Principal components (PC). The ANFIS model considered as a dynamic model, also applied, on initial variables based on supervised learning. The present work aims to couple between the static model and the dynamic model by ANFIS.

PCA-ANFIS hybridization was studied by several authors using the PCA as data clustering tool, example includes the work of Hang [18] that used principal component analysis (PCA) to identify model architecture and extract and optimize the fuzzy rule of the network performance, the system includes an ANFIS predictive model and an ANFIS controller in order to improve them by reducing and optimizing the number of rules. Other researchers used PCA to the data before processing the model used in the Pc main components in order to eliminate outliers, in other words, the PCA has been used for the projection of individuals on the main axes.

A PCA model was constructed to obtain the projection initial axis that was used in learning data by ANFIS to simulate the energy consumption schematically in the following figure.

With the aim of appreciating the functioning of the plant, we are interested in the Energy consumption (explained variable) necessary to achieve the treatment objectives expressed by elimination yields on (explanatory variables) (Y_{SS}, Y_{COD}, Y_{BOD}, Y_{NH4}).

DESCRIPTION OF THE ACTIVATED SLUDGE PLANT

The activated sludge plant is located in Boumerdes coastal area 50 Km east of Algiers. It is intended for purifying urban sewage of the city of Boumerdes and neighboring municipalities.

The pretreated water is directed to 3 aeration basins that are mixed with an aerated biomass and kept in suspension; each basin comprises 3 aerators that provide oxygen to the mixing. We get mixed liquor composed of flocculated sludge and treated water directed to the clarifiers where the solids settle and are separated from treated wastewater. In output thereof, the biomass is separated by decantation; a part of the biomass is recirculated in the basins. The excess biomass is removed from the system and constitutes the secondary sludge. At the end of the process, the clarified water passes into a concrete structure ensure prolonged contact between the water to be disinfected and chlorinated water. At the exit of the plant, Water is discharged into the natural environment.

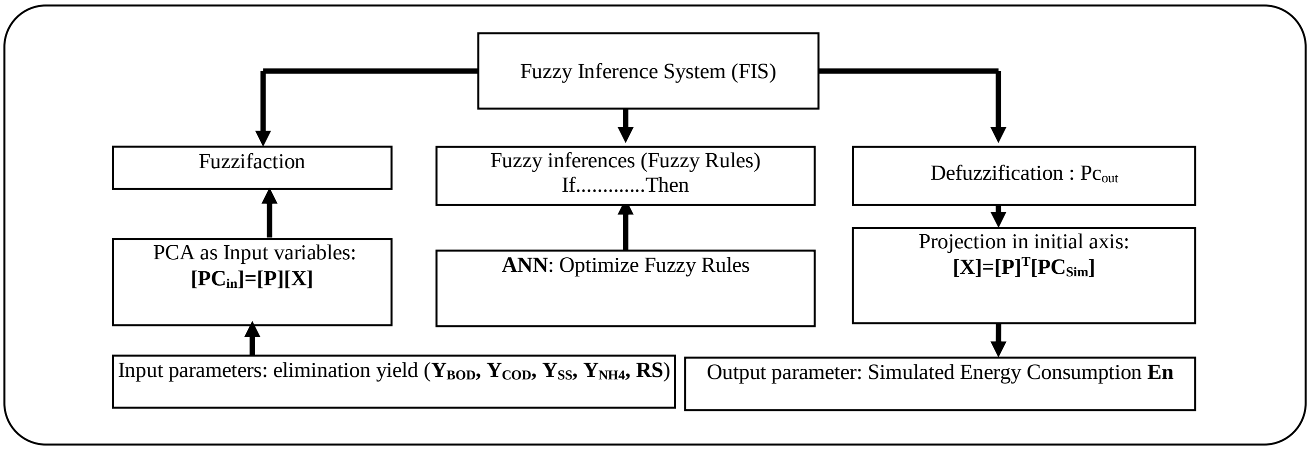


Fig1: Schematic of PCA-ANFIS

The analysis of wastewater characteristics in the WWTP is carried weekly. Pollutant parameters such as BOD, COD, $NO3^-$, NH_4^+, NTK and PO_4^{3-} are measured at the site of the plant.

RESULTS AND DISCUSSIONS

In order to rationalize the energy consumption of an activated sludge treatment plant, a modeling by three means was performed for the description of a phenomenon so complex and evolving as biological treatment applied to an urban water purification plant.

