

Modeling rheological properties of High temperature and high pressure gas well cement slurries using artificial neural networks.

ABSTRACT

Artificial neural networks (ANN) was used to predict the rheological properties of high temperature high pressure gas well cement slurries. Seven different materials were used as additives which includes: fresh water, dyckerhoff, silica flour, antifoam, extender, fluid loss, dispersant, retarder, anti-settling agent, gas control agent, dry viscosifier, potassium chloride and accelerator. Four recipes were prepared using these additives in different mixtures. Recipe four have all the additives. The rheological properties were investigated at different temperatures in the range of 23 to 60°C using an advanced shear-stress/shear-strain controlled rheometer. Experimental data thus obtained were used to develop predictive models based on back-propagation artificial neural networks. It was found that ANN depicted good agreement with the experimental data, with ANN achieving more accurate predictions. The developed models could effectively predict the rheological properties of new slurries designed within the range of input parameters of the experimental database with an absolute error of 3.43, 3.17, and 2.82%, in the case of ANN, for the different recipes. The flow curves developed using ANN allowed predicting the Bingham parameters (yield stress and plastic viscosity) of the oil well slurries with adequate accuracy.

Keywords: Temperature; pressure; cement slurry; gas well; artificial neural networks.

INTRODUCTION

The rheological properties of gas well cement slurries are important in assuring that such slurries can be mixed at the surface and pumped into the well with minimum pressure drop, thereby achieving effective well cementing operation. The rheological properties of gas well cement slurries depend on various factors including the water-cement ratio (w/c), size and shape of cement grains, chemical composition of the cement and relative distribution of its components at

the surface of grains, presence and type of additives, compatibility between cement and chemical admixtures, mixing and testing procedures, time and temperature, etc. The interactions among the above mentioned factors play a vital role in altering the rheological properties of gas well slurries. Moreover, a wide range of bottom-hole pressure and temperature makes the characterization of the rheology of gas well cement slurries more challenging than that of normal cement paste. Therefore, a clear understanding of this complex behavior is important in order to successfully predict the rheological properties of gas well cement slurries. Much work has been conducted over the last few decades to investigate the rheological behaviour of cementitious systems such as cement paste, mortar, grout, slurry and concrete. A number of shear stress-strain rate relationships have been developed for cement slurries. However, there exists no model that explains the interactions among the materials used for preparing such slurries and test conditions such as temperature, shear rate, etc. The power-law, Bingham, and Herschel-Bulkley models are the most commonly used in the well cementing industry [Guillot 2006]. Such models are comprised of empirical expressions derived from the analysis of limited experimental data and based on simplifying assumptions [El-Chabib and Nehdi 2005]. Moreover, they do not have true predictive capability outside the experimental domain and when different materials are used [El-Chabib et al. 2003], and do not explain the interactions among test parameters.

The first step to design a High Pressure High Temperature and gas well cementing job is to know the well construction. (Kris 2008). The depth, hole size, casing hardware and deviation are the basic parameters required to start a design and these are information which must be supplied by the client in the geotechnical order before any design can be done; Temperature, Mud characteristics, Pore pressure and fracture pressure, Information about previous offset wells, Casing seat depths, Stratigraphy, Drilling data (If losses occurred or if there was influx during drilling operation), Casing types to be used and Open hole sizes with desired excesses to mention but a few. Proper prediction of Bottom Hole Circulating Temperature using Bottom Hole Static Temperature, flow rates, steel temperatures etc., is very important as this Bottom Hole Circulating Temperature determines the kind of additives to be used and it also shows cement slurry behavior during the operational and placement time of the job.(Sasso, 2017) The operational time includes the ramp up time from when the first barrel of cement is pumped till it gets to the shoe before it turns in the annulus and up to the placement time in the annulus where it begins to develop compressive strength.

Artificial neural network, ANN is a powerful computational tool that allows overcoming the difficulty of assessing the complex and highly nonlinear relationships among model parameters through self-organization, pattern recognition, and functional approximation. ANN simulates the structure and internal functions of the biological brain. Unlike conventional models, ANN does not assume a model structure between input and output variables. It rather generates the model based on the database provided for training the network. An ANN solves problems by creating parallel networks and the training/learning of those networks, rather than by a specific programming scheme based on well-defined rules or assumptions (Bruni et al. 2006).

