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Intelligent system for improving dosage control

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ABSTRACT. Coagulation is one of the most important processes in a drinking-water treatment plant, and it is applied to destabilize impurities in water for the subsequent flocculation stage. Several techniques are currently used in the water industry to determine the best dosage of the coagulant, such as the jar-test method, zeta potential measurements, artificial intelligence methods, comprising neural networks, fuzzy and expert systems, and the combination of the above-mentioned techniques to help operators and engineers in the water treatment process. Current paper presents an artificial neural network approach to evaluate optimum coagulant dosage for various scenarios in raw water quality, using parameters such as raw water color, raw water turbidity, clarified and filtered water turbidity and a calculated Dose Rate to provide the best performance in the filtration process. Another feature in current approach is the use of a backpropagation neural network method to estimate the best coagulant dosage simultaneously at two points of the water treatment plant. Simulation results were compared to the current dosage rate and showed that the proposed system may reduce costs of raw material in water treatment plant.

Keywords: water treatment plant, process control, coagulant dosage, artificial neural networks, optimization.

Inteligência artificial aplicada ao controle da dosagem de coagulante em plantas de tratamento de água

RESUMO. A coagulação é um dos processos mais importantes em uma planta de tratamento de tratamento de água e é utilizado para desestabilizar as impurezas contidas na água para possibilitar a floculação. Atualmente, algumas técnicas têm sido utilizadas na área para determinar a melhor dosagem, como ensaios de jar-teste, medidas do potencial zeta e métodos de inteligência artificial, como Redes Neurais Artificiais, Fuzzy e Sistemas Especialistas, as quais permitem combinações de técnicas para auxiliar os operadores e engenheiros no processo de tratamento de água. Este artigo apresenta uma abordagem de rede neural artificial para a avaliação da dosagem de coagulante otimizada em vários cenários de qualidade da água bruta, utilizando alguns parâmetros, tais como a cor da água bruta, turbidez das águas bruta, decantada e filtrada, além de uma entrada calculada, denominada *Dose Rate* para monitorar o processo de filtração. Outra característica presente nesta abordagem é a utilização do método b*ackpropagation* nas redes neurais artificiais para estimar a melhor dosagem coagulante em dois pontos da instalação de tratamento de água simultaneamente. Os resultados da simulação foram comparados com a dosagem atual e apontaram que o sistema proposto pode trazer redução nos custos de matéria-prima na estação de tratamento de água.

Palavras-chave: planta de tratamento de água, controle de processos, dosagem de coagulante, redes neurais artificiais, otimização.

Introduction

Water is one of the most important elements for sustaining life. Undesired substances and microorganisms should be removed when it is used for human consumption. Water treatment process comprises several steps to obtain treated water, one of which is the coagulation stage aimed to destabilize the dirt particles in raw water. Since decisions on the coagulation process are often carried out based on the experience of the human operator, several studies have been conducted on resources of computational intelligence at this stage of water treatment process, with good results in predicting coagulant dosage.

Artificial intelligence techniques and mathematical models have demonstrated their efficiency and optimal results, particularly when applied in a multivariable and nonlinear system, such as water treatment plants (Böling, Seborg, & Hespanha, 2007). For example, the use of mathematical modeling in water treatment process foregrounds the study of variations in costs and inputs at various stages, including clotting, according to operating conditions (Malzer & Strugholtz, 2008; Mostafa, Bahareh, Elahe, & Pegah, 2013; Ogwueleka & Ogwueleka, 2009).

Intelligent methods, such as fuzzy systems, artificial neural networks and expert systems, are currently employed to overcome the complexity of water treatment processes (Dharman, Chandramouli, & Lingireddy, 2012; Wu & Lo, 2010; Zhang, Achari, Li, Zargar, & Saqid, 2013).

Dosage methods based on historical data have proved to be useful for intelligent approach, when the raw water parameters change rapidly (Heddam, Bermad, & Dechemi, 2012; Valentin & Denoeux, 2001; Wu & Lo, 2008; Zhang & Luo, 2004).