Application of PCA model

The problem thus defined in the vector space generated by the initial variables, characterized by a large number of parameters, is transformed into a smaller space (factored) generated by the principal components.

An inverse transformation via the passage matrix allows the communication of information between the two species, besides the variable to explain (En).

The components that rate of explanation considered low will be neglected for this purpose, which contributed to the simplification of the problem thus defined.

A Principal Component Analysis (PCA) was performed on the daily data table, which contains 9 variables and 250 observations, after removing all non-concomitant data.

It has been found in previous works that the performance of the purification process of our WWTP is related to the removal of organic matter : BOD, COD, and SS, mainly characterized by domestic water, and excessive removal of SS, BOD and COD more than the required standard has been found [8, 33]. Therefore, we only considered the organic parameters (BOD, COD, and SS). The energy is related to the removal of organic matter as well as the elimination yield of NH_4^+ expressing the degree of nitrification.

With the aim of appreciating the functioning of the plant, we are interested in the Energy consumption (explained variable) necessary to achieve the treatment objectives expressed by elimination yields on (explanatory variables) (Y_{SS}, Y_{COD}, Y_{BOD}, Y_{NH4}).

The energy ratio (En (Kwh/m^3)) represents the report between the energy consumed and the flow entering the station.

For the purpose of simulant, the energy consumed, PCA modeling was performed. The data collected for this purpose including the parameters yield: Y_{SS}, Y_{COD}, Y_{BOD} and Y_{NH4} that results from grouping them with energy, by application of PCA, are the input parameters; the output parameter is energy ratio (En).

We construct a linear PCA, from the training data, which can express the initial variables after centered-reduced this latest on a new basis Ortho normed generated by the main components. The variable energy (En) is expressed by the main axis F2, while variables SS, BOD_5, COD and NH_4^+ are expressed by the main axes F1, F3. We expressed En depending on the main axes (F1, F3).

From the matrix of the cosine squares of variables, we deduct that:

- The axis F1 explains respectively the elimination yields of SS, BOD, and COD.

- The axis F2 explains the energy ratio.

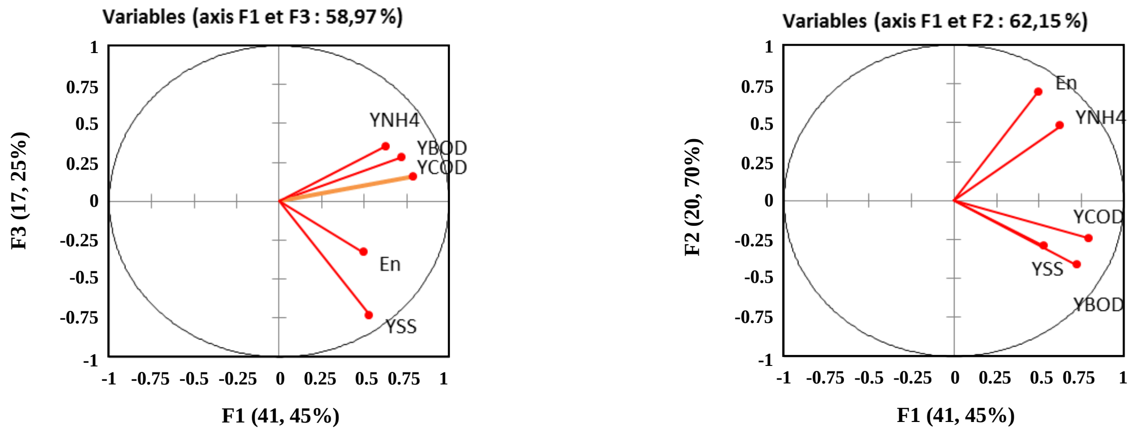


Fig 2: Projection of the input/output variables on the axis (a) F1, F3 (b) F1, F2.

- The axis F3 explains the drawdown of NH_4^+.

The equations obtained from the multiple regression of each axis are given in the following:

The matrix of thepassage is given in following:

$$\begin{bmatrix} F_1 \\ F_2 \\ F_3 \\ F_4 \\ F_5 \end{bmatrix} = \begin{bmatrix} 0.45 & 0.43 & 0.56 & 0.41 & 0.33 \\ 0.10 & -0.59 & -0.14 & 0.05 & 0.80 \\ -0.63 & -0.04 & -0.02 & 0.77 & 0.44 \\ 0.52 & 0.60 & -0.03 & -0.39 & 0.51 \\ 0.33 & 0.38 & 0.81 & -0.26 & 0.08 \end{bmatrix} \begin{bmatrix} Y_{SS} \\ Y_{BOD} \\ Y_{COD} \\ Y_{NH_4} \\ En \end{bmatrix} \quad (8)$$

The energy is explained by the main axis F2.