The ability of the models thus developed to evaluate the sensitivity of rheological properties to the variation of shear rate, admixture dosage, and test temperature was investigated. Hence, a shear stress-shear rate curve for gas well cement slurries can be predicted at different temperatures prior to fitting the data to conventional rheological models. Consequently, the rheological properties of gas well cement slurries can be predicted as a function of mixture composition and test conditions for the first time.

This research is centered on Modeling rheological properties of High temperature and high pressure gas well cement slurries using artificial neural networks.

MATERIALS AND METHODS

The materials used for this research are as follows: Antifoam/Defoamer, Fluid Loss Additive, Retarder, Gas Migration Control Additive, Fresh Water/Seawater, API Class “G” Cement, Extenders, Accelerators and Strength Retrogression Material. While the equipment/apparatus that were used includes: Syringes, Plastic Petri dishes, Automated Weighing Balance (Kern Model), Viscometer (Fann 35), Warring Blender, Atmospheric Consistometer (Fann Model 165 AT Consistometer), High Pressure High Temperature Consistometer (Chandler Model 7025 Dual Cell HPHT Consistometer), Multiple Analysis Cement System (MACS II), Multiple Analysis Cement System (MACS II).

METHODOLOGY

CEMENT SLURRY SELECTION

Cement slurries are usually selected based on well objectives and requirements. The following would be used for this study.

Table 1: Properties of Materials

MATERIALS	FUNCTION	SPECIFIC GRAVITY	CONCENTRATION	UNITS
Fresh Water	Mixing water	1.000	3.744	gps
Dyckerhoff	Cement "G"	3.140	100.00	%
Silica Flour	Strength Retrogression	2.630	35.00	%
Antifoam	Foam Preventer	0.880	0.011	gps
Extender	Extender	0.830	2.030	gps
Fluid Loss	Fluid Loss	1.050	0.450	Gps
Dispersant	Dispersant HT	0.921	0.510	Gps
Retarder	Retarder MT	1.026	0.010	Gps
Anti-Settling	Extender	0.880	0.300	Gps
Gas Control Agent	Gas Control	0.902	2.800	Gps
Dry Viscosifier	Weighting Material	-	0.100	%
KCL	Salt	1.162	19.149	Kg/tonne

Table 2: Composition of Cement Slurry

MATERIALS	RECIPE 1	RECIPE 2	RECIPE 3	RECIPE 4
Fresh Water	✓	✓	✓	✓
Dyckerhoff	✓	✓	✓	✓
Silica Flour	✓	✓	✓	✓
Antifoam	✓	✓	✓	✓
Extender	✓	✓	✗	✓
Fluid Loss	✓	✓	✓	✗
Dispersant	✓	✓	✓	✓
Retarder	✓	✓	✓	✓
Anti-Settling	✗	✓	✗	
Gas Control Agent	✗	✗	✓	✓
Dry Viscosifier	✗	✗	✓	✗
KCL	✗	✗	✗	✗
Accelerator	✗	✗	✗	✗

PREPARATION OF CEMENT SLURRY

The recommended cement slurry volume for laboratory testing is 600ml (API RECOMMENDED PRACTICE 10B-2). The preparation of cement slurries varies from that of classical solid/liquid mixtures due to the reactive nature of cement, shear rate and time at share are important factors in the mixing of cement slurry in the laboratory. Before any test is carried out, a laboratory calculation sheet is designed which shows the required volumes of the mix water and additives as well as specified temperature, pressure and time. The Warring blender is placed on the scale and set to zero, then fresh water/seawater is added to the blender on top of the scale till it reaches the desired weight on the laboratory calculation sheet for each of the designed cement slurry. Syringes are used to weigh liquid additives. It is recommended to use new syringes each time an additive is to be measured to ensure that there is no form of contamination. To measure the liquid additive, the syringe is used to siphon some product into it and emptied, the dead weight is measured by setting scale to zero and measuring this emptied syringe containing particles of the future fluid to be measured, then the desired volume of liquid additive from the laboratory calculation sheet is measured and kept aside till all liquid additive to be added to the mix water are measured and weighed. This pattern of measurement is done for all liquid measurement to be used per cement slurry. Plastic petri dishes are cleaned and placed on the measuring scale which is then set to zero. The dry additive is then added to the plastic petri dish till the desired volume from the laboratory calculation sheet is reached. The dry additive is kept aside until it is time to be added to the mix water in the warring blender. The recommended API mixing and blending procedure would be followed:

1. The Warring blender containing only the mix water is placed in the mixing chamber.
2. The motor is turned on and kept at $4000 \text{ r/min} \pm 250 \text{ r/min}$ mixing speed.
3. The liquid additives are added into the warring blender still on low speed in the specified order that they would be added on the field.
4. Add Cement into the mix water which now contains other liquid additives and ensure the addition doesn't exceed 15secs. (This is to cater for flash setting which is a factor of Time to Add Cement). Cover the warring blender.
5. Turn the speed on the motor to high speed $12000 \text{ r/min} \pm 250 \text{ r/min}$ for not more than $35\text{s} \pm 1\text{s}$ to get a vortex in the blender.
6. Stop the mixer after 35 secs and proceed with desired test.

Artificial Neural Network – MATLAB

Artificial neural networks are basically made up of input, hidden, and output layers. Inputs for the network are fed into the system through the input layer, the bulk of the training/learning takes place in the hidden layer, and the results are brought out of the system through the output layer. Each of the layers usually consists of one or more neurons (also called nodes). The number of neurons in the input layer is the number of parameters which are to be used as inputs for the

model. In this work, they are: temperature, pressure, density, and recipe identifier. The number of neurons in the output layer is similarly the number of parameters we are predicting (that is, outputs of the model). In this work, it is the transit time. Figure 1 illustrates the architecture of the neural network used. The structure of this work already dictates that the architecture of the neural network to be used should have 4 input layer neurons and 1 output layer neuron.

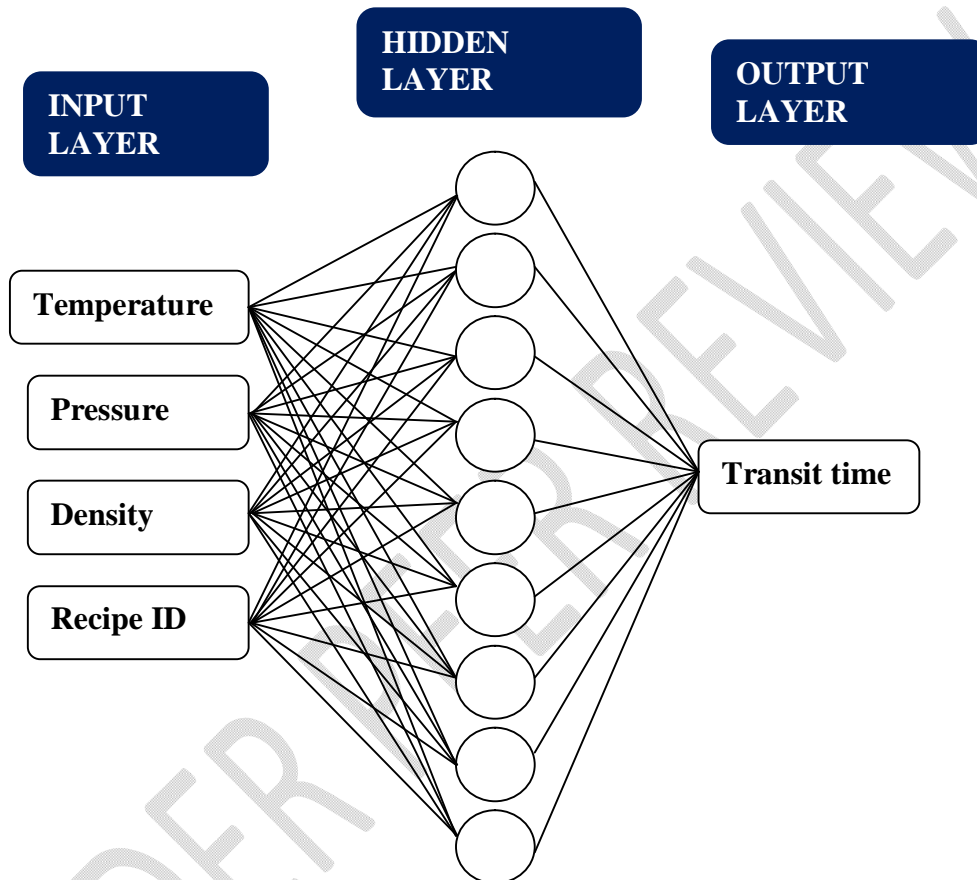


Figure 1. Structure of the neural network used.