In this context, the proposed system employs a multilayer perceptron network particularly designed to determine the best coagulant dosage at two distinct sites of the water treatment plant, especially by using two additional dose rates as inputs for neural network, to guarantee the best performance for the filtration stage.

Water treatment process

Treatment of water for distribution and consumption is mandatory. In some cases, only chlorine and fluoride are added when raw water is collected from wells. Nevertheless, when raw water comes from reservoirs or rivers, conventional treatment may be required. For instance, the addition of chlorine and lime should guarantee quality in distribution systems and avoid dirt in water. Treatment generally comprises pre-chlorination, pre-alkalinization, coagulation, flocculation, sedimentation, filtration and disinfection.

During the first steps, water undergoes coagulation, or rather, coagulants are added to raw water to destabilize particles, for subsequent agglomeration, with the formation of flocs that will separate from the water in sedimentation tanks.

In some cases, coagulation process is described in terms of destabilization of colloids initially present in a water supply. However, coagulants are used not only to destabilize colloidal particles but also to remove natural organic matter (Pernitsky & Edzwald, 2006; Xie et al., 2012).

Many primary coagulants, such as aluminum sulfate, polyaluminum chloride, ferric chloride and ferric sulfate, may be added for water coagulation (Annadurai, Sung, & Lee, 2003; Griffiths & Andrews, 2011). The choice of coagulants and coagulant dosage depends on raw water quality, which varies from one reservoir to another, on the occurrence of rains or alga blooms.

Two techniques are widely used to determine optimum dosage of coagulants, namely, specific equipment in zeta-potential measurements and jar tests (Joo, Choi, & Park, 2000). However, these techniques are time-consuming, expensive and usually less adaptive to changes in raw water quality in real time (Wu & Lo, 2008; 2010).

In general, few adjustments are required when raw water quality is stable although, when variations are substantial, new dosages are required and jar tests must be carry out to obtain a new reference value. As explained above, these tests take a relatively long time and the operators use reference rates based on their intuition and experience. Whenever a process is controlled by personal experiences, mistakes may occur, i.e., bigger dosages than necessary (Wu & Lo, 2010).

Moreover, coagulation dosing is related to the raw water's chemical and physical features. Thus, the control of optimal coagulant rate consists of a challenge for the operators and engineers, especially when weather conditions contribute to the changes of parameters such as turbidity, temperature, pH and others. Therefore, optimum dosage usually depends on the above characteristics of the raw water. Since in this type of process, features like turbidity, conductivity, pH, temperature, and reactions between the particles are non-linearly, it is very hard to obtain the coagulant dosage by conventional methods (Zhang & Luo, 2004).

Material and methods

Water treatment plant

The water treatment plant in current study has a 1.25 $m^3\ s^{-1}$ water purification capacity and provides drinking water for about 400,000 inhabitants. According to information on this particular water plant, there are two dosage points wherein the operators must determine the best dosage rate. The first one is located at site "A" where the water is obtained by gravity and the other one, called site "B", where the water comes from a pumping system. Eventually, the raw water comes from the same place. Figure 1 shows the schematic diagram of the water treatment plant.

A large and a smaller dam form the source (wellspring) of the water plant. The volume of water is transferred from the larger to the smaller dam, where the raw water that will be used in the process is retrieved. Thus, the process uses distinct systems for flocculation and coagulation, considering the water source from the smaller one. For operational purposes, coagulant dosage is set by an automatic control by Supervisory Control and Data Acquisition (SCADA) systems and Programmable Logic Controller (PLC) devices.

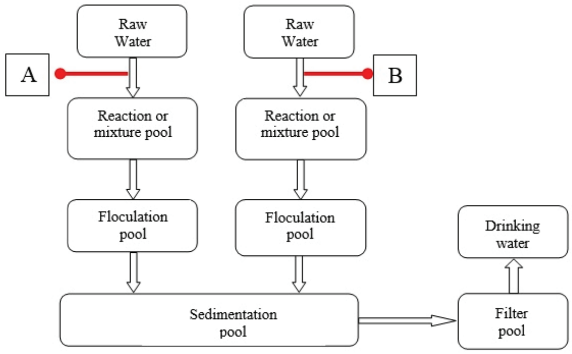

Figure 1. Synopsis of the water treatment plant.