The equation of this model given as follows:

$En = 0.77\ Y_{SS} - 0.37\ Y_{COD} + 0.7\ Y_{NH4}$

The first principal's components (F1, F2, F3) were taken, with an explanation rate of 80%. We write the elimination yield (Yi) as a function of the Fi (F1, F2, and F3), among others the variable to explain energy.

$$\begin{bmatrix} Y_{SS} \\ Y_{BOD} \\ Y_{COD} \\ Y_{NH_4} \\ E_{sim} \end{bmatrix} = \begin{bmatrix} 0.45 & 0.11 & -0.63 \\ 0.44 & 0.59 & -0.04 \\ 0.56 & -0.14 & -0.02 \\ 0.41 & 0.00 & 0.77 \\ 0.34 & 0.78 & 0.00 \end{bmatrix} \begin{bmatrix} F_1 \\ F_2 \\ F_3 \end{bmatrix} \quad (9)$$

Replacing F1, F2, and F3 with their equations the energy equation will give as a function of 5 variables

$$\left(Y_{SS}, Y_{BOD}, Y_{COD}, Y_{NH_4}, En\right) \quad (10)$$

$$E_{sim} = 0.24Y_{SS} + 0.32Y_{BOD} + 0.082Y_{COD} + 0.18Y_{NH_4} + 0.73En$$

The Input parameters are calibrated with the output parameter (En) for PCA model. The performance of the model is tested during the test period to judge its predictive ability. The validation criteria of the model, both during the learning period and during the validation period, are shown in the Table 1.

We can conclude that the quality of the model resulting from the PCA for the calibration part is average and confirms the interpretation of the distribution of the scatter plot around the trend curve.

The correlation coefficient is (63.86%) for the validation period, a slight increase is observed with regard to the R^2 obtained in the calibration period, therefore the correlation between the observed energy and the simulated energy is average.

Development of ANFIS model

To approximate the function between the input and the output of the system, the learning (supervised) process must define the basis of the fuzzy rules; their number, premises, and conclusion minimize the gap between the desired outputs and those inferred by the fuzzy set [19]. ANFIS used for estimation the energy consumption in water purification plant, based on results of PCA.

Adaptive-Network-based Fuzzy Inference System (ANFIS) is a multi-layer feedforward network in which each node performs a particular function on incoming signals. The parameters associated with these nodes are updated according to a given training data and a gradient based learning procedure in order to achieve a desired

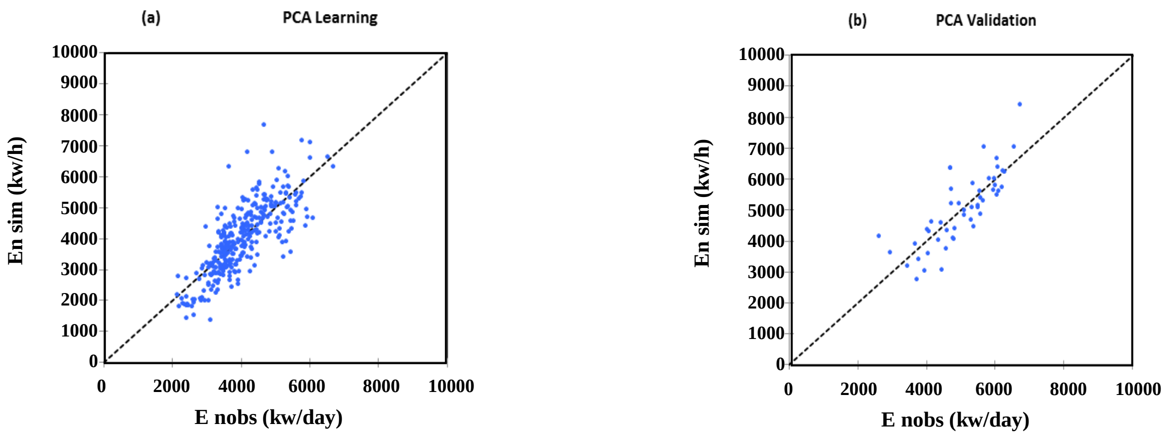
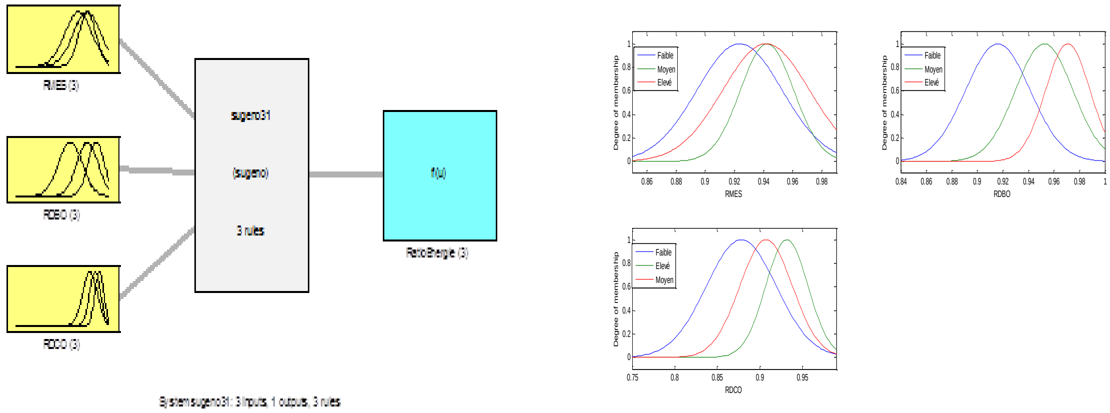