What about the number of hidden layer neurons? Some procedure is usually required to decide an appropriate number of hidden layer neurons for a given neural network training. There are no specific rules for choosing the number of hidden layer neurons, but the following knowledge on behavior of neural networks helps. Using too few hidden layer neurons usually leads to a scenario known as under-training in which the neural networks do not learn adequately from the presented dataset, and so do not have the capability to make accurate predictions. On the other hand, using too many hidden layer neurons will lead to a contrary scenario known as over-

training in which the neural networks learn so much from the presented dataset that they even memorize it. This is not good because such neural networks have capability to make accurate predictions of dataset which was used for their training, but they are not capable of accurately predicting dataset that is outside the training dataset. A good balance for the number of hidden layer neurons is therefore required to train neural networks that can generalize well. Such networks should not have too few or excessive number of hidden layer neurons, so that they can make accurate predictions for both data which are within and outside of the training dataset. What number is considered appropriate (not too few and not excessive)? This is usually a major question to answer during neural network trainings. The next paragraphs contain details of the processes which have been used in this work to answer this question.

Prior to the neural network training, the dataset was split systemically into 3 categories: first category for training (70% of the dataset), second category for validation (~15%), and third category for testing (~15%). The training dataset was used for actual training of the networks. The validation dataset was used to check and ensure that the trained networks generalize well, and to produce an optimal network. The testing dataset was used to test the prediction accuracy of the produced optimal network. The dataset in this work was systematically split into training, validation, and testing dataset based on the following criteria:

1. To constitute the validation dataset, 1 data point was first taken from each of the 11 recipes. In each recipe, the data point was randomly selected between the second and ninth cases. This gave 11 data points for the validation dataset. An additional data point was again taken from each of 5 recipes that were randomly selected from the 11 recipes. This gave another 5 data points, making a total of 16 data points for the validation dataset. The 5 additional data points were selected such that two of them are the first cases of their recipes, another two of them are the tenth cases, and the fifth one is randomly chosen from between the second and ninth cases of its recipe. The 16 data points chosen for the validation process therefore represents 14.55% of the entire dataset.
2. To constitute the testing dataset, 1 data point was first taken from each of the 11 recipes. In each recipe, the data point was randomly selected between the second and ninth cases (not including any data point that had been previously chosen for the validation dataset). This gave 11 data points for the testing dataset. An additional data point was again taken from each of the 6 remaining recipes (not including any of the 5 recipes in step 1 above).

This gave another 6 data points, making a total of 17 data points for the testing dataset. The 6 additional data points were selected such that two of them are the first cases of their recipes, another two of them are the tenth cases, and the other two are randomly chosen from between the second and ninth cases of their recipes. The 17 data points chosen for the testing process therefore represents 15.45% of the entire dataset.

3. Steps 1 and 2 above leave us with 7 data points in each of the 11 recipes, giving a total of 77 data points for the training process, and this represents 70% of the entire dataset.

The above criteria for splitting the dataset was designed to ensure that there is a good spread of the data attributes/properties across each of the training, validation, and testing datasets. At least one data point was taken from each recipe to constitute each of the validation and testing datasets. Seven data points were consistently taken from each recipe to constitute the training dataset. Each of the training, validation and testing datasets were also ensured to contain some of the field data (first cases in each recipe), high temperature/pressure data (tenth cases in each recipe), and a random distribution of the rest of the laboratory data (second to ninth cases).

Deciding the number of hidden layer neurons.

To decide the appropriate number of hidden layer neurons, 100 different neural networks were trained. The difference between the 100 neural networks was in the number of hidden layer neurons used for their training; the number of hidden layer neurons used was varied starting from 1 to 100 in steps of 1. After training the 100 neural networks, the performance of each network was evaluated using the root-mean-square error (RMSE) between the neural network predictions and the actual measurements. The following is how it was done:

1. Each of the 100 networks was used to predict the transit time corresponding to the validation dataset which was set apart from the training set.
2. The neural network predictions were compared to the actual measurements, and the errors of the predictions were computed as the differences between the neural network predictions and the actual measurements. That is: error = neural network prediction – actual measurement.
3. The RMSEs for each of the 100 neural networks were then computed using equation (1).

$$RMSE = \sqrt{\frac{\sum_i^n (error_i)^2}{n}} \quad (1)$$

The results of the computed RMSE values are shown in Figure 2. To study the behaviour of the neural networks in terms of over-training/under-training, the procedure of computing the RMSEs were repeated using the training and test datasets. Ideally, the best performing networks will predict transit times which are closest to the measured transit times, therefore their errors/RMSEs will be minimal.