Data collection and knowledge base

Knowledge base for training the back-propagation neural network was built on process-controlled data between April 2010 and June 2012, or rather, more than 3700 sets of data were used to develop the present approach. Moreover, water samples from July 2012 to September 2012 were collected and used for checking the simulation results after the learning step. Therefore, the input and output data were selected not only for training, but also to validate artificial neural network model in the application.

In current study, quality parameters, such as raw water color, raw water turbidity, clarified water turbidity and filtered water turbidity were used to build the knowledge base. Further, an additional parameter was used to improve the filtration process, namely, a specific dosage rate was calculated:

$$Rate_{t} = \left(\frac{C_{Bt} \times D_{t-1}}{T_{Bt}^{2}}\right) \times \left[1 - \left(\frac{0.5 - T_{Ft}}{T_{Dt}}\right)\right] \quad (1)$$

where:

C_{Bt} = raw water color;
T_{Bt} = raw water turbidity (NTU);
T_{Dt} = clarified water turbidity (NTU);
T_{Ft} = filtered water turbidity (NTU);
D_{t-1} = previous coagulant dosage (mg L^{-1}).

In the above equation, factor 0.5 was employed for rate calculation since this value is an important reference to enhance the filtration step.

The artificial neural network model

Artificial neural networks (ANN) are commonly referred as “neural networks” since they process data similarly to the human brain. Thus, the artificial technique usually provides information from complex and nonlinear data (Russel & Norvig, 2010).

In current assay, an artificial neural network modeling has been applied to determine the best coagulant rate in the water treatment plant according to a back-propagation training method. Definition of the input parameters was based on the operators’ experience and the historical data retrieved from the water treatment plant.

Input data are composed of six parameters and the output data consist of two signals, particularly the coagulant dosage rate related to “A” and “B” in the plant. Table 1 shows the process data selected for learning and validation phases and they are related to the maximum and minimum rates of the input parameters of neural network. The magnitude of the parameters, such as raw water and dosage rates, are determined in different weather conditions and reference rates. Inputs of the neural network and output rates are shown in Table 1 and Table 2, respectively.

Table 1. Water parameters used as inputs for neural network.

Water parameter	Minimum	Maximum
Raw water color (UC)	28	135
Filtered water turbidity (NTU)	0.2	0.6
Raw water turbidity (NTU)	3.3	23.9
Clarified water turbidity (NTU)	0.9	1.8

Table 2. Chemical coagulant dosage range used as outputs for neural network model.

Coagulant Dosage	Minimum	Maximum
Coagulant dosage at A (mg L^{-1})	9.40	45.29
Coagulant dosage at B (mg L^{-1})	8.50	44.83

The neural network architecture, i.e. its optimum number of hidden layers and the number of nodes, were defined by trial and error. Figure 2 shows the main structure of the neural approach using only one hidden layer of neurons. The rate points, as calculated by Equation 1, are named rate “A” e rate “B”.

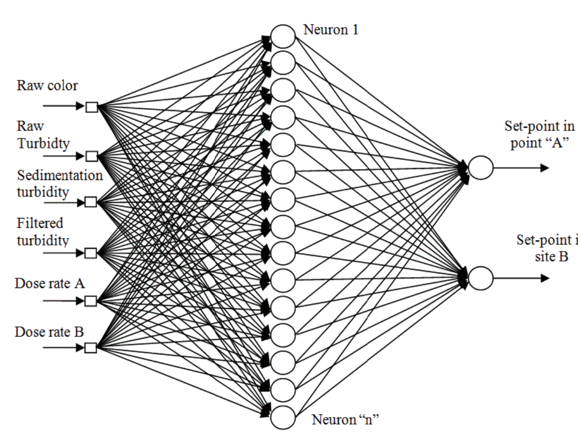

Figure 2. The structure of artificial neural network used to determine the dosage in two sites.

Control system for coagulant dosage

The coagulant dosage is controlled by an automated system composed of programmable logic controllers (PLCs) and supervisory software (SCADA). The system allows the operator to adjust the reference rate (RA or RB), or desired output, for each control closed-loop in the water treatment plant.