Fig 3: Simulated energy correlations with the energy observed during (a) learning and (b) validation period (PCA model).



(a) Representation of the ANFIS model (b) Membershipfunction

Fig 4: Description of Ren's ANFIS model as a function of organic matter with clustering of data

input-output mapping. ANFIS [36,37] can be used to optimize membership functions and has the advantage of being able to construct fuzzy IF-THEN rules representing these optimized membership functions [19].

Modeling is a valuable tool in both design and operation and can be used for process optimization and testing of control strategies in order to meet effluent quality requirements at a reasonable cost. Neurofuzzy modeling is performed to simulate the energy consumption.

The ANFIS model chosen is Sugeno type with three parameters of (Y_{SS}, Y_{BOD}, Y_{COD}, Y_{NH4}) of input parameters, the energy ratio (En) is an output parameter (figure 4 (a)).

The architecture of ANFIS model is characterized by four layers, each has several nodes (figure1 (b)).

The basic structure of ANFIS for prediction is composed of **four layers**. The relationships between elements are showed in Fig. 2.

Three membership functions associated with three parameters are considered in this model. Each of these functions consists of three premises. Clusterization the input data are the considered parameter (see figure .1 (c)). Fuzzy rules are made following to a fuzzification of input parameters. The number of fuzzy rules is an equivalent number of combinations of the premises.

The Input parameters are calibrated with the output parameter (En) for ANFIS model. The performance of the model is tested during the validation period to judge its predictive ability.

From the curve of the learning data, we notice that some points are distant from the first bisector, it means that the points

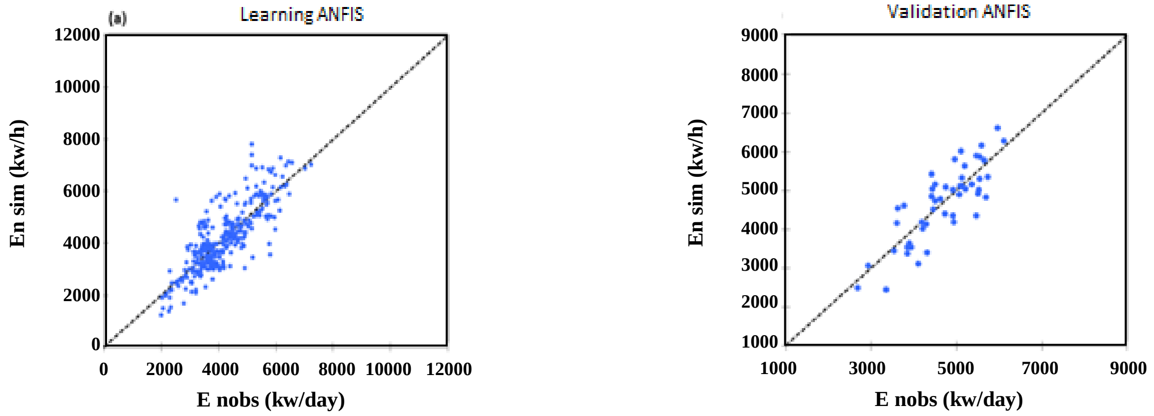


Fig 5: Simulated energy correlations in the energy observed during (a) learning and (b) validation period (ANFIS).

were not simulated correctly, and that the deviation between the observed energy and the simulated energy is important.

