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Gas Oil Color (ASTM) Inference with Neural Network in an Oil Refinery Distillation Column

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Abstract

The first operation in an oil refinery is the atmospheric distillation. To maximize the extraction of some products like Gas Oil, a proper set of on line analysis instruments is required. These kinds of instruments are not always available, especially in medium and small size processing plants.

Due to the fact that color is a limiting specification, it constitutes a restriction for production optimization. Availability in real time of a good value estimate is what allows work to be carried out permanently in operative conditions where the process is most beneficial.

In this work a Neural Network (NN) approach to infer the color is proposed. A feed forward NN structure is used to identify the non-linear mapping from available process variables to that property.

To acquire representative I/O data, a set of dynamic experiments (move test) was developed in the plant. After that, a rigorous analysis to select the set of input variables was performed. In this study, process engineer’s knowledge as well as some mathematical tools were used to evaluate a minimum set of inputs. From this analysis, the set of forty-three available inputs is reduced to the eight most sensitive with respect to the color representation.

Furthermore, rather than represent the entire transformation from the set of inputs variables to the output variable by a single neural network function, we analyze the possibility of breaking down the mapping into an initial pre-processing stage followed by a parameterized neural network model.

Inferences with Neural Networks

Modelation techniques are based on three different focuses to describe the relation between inputs and outputs. These are *mechanistic*, *linear regression* and *black box*. Neural Networks are included in the latter. In this kind of technique, where we obtain models with undefined structure, the main idea is that a system composed by simple processing elements, connected in parallel, can learn the complex relations that exist between a large number of inputs and outputs. Once we have a trained net it can predict the output for any given input with great accuracy.

Neural Networks can be composed of several layers. The first one acts as a distribution node, transferring input data to all the neurons in the second layer. The last layer returns the output of the predicted variable. Between these first and last layers, we have the hidden layers, which are typically formed by only one layer. Each neuron in the input layer is connected to every neuron in the hidden layer and all these are connected to all the output neurons. All these connections are weighted and these weights are the determinant of the global function of the net. The basic structure of a NN is shown in fig. 1.

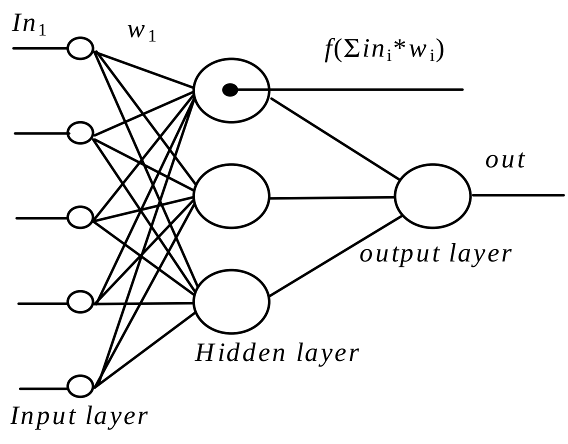

Fig. 1 – Basic Structure of a Neural Network

Inside each neuron, we can see two different stages, the first one is the summatory of the inputs multiplied by the weights and the second is an activation function (generally sigmoidal) that affects this summatory to generate the output.

The summatory includes an extra value called the *bias* that always has the same value.

The first stage, during the process of modeling using NN, is the *training stage*. Here the weights are adjusted in order to reproduce a given input-output set of data.

During the training stage, the data set is divided into two parts, *training set* and *validation set*. As the training proceeds, the weights are adjusted to obtain the best results with the training set, hence the error in the training set always decreases. On the other hand, in the validation set the error decreases until overfitting is achieved. After that the generalization of the network deteriorates. This occurs because the net adjusts the weights to obtain the best results with the training set. We use the weights that give the minimum error with the validation set for the final implementation of the net, because, in general, the input data is not going to be included in the training set.

Typically, we obtain the measure of an accurate net by minimizing the sum of the squared errors. NNs can generally satisfactorily approximate any continuous input-output relationship, but depending on this relationship a large data set may be needed, and these data should cover all the range of possible values of each variable. Out of these range of data the net will not reproduce the system behavior.

In Control Systems which use sampled data the multivariable processes can be represented as shown:

$$Y_k = f(Y_{k-1}, Y_{k-2}, ..., Y_{k-m}, X_{k-1}, X_{k-2}, ..., X_{k-n})$$

Where Y_k y X_k represent the output and input data respectively. *k* indicates the sampling moment and *f* indicates the functional relation between inputs and outputs.

Normally we should specify the form and the parameters of function *f*. Since chemical processes are generally non linear, it is not always possible to specify the *f* function that relates inputs and outputs. It is known that NN are very useful for these applications because they do not require specification for the form of the function: we only need to specify a certain structure or topology.

We specify the structure of the net by determining the number of neurons in the input, hidden and output layers. The quantity of neurons in the input and output layers are established by the quantity of inputs and outputs respectively. These must take into account the delays that should be applied to each one. We obtain the number of neurons in the hidden layer by mathematical tests such as singular value decomposition, bottleneck net implementations, etc.