The goal of the process is to choose the network that minimizes the prediction errors/RMSEs. There is however need to avoid an over-trained network. Over-trained networks memorize the training dataset, and so they predict the training dataset with high accuracy (the RMSEs are very small or close to zero). On the contrary, such over-trained networks are not capable of accurate predictions of other datasets outside of the training dataset (e.g., the validation and test datasets). This scenario is witnessed in Figure 2 where the RMSEs associated with the training dataset become too small as the number of hidden layer neurons increase, but the RMSEs associated with the validation and testing datasets rather increase as the number of hidden layer neurons increase beyond ~9. The figure shows that over-training of the networks sets in around the scenario when the number of hidden layer neurons exceeds 9. Figure 3 (showing RMSEs associated with only the validation dataset) demonstrates that the network with 9 hidden layer neurons gave the least RMSEs, and it is this network that has been adopted as the network for the final model development in this work.

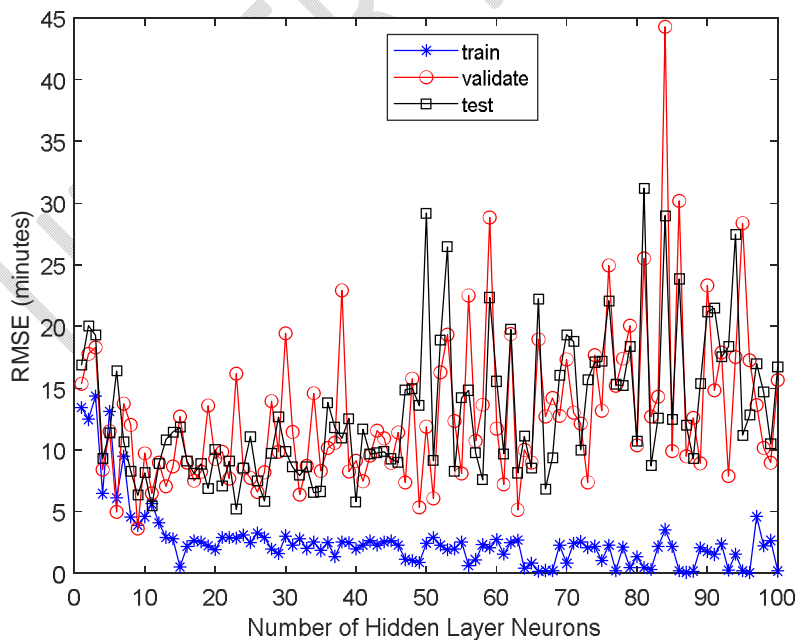


Figure 2: RMSEs associated with the training dataset

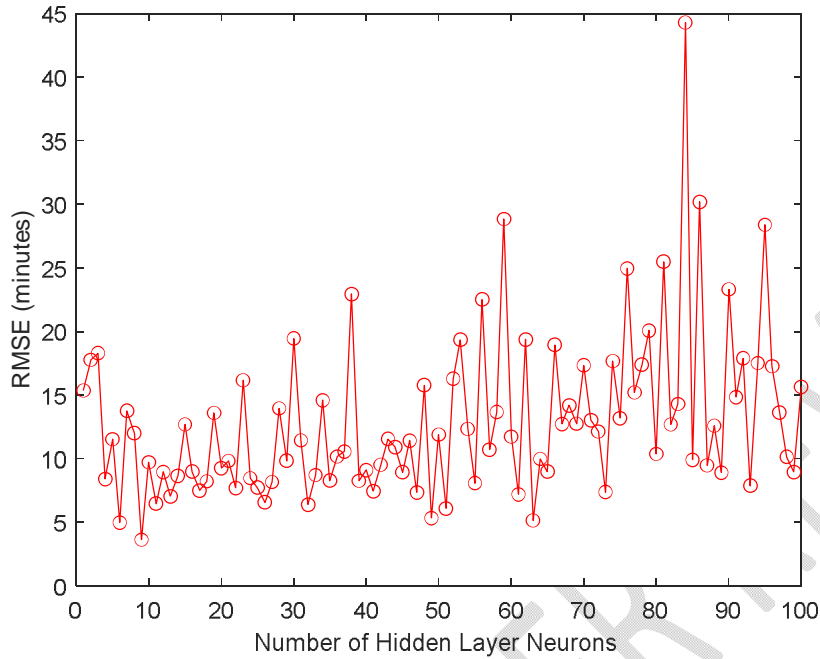


Figure 3: RMSEs associated with only the validation dataset

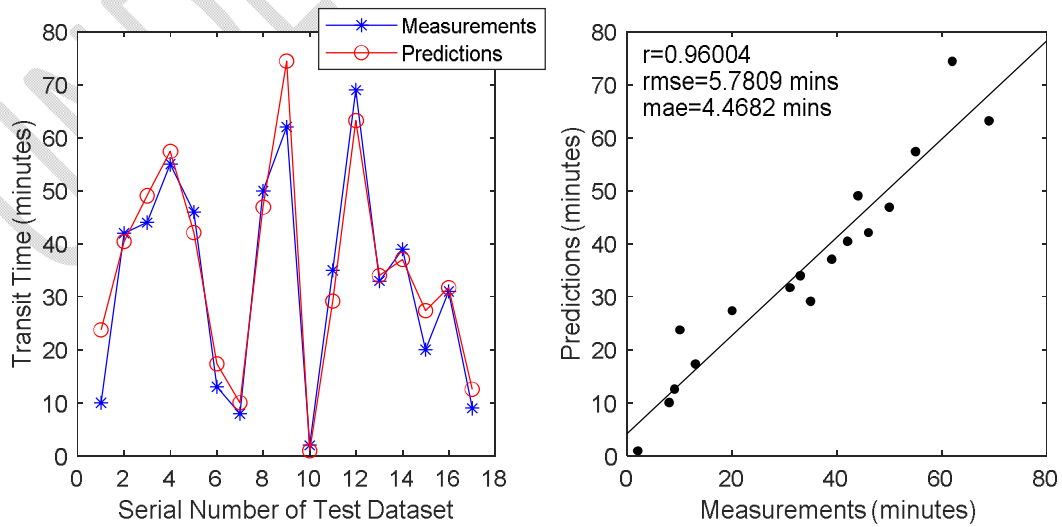


Figure 4: Neural Network testing based on the satisfactory performance of the developed ANN models

Based on the satisfactory performance of the developed ANN models in predicting the shear stress of gas well cement slurries, the down flow curve for a particular mixture was predicted by changing the shear rate and keeping the admixture dosage and temperature unchanged. Subsequently, stress-shear