The coefficients correlation of both learning and validation periods are respectively 66 % and 68%(table (1)), the correlation between the energy observed and the energy simulated by Neuro-fuzzy model is average with a slight improvement compared to the model resulting from the PCA, and this confirms the interpretation of the distribution of the scatter plot around the curve of the trend. Therefore, the correlation between the observed energy and the simulated energy is better.

Development of Coupling PCA-ANFIS approach

The input parameters, including the yields of parameters (SS, BOD_5, COD and NH^+_4) are reported and calibrated with the output parameter energy ratio (Ren) in the Fuzzy-Neural model.

In order to obtain our matrix of data calibration and validations, we proceeded as follows:

- The data of the calibration part are those obtained by ACP (matrix of the coordinates of the observations)
- The data of the validation part were calculated from the transition matrix1.

The data matrix of the validation period is obtained by replacing Y_{SS}, Y_{BOD}, Y_{COD}, $Y_{NH4}$and energy. Then we pass to the simulation of the axis F2 by the Neuro-fuzzy model.

From the transition matrix, we obtain the following model which will allow us to simulate the energy from a ANFIS-PCA coupling for the calibration part as well as for the validation part:

$$E_{sim} = 0.34F_1 + 0.83F_{2_{sim}} - 0.005F_3 + 0.52F_4 - 0.083F_5 \quad (11)$$

In the ANFIS-PCA coupling, the variable Ren can be express depending on the main axis as following:

$$E_{sim} = 0.34F_1 + 0.68F_2 - 0.35F_3 - 0.187F_5 \quad (12)$$

The Input parameters are calibrated with the output parameter (En). The performance of the model of coupling PCA-ANFIS is tested during the validation period to judge its predictive ability. The validation criteria of the model, both during the learning period and during the validation period, are shown in the Table 3.

The best results with respect to the RMSE criterion obtained with coupling PCA-ANFIS model for the learning period (11.69) (Table (1)). A better measurement of the energy stemming of coupling of models (PCA and Fuzzy-Neural) hence the reduction of distortions between the simulated and observed values is obtained. By against the results from the PCA model is poor compared to the results from the Fuzzy-Neural model.

Fig. 5 shows a good correlation of the energy values; the correlation coefficient is better and the distortions are decreased compared to the PCA model and Fuzzy-Neural model. However, the correlation model performs better during the learning period correlation coefficients (approximately 88.36%) (Table 1).

According to the graphical representation of the results of the coupling ANFIS- PCA modeling of the validation part, the points are closer to the first bisector

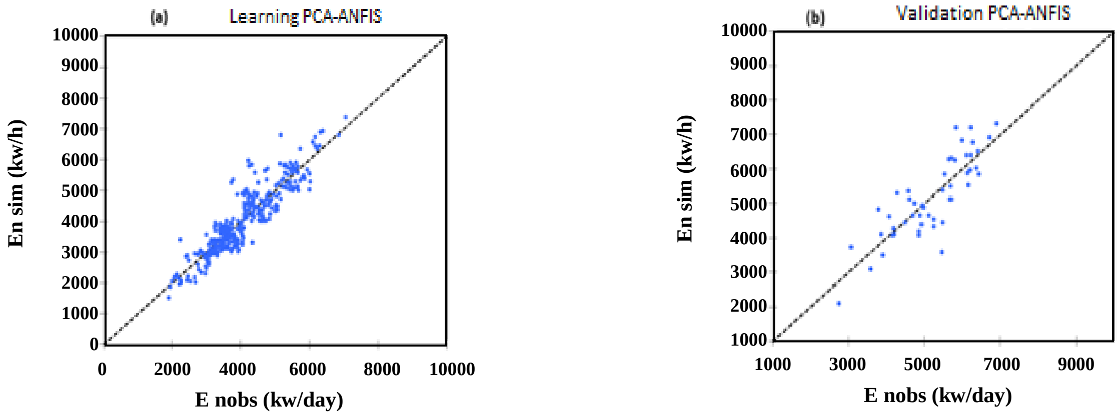


Fig. 6: Simulated energy correlations in the energy observed during (a) learning and (b) validation period (PCA -ANFIS)