The reference for coagulant dosage is usually defined preliminary by jar-tests or by only considering the background of the operators in the plant. Figure 3 shows the control closed-loop for coagulant dosage in A and B in the present water treatment system.

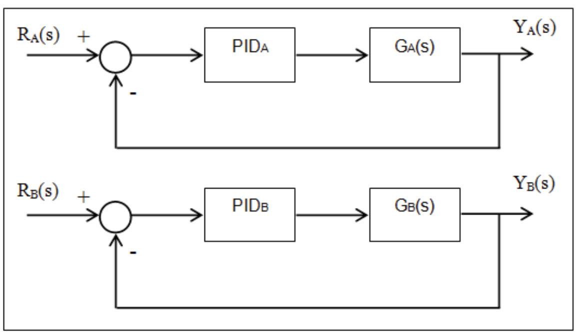

Figure 3. Control closed-loop for dosage coagulant in A and B.

In Figure 3, dosage coagulant references in A and B are identified respectively by RA(s) and RB(s), while YA(s) and YB(s) are the process´s output. In this type of control, GA(s) and GB(s) are the transfer function and PIDA and PIDB are the control rule for A and B. In current paper, only one artificial neural network provides the dosage coagulant references (RA(s) and RB(s)) for each control closed-loop in points A and B.

Results and discussion

In current assay, three neural network topologies were tested to define the best performance for chemical coagulant in two dosage points. In these cases, Levenberg-Marquardt Back-propagation Algorithm was used for training neural networks. The first one was trained by using 40 neurons. The second one was trained by using 60 neurons and the third used 80 neurons in the hidden layer. There is one hidden layer in all topologies. The hyperbolic tangent activation function has been chosen for neurons model and in all cases 1000 interactions were applied for the learning phase. Table 3 shows the mean square error and the average rates for each neural topology during learning phases and validation steps.

Figures 4 (a), (b) and (c) illustrate the comparison between the desired rate and the rates generated by the neural networks during the training phase for the topologies with 40, 60 and 80 neurons in the hidden layer, respectively.

Table 3. Mean square error and average during learning and validation step.

	Training		Validation	
Number of Neurons	MSE	MAE (mg L^{-1})	MSE	MAE (mg L^{-1})
40	0.002244	0.4860	0.001007	0.3766
60	0.001759	0.4590	0.004814	0.6093
80	0.001647	0.4720	0.001631	0.5324

