

Modeling and Optimization of Poly Electrolyte Dosage in Water Treatment Process by GMDH Type- NN and MOGA

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ABSTRACT

Coagulation-flocculation is the most important parts of water treatment process. Traditionally, optimum pre coagulant dosage is determined by used jar tests in laboratory. However; jar tests are time-consuming, expensive, and less adaptive to changes in raw water quality in real time. Soft computing can be used to overcome these limitations. In this paper, multi-objective evolutionary Pareto optimal design of GMDH Type-Neural Network has been used for modeling and predicting of optimum poly electrolyte dosage in Rasht WTP, Guilan, Iran, using Input - output data sets. In this way, multi-objective uniform-diversity genetic algorithms (MUGA) are then used for Pareto optimization of GMDH networks. In order to achieve this modeling, the experimental data were divided into train and test sections. The predicted values were compared with those of experimental values in order to estimate the performance of the GMDH network. Also, Multi Objective Genetic Algorithms (MOGA) are then used for optimization of influence parameters in pre coagulant (Poly electrolyte) dosage.

Keywords: GMDH, Jar Tests, Multi Objective Genetic Algorithms (MOGA), Poly Electrolyte, Solve Normal Equation (SNE)

1. INTRODUCTION

The input-output data sets are used for modeling and determining the identity of complex systems behavior. The mathematical relationship among input-output data sets must be known. This problem is solved by using soft computing as fuzzy logic, neural network and genetic

algorithm that have high ability to identify and control these nonlinear systems.

Drinking water treatment plants have to provide high quality drinking water in shortest possible time with minimal costs (Bratby, 2006). The treatment process used depends on the quality and nature of the raw water. Conventional treatment process, consisting of

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primary sedimentation, coagulation/flocculation, secondary sedimentation, and followed sedimentation and filtration are still the major process used for drinking water (Robenson, Shukor, & Aziz, 2009).

Most researches were done on such parts of water treatment process as influence of parameters of raw water in water treatment process on drinking water quality and coagulant dosage in coagulation process in water treatment (Robenson et al., 2009; Van Leeuwen et al., 2003).

Temperature of the raw water can have a significant effect on coagulation and flocculation (Kang & Cleasby, 1995). The pH of raw water is also a critical factor in coagulation process, optimal ALUM dosage accrues at pH between 6-8 (Xie et al., 2012). Turbidity (TU) can affect or be affected by the physical, microbiological, chemical and radiological characteristics of water (Apostol, Kouachi, & Constantinescu, 2011). Raw water alkalinity and water temperature are the most important raw water quality variables in terms of selecting a particular coagulant (Kang & Cleasby, 1995; Xie et al., 2012). Electrolytic conductivity also called specific conductance is a useful test in raw water for quick determination of minerals. Other important parameters that influence coagulant dosage in the water treatment process are color and suspended solids (Heddam, Bermad, & Dechemi, 2012).

Generally, jar tests are used to evaluate coagulant dosage in coagulation process of water treatment (Maier, Morgan, & Chow, 2004; Zhao et al., 2012). The coagulant dosage depends on raw water parameters such as temperature, pH, Turbidity, Suspended solids, Electrolytic conductivity and color.

Nowadays, many studies are being performed on coagulant dosage in drinking water treatment. So far, the polynomial equation, neural network models, and fuzzy structures have been used for predicting and modeling of coagulant dosage. For example, Bazer-Bachi et al. developed two separate models based on polynomial equations used to determine coagulant feed rates for the Clairfont water

treatment plant in France (Bazer-Bachi, Puech-Coste, Aim, & Probst, 1990). Van Leeuwen et al. and Baxter et al. developed an ANN model for the prediction of optimal alum doses based on jar tests conducted on surface waters collected in southern Australia and Edmonton, Alberta, Canada (Baxter et al., 2001; Van Leeuwen, Daly, & Holmes, 2005). Also Maier et al. developed artificial neural networks for predicting optimal alum doses and treated water quality parameters in Australia (Maier et al., 2004). Adaptive Neuro-Fuzzy Inference System (ANFIS) method has just been reported by Wu, Guan-De, and Lo Shang-Lien; in order to understand the effect of fuzzy theory in ANN, the authors developed and compared the performance of ANN and ANFIS approaches. The study was conducted at the water treatment plant in Taipei County, Taiwan, and the models were used to model poly aluminum chloride dosing. According to the comparisons, it was found that the ANFIS technique could be employed successfully in modeling coagulant dosage from the available raw water data (Wu & Lo, 2008). Recently, a multi-objective uniform-diversity genetic algorithm (MUGA) has been presented in (Jamali, Hajiloo, & Nariman-Zadeh, 2010; Jamali, Nariman-zadeh, & Atashkari, 2008) which will also be used in this work.

In this paper, MUGAs are used for Pareto optimal design of a GMDH type-neural network in order to model and predict optimum pre coagulant dosage in Rasht WTP, Guilan, Iran, using Input-output data sets. In this way, SNE methods are used to optimize the linear parameters of the GMDH model. The important conflicting objectives of GMDH networks considered in this work are, namely, the Training Error (TE) and Prediction Error (PE) of the GMDH models that are simultaneously optimized.

Poly electrolyte Pre coagulant was used in drinking water treatment process. The Poly electrolyte dosage was used as a model output separately. The inputs of model were raw water parameters including Temperature, pH, Turbidity, Electrolytic conductivity, color and suspended of solid.

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