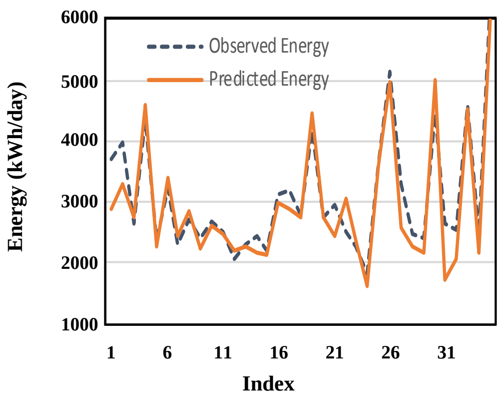


Fig. 7: Simulated energy during validation period.

compared to the last two models (ANFIS-ACP). This shows that the neuro-fuzzy ACP coupling model allowed to simulate the energy well and that the difference between the simulated energy and the observed energy is low for most of the points of the sample. The ANFIS-ACP coupling model allowed us to improve advantage the results.

The developed PCA-ANFIS was compared with PCA model and ANFIS ones, this research indicates a significant improvement in the correlation coefficient obtained for the PCA-ANFIS coupling (88.3%) compared to the PCA model (60.60%) and ANFIS model (66.00%) for the learning period, and a smaller RMSE 18,33 compared to PCA and ANFIS (19.43; 31.88) respectively (as shown in Table 1). The result shows that the coupling PCA-ANFIS can be used to extract information from data and to describe the nonlinearity of complex wastewater treatment processes. Satisfactory results obtained with the coupling PCA-ANFIS justify a high reasoning of this approach and its capacity to optimize the energy consumed during the aeration phase.

CONCLUSIONS

The proposed approach constitutes a methodology for the data processing contained in the various observations registered in a water-treatment plant in the aim of extracting the maximum of useful information for the understanding and the optimization of the treatment process.

However, a comparison between different models is making. First, a linear model by Principal Component Analysis (PCA) was established. The unsatisfactory results were found. To improve the results of the modeling of this phenomenon, we used the second model that is ANFIS. This has allowed improving the results. In order to further improve the results, a coupling CPA and ANFIS was established.

In order to minimize water treatment costs, while maintaining an adequate level of performance, we decided to combine the benefit of the Principal Component Analysis (PCA) and the ANFIS model in order to have better modeling of our phenomenon. The results showed that coupling PCA-ANFIS applied to energy consumption based on drawdowns pollution parameters gave very satisfactory results, thus expressing the higher qualities of coupling PCA-ANFIS, which justifies the predictive power of the model developed. Coupling PCA-ANFIS model is the best representation

Table 1: Validation criteria for the learning and validation periods

		PCA	ANFIS	ANFIS-PCA
Learning period	RMSE	30.95	19.64	11.69
	R^2	60,60	66,00	82,43
Validation period	RMSE	31.88	19.43	18.33
	R^2	63 ,90	68,00	70,00

of our phenomenon, it can be used to extract information from data and to describe the nonlinearity of complex wastewater treatment processes.

Nomenclature

AI	Artificial Intelligent
ANFIS	Adaptatif Neuro Fuzzy Inference System
BOD	Biological Oxygen Demand
COD	Chemical Oxygen Demand
$PO_4^{3-}-P$	Phosphorus
NH_4^+-N	Ammoniac
TKN	Total Kjeldahl Nitrogen
NO_2^--N	Nitrite
NO_3^--N:	Nitrate
SS	Suspended solids

Acknowledgments

The authors would like to express their deepest gratitude to the NOS (National Office of Sanitation of Algeria). This work was developed with the support of the PRFU-MESRS Project named “Development of a Dashboard for optimal management of the functioning of the activated sludge treatment plants”.

Received : May 24, 2018 ; Accepted : Sep. 15, 2018

REFERENCES

[1] Holenda B., Domokos Y., Reédey A´., Fazakas J., Aeration Optimization of a Wastewater Treatment Plant Using Genetic Algorithm, *Optim. Control Appl. Meth.*, **28**: 191–208 (2007).

[2] Ozturk M. C., Serrat F.M., Teymour F., Optimization of Aeration Profiles in the Activated Sludge Process, *Chemical Engineering Science*, **139**: 1–14 (2016).