These tests result, in a first approximation, which could be the necessary number of neurons, but sometimes this number is adjusted by some stages of trial and error.

Determination of measured variables that influence or inform about change in color

At this stage, technical personnel of the plant analyze the process to determine all the possible scenarios of normal operation, in order to plan the plant tests during which small disturbances are introduced to analyze the process response.

The importance of appropriate determination of the types and magnitudes of these movements of the plant reside in the knowledge that the smallest disturbance possible of the productive system should be able to cover the majority of the work regions of the process. This is because the NN are excellent for interpolation of data but not for extrapolation.

This part of the Unit has 43 sensors, which are too many since some of these are redundant or do not give any useful information for the NN. For this reason we made an analysis to identify those variables with greatest influence in the color of the Gas Oil.

Initially we used mathematical methods to identify the variables that offer the greatest quantity of information. However, we observed that these methods (such as singular value decomposition and cross correlation) prioritize the greater variability of the data and not their grade of behavior nor the relation between the input and the output. So it was necessary to make a deeper analysis of the process to establish that the most influential variables were:

TI-200-17	Feed section temperature of crude tower
TI-200-18	Pan heavy gas oil temperature
TI-200-19	Pan light gas oil temperature
TI-200-20	Pan kerosene temperature
FI-219	Steam flow to bottom crude tower
FIC-235	Light gas oil flow to storage
FIC-236	Heavy gas oil flow to storage
PI-228	Feed section pressure of crude tower

The information obtained from the thermocouples TI-200-17 and TI-200-18 is not as important as its relative difference. So we decided to use directly the difference between both of them allowing the simplification of the structure of the net. Tests ran subsequently indicated that this simplification did not affect the results. Figure 2 shows a schematic of the tower.

The field variables are registered by the distributed control system (DCS) of the refinery, which later exports them to a plant information system that allows the processing of these signals on a PC in real time.

The only drawback found was that the thermocouples show a measurement noise of ±1 ºC, which made the instantaneous values obtained not precise. This was solved by using a dynamic average of the last five values of temperature registered in each sample. Subsequently, we configured first order filters on the DCS.

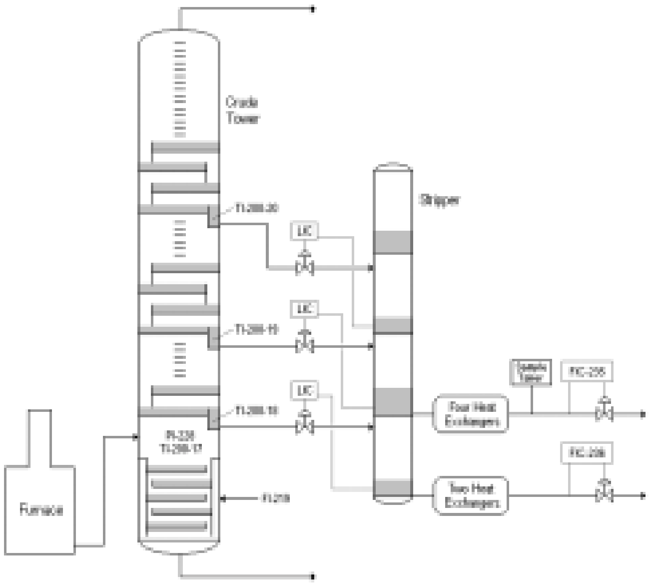

Figure 2: Schematic of the distillation tower and the variables that we use to infer the ASTM color.

Finally we used PCA (Principal Component Analysis) techniques to detect those samples that could contain misleading information among the input and output data. The result obtained was that two of the 1078 samples used where so different from the principal component that had to be discarded.

Acquisition of data for the training of the nets

To train the NN we need a very high number of input and output samples. This volume of information was not available because only one sample was taken daily to the laboratory and the sampling time was not exactly registered, therefore the first thing we did was to create a strategy to achieve enough quantity of data to train the nets.

In order to do so we installed a sampling system in the plant to fill bottles at an appropriate temperature of the product. The sampling regime was of 49 bottles per day filled every five minutes during four hours. These bottles were then transported to the lab to run the corresponding color analysis. Before the analysis was run, the samples where prepared by heating to eliminate traces of water and paraffins.

It is important to bear in mind that the data obtained from the sensors of the distillation column do not coincide in time with the samples analyzed in the lab, since the sampling system is physically separated (downstream) from the column. For this reason, by calculation, we determined that the delay between the process in the column of distillation and the sampling point was of 13 minutes. This is important to be able to correlate the input value with the output value.

The input data in concordance with these output data are easily obtained because they are stored in the control system of the plant (DCS).

Experimental results

Before starting with the net trainings, we pre-processed the data to roughly determine, which would be the minimum necessary number of inputs, once the seven inputs stated before had been selected. This was done to eliminate redundancy or useless information, to achieve this we used a NN with a *bottleneck* structure (See figure 3). This net is composed of five layers: input, mapping, bottleneck, de-mapping and output.