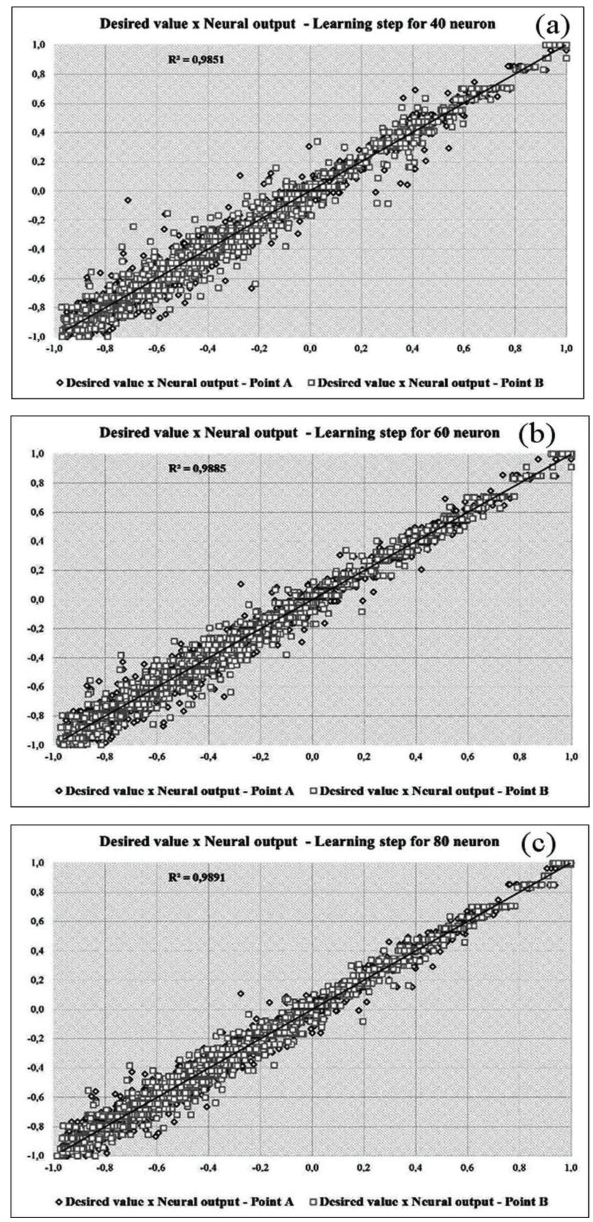

Figure 4. Desired rate and neural output during learning phase for 40 (a), 60 (b) and 80 (c) neurons.

Figure 5 shows the validation data for A and B, taking into consideration distinct neurons in the hidden layer. The figures reveal a good fitting between neural network output and desired rate for ANN topology using 40 hidden neurons, as shown in Figures 5(a) and 5(b). During the validation process, the neural network with 40 hidden neurons showed a dosage difference rate of 0.3766 mg L^{-1} when compared to current dosages used in the water treatment plant (WTP).

Dosage method control: a case study

The proposed system has been implemented in a water treatment plant in Cotia SP Brazil, to provide the coagulant dosage references in real time for A and B. Figure 6 shows an industrial process screen in the supervisory system (SCADA), according to the coagulant dosage control and a button with a caption "ANN", wherein the operator is able to turn on the artificial neural network technique (Figure 7). In the screen one may see the dosage pumps and the set-point fields used by operation or determined by ANN.

Figure 7 shows the screen in which the fields are ready for the insertion of the physicochemical parameters determined in bench for neural network to process appropriate to the current scenario values of set points. The "Current" fields are the current parameters rates in use, while the "Prediction" fields show the new rates to be used after the processing of artificial neural network. Some additional options such as "Save data" and "Data visualization" are available for further analysis of the system's historical usage. Results revealed that it is possible to reach a reduction of the coagulant dosages presented in the neural network of 0.3766 mg L^{-1} lower than those compared to the current data; this means a 17,000 kg of aluminum sulfate savings during one year of the proposed use with the nominal flow production WTP of 1.25 m^3 s^{-1}.