rate curve corresponding to a zero shear rate, and the plastic viscosity was the slope of the curve. One slurry mixture for each of the admixtures was randomly selected from the testing data and used to develop the down flow curve at different temperatures (23°C, 45°C, and 60°C). These gas well cement mixtures were made with 0.5% of each additives.

CONCLUSION

In this study, the relationships amongst the pressure, density, temperature, recipe type and dosage for gas well cement slurries have been analyzed. The rheological properties of gas well cement slurries were modeled using a feed-forward back-propagation artificial neural network. The models were then used to develop flow curves, which were used to calculate the yield stress and plastic viscosity values for gas well cement slurries with different recipes and at different test temperatures. Based on this study, the following conclusions can be drawn:

- The flow curves developed using the ANN based models allowed predicting the Bingham parameters (yield stress and plastic viscosity) of gas well cement slurries with an acceptable accuracy and were found to be in good agreement with experimental results.
- The models proposed by the approach was found to be sensitive to the effects of temperature increase and admixture dosage on the rheological properties of gas well cement slurries.
- The ANN-based model performed relatively better in predicting the rheological properties of gas well cement slurries.
- The proposed ANN based models can be extended and used to limit the number of laboratory trial mixtures and develop gas well cement slurries with suitable rheological properties, thus saving time and reducing the cost of gas well cement slurry design for specific applications.

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