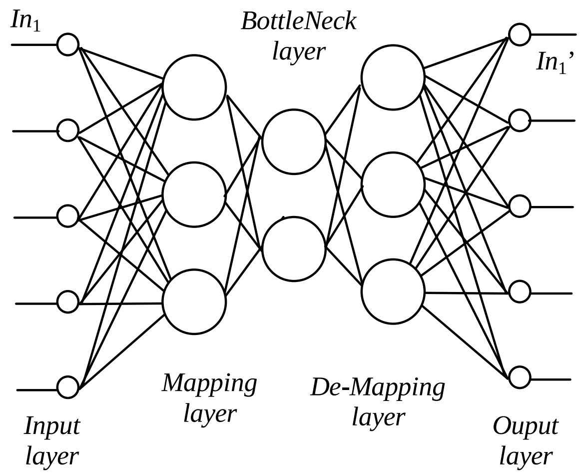

Fig. 3 – BottleNeck Structure of a Neural Network.

This net is trained to obtain at the output the same data available at the input, i.e. we do not want to lose information passing through the net. For the net to achieve this, all the information available at the input should also be available at the output of the bottleneck layer. If the number of neurons in this layer is less than the number of inputs, then we can assure that some of the inputs contain redundant information. Applying this technique we could observe that the minimum number of neurons for the net to copy all the information, was seven. This indicates that the preselected inputs were, in principle, all necessary.

After pre-processing the data, we could initially determine that for a NN using only seven inputs (no regressors) it would be enough to use three neurons in the hidden layer. Nevertheless, during the design of the NN we realized that the best net would be using fourth order regressors of certain inputs and only two neurons in the hidden layer.

The first trainings showed a poor behavior of the net. Even though it followed the general trends of color variations, mean errors were too high. This implies that the inference is not useful as a feedback control variable or as an accurate indication. Figure 4 shows these results.

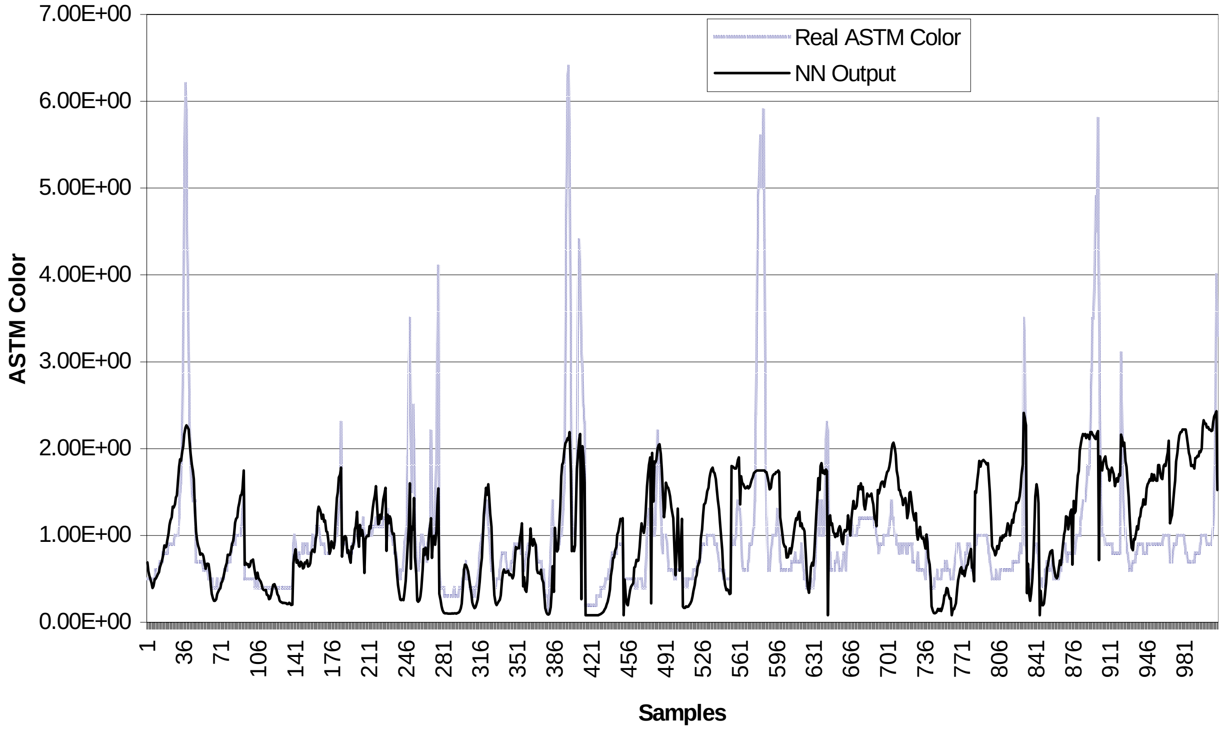

Fig. 4 – First inference of a NN with standard training, without considering dynamics of the process (*i.e.* without regressors of the inputs).

According to the analysis of the curves we decided to carry out the trainings taking into account previous values of certain inputs. Plant personnel analyzed which were variables with the most influent history in color changes and these were used to construct auto-regressive models. These models allowed us to obtain a better approximation of the color tendency, which is very important if we expect to use this as an indicator. Figure 5 shows these results.