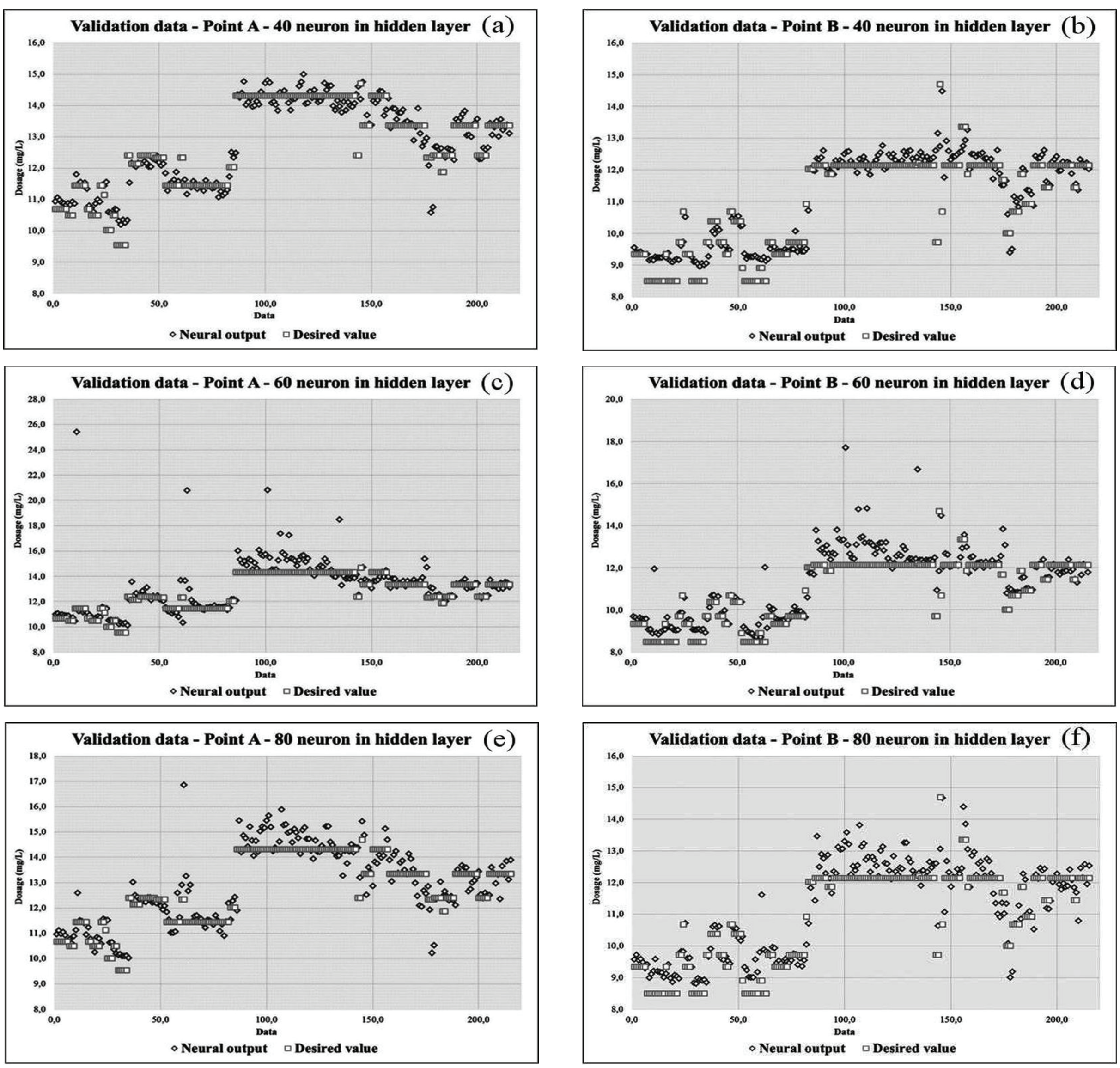

Figure 5. Validation data for points A and B.

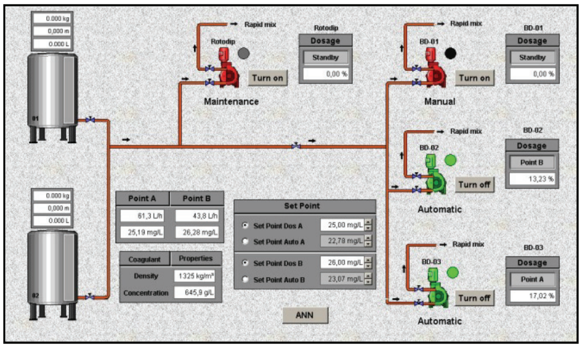

Figure 6. Coagulant dosage system in SCADA.

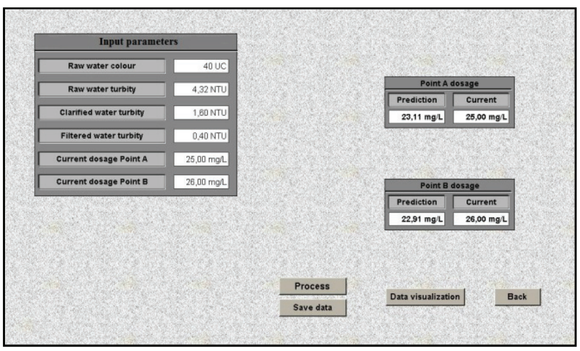

Figure 7. Artificial neural network screen in SCADA system.

Conclusion

In current assay, a neural network-based system has been applied to predict the optimum coagulant dosage rate in a water treatment plant. A range of parameters has been used for determining the best water process control conditions according to the plant's historical data. The system has been implemented to estimate the optimum coagulant dosage simultaneously at two sites of a water treatment plant in the state of São Paulo, Brazil, and the predicted rates would import in a reduction of raw material. Further investigations will be conducted to improve the results on cost reduction and raw material consumption.

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