[3] Rieger L., Alex J., Gujer W., Siegrist H., Modelling of Aeration Systems at Wastewater Treatment Plants, *Water Science & Technology*, **53**: 439–447 (2006).

[4] Fernandez F.J., Castro M.C., Rodrigo M.A., Canizares P., Reduction of Aeration Costs by Tuning a Multi-set Point on/off Controller: A Case Study, *Control Engineering Practice*, **19**: 1231–1237 (2011).

[5] Duchène Ph., Cotteux E., Capela S., Applying Fine Bubble Aeration to Small Aeration Tanks, *Water Science & Technology*, **44**(2–3): 203–210 (2001).

[6] Gujer W., Henze M., Mino T., Van M., Activated Sludge Model No. 3, *Water Sci. Technol.*, **39**: 183–193 (1999).

[7] Henze M., Gujer W., Mino T., Matsuo T., Wentzel M.C., Gerrit v. R. Marais, Mark C. M. Van Loosdrecht, , Activated Sludge Model No.2d, ASM2D, *Water Sci. Technol.*, **39** (1): 165-182 (1999).

[8] Maachou R., Lefkir A., Bermad A., Djaoui T., Khouider A., Statistical Analysis of Pollution Parameters in Activated Sludge Process, Desalination *and Water Treatment*, **72**: 85–91 (2017)

[9] Qiao J., Li W., Han H., Soft Computing of Biochemical Oxygen Demand Using an Improved T–S Fuzzy Neural Network *Chinese Journal of Chemical Engineering*, **22**: 1254–1259 (2014).

[10] Civelekoglu G., Yigit N.O., Diamadopoulos E., Kitis M., Modelling of COD Removal in a Biological Wastewater Treatment Plant Using Adaptive Neuro-Fuzzy Inference System and Artificial Neural Network, *Water Science & Technology—WST*, 60.6, (2009)

[12] Maachou R., Lefkir A., Merabtene T., Hamriche A., Bermad A., Contribution to Optimize Decision Parameters in Activated-Sludge Process Using ANFIS Model, *MATEC Web of Conferences*, **120**: 05001 (2017)

[13] Agheri M., Mirbagheri S.A., Bagheri Z., Kamarkhani A.M., Modeling and Optimization of Activated Sludge Bulking for a Real Wastewater Treatment Plant Using Hybrid Artificial Neural Networks-Genetic Algorithm Approach, *Process Safety and Environmental Protection*, **95**: 12–25 (2015).

[14] Huang M., Ma Y,Wan J, Zhang H, Wang Y,. Modeling a Paper-Making Wastewater Treatment Process by Means of an Adaptive Network-Based Fuzzy Inference System and Principal Component Analysis, *Ind. Eng. Chem. Res.*, **51**: 6166−6174 (2012).

[15] Wan J., Huang M., Maa Y., Guoa W., Wanga Y., Zhangc, H Weijiang., Prediction of Effluent Quality of a Paper Mill Wastewater Treatment Using an Adaptive Network-Based Fuzzy Inference System, *Applied Soft Computing*, **11**: 3238–3246 (2011).

[16] Dong-Jin Choi, Heekyung Park, A Hybrid Artificial Neural Network as a Software Sensor for Optimal Control of a Wastewater Treatment Process, *Wat. Res.*, **35**: 3959–3967 (2001).

[17] Huang M., Yongwen Ma, Jinquan Wan , Yan Wang, Yangmei Chen, Changkyoo Yoo., Improving Nitrogen Removal Using a Fuzzy Neural Network-Based Control System in the Anoxic/Oxic Process , *Environ Sci Pollut Res.*, **21**: 12074–12084 (2014).

[18] Huang M., Wan J., Yan Wang, Yongwen Ma., Modeling of a Paper-Making Wastewater Treatment Process Using a Fuzzy Neural Network, *Korean J. Chem. Eng.*, **29**(5): 636-643 (2012).

[19] Maachou R., Lefkir A., Khouider A., Bermad A., Modeling of Activated Sludge Process Using Artificial Neuro-Fuzzy-Inference System (ANFIS), *Desalination and Water Treatment*, **57**:45, 21182-21188, (2016).

[20] Ghaedi M., et al, Principal Component Analysis-Adaptive Neuro-Fuzzy Inference System Modeling and Genetic Algorithm Optimization of Adsorption of Methylene Blue by Activated Carbon Derived from Pistacia Khinjuk, *Ecotoxicology and Environmental Safety*, **96**: 110-117 (2013).

[21] Huang M., Ma Y., Wan J., Chen X.A,. Sensor-Software Based on a Genetic Algorithm-Based Neural Fuzzy System for Modeling and Simulating a Wastewater Treatment Process, *Applied Soft Computing*, **27**: 1–10 (2015)

[22] Huang M., Han W., Wan J., Ma Y., Chena. X.O., Multi-objective Optimisation for Design and Operation of Anaerobic Digestion Using GA-ANN and NSGA-IIJ *Chem Technol Biotechnol*, (2014).

[23] Traoré A., Grieu S., Frédérik T., Monique P., Colprim J., Control of Sludge Height in a Secondary Settler Using Fuzzy Algorithms, *Computers and Chemical Engineering*, **30**: 1235–1242 (2006)

[24] Wangyani., Control of Sludge Recycle Flow in Wastewater Treatment Plants Using Fuzzy Logic Controller., *AISC*, **180**: 313-318 (2013)

[25] Huang M., Ma Y., Jinquan W., Yan W., Yangmei C., Changkyoo Y, Improving Nitrogen Removal Using a Fuzzy Neural Control System in the Anoxic/Oxic Process, *Environ Science Pollution Reseach*, **21**: 12074–12084 (2014)

[26] Tsai Y., Ouyang C F., Chiang W.L., Wu M.Y., Construction of an on-Line Fuzzy Controller for the Dynamic Activated Sludge Process, *Water Research* ,**28**: 913-921 (1994)

[27] Fu C.S., Poch M., Fuzzy Model and Decision of COD Control for an Activated Sludge Process, *Fuzzy Sets and Systems*, **93**: 281-292 (1998).

[28] Alex J., Jumar U., Tschepetzki R., "A Fuzzy Controller for Activated Sludge Waste Water Plants, Artificial Intelligence in Real Time", Control, Valencia, Spain, (1994).

[29] Anderson J.S., Kim H., McAvoy T.J., Hao O.J., Control of an Alternating Aerobic–Anoxic Activated Sludge System Part 1. *Control Engineering Practice*, **8**: 271–278 (2000).

[30] Hao O.J., Huang J., Alternating Aerobic–Anoxic Process for Nitrogen Removal: Performance Evaluation, *Water Environment Research*, **68**(1): 83–93 (1996).

[31] Huang J., Hao O.J., Alternating Aerobic–Anoxic Process for Nitrogen Removal: Dynamic Modeling, *Water Environment Research*, **68**(1): 93–101 (1996).

[32] Heduit A., Ducheme P., Sintes L., Optimization of Nitrogen Removal in Small Activated Sludge Plants, *Water Science and Technology*, **22**(3–4): 123–130 (1990).

[33] Lefkir A, MaachouR., Bermad A., KhouiderA., Factorization of Physicochemical Parameters of Activated Sludge Process Using the Principal Component Analysis, *Desalination and Water Treatment*, 57:43, 20292-20297 (2016).

[34] Jiao, Wei, Xiang, Shuguang, Quantitative Safety and Health Assessment Based on Fuzzy Inference and AHP at Preliminary Design Stage, *Iran. J. Chem. Chem. Eng. (IJCCE)*, **35**(4): 153-165 (2016).

[35] Teppola P., Mujunen S.P.,.Minkkinen P., Adaptive Fuzzy C-Means Clustering in Process Monitoring *Chemometrics and Intelligent Laboratory Systems*, **45**: 23-38 (1999).

[36] Saghatoleslami N., Mousavi M., Sargolzaei J., Khoshnood M., A Neuro-Fuzzy Model for a Dynamic Prediction of Milk Ultrafiltration Flux and Resistance, *Iran. J. Chem. Chem. Eng. (IJCCE)*, **26**(2): 53-61 (2007).

[37] Mohammed N., Ramli M., Azlan H., Badrul M.J., Bawadi A., Online Composition Prediction of a Debutanizer Column Using Artificial Neural Network, *Iran. J. Chem. Chem. Eng. (IJCCE)*, **36**(2): 153-175 (2017).

[38] Hreiz R., Latifi M.A., Roche N., Optimal Design and Operation of Activated Sludge Processes: State-of-the-Art, *Chemical Engineering Journal*, **281**: 900-920 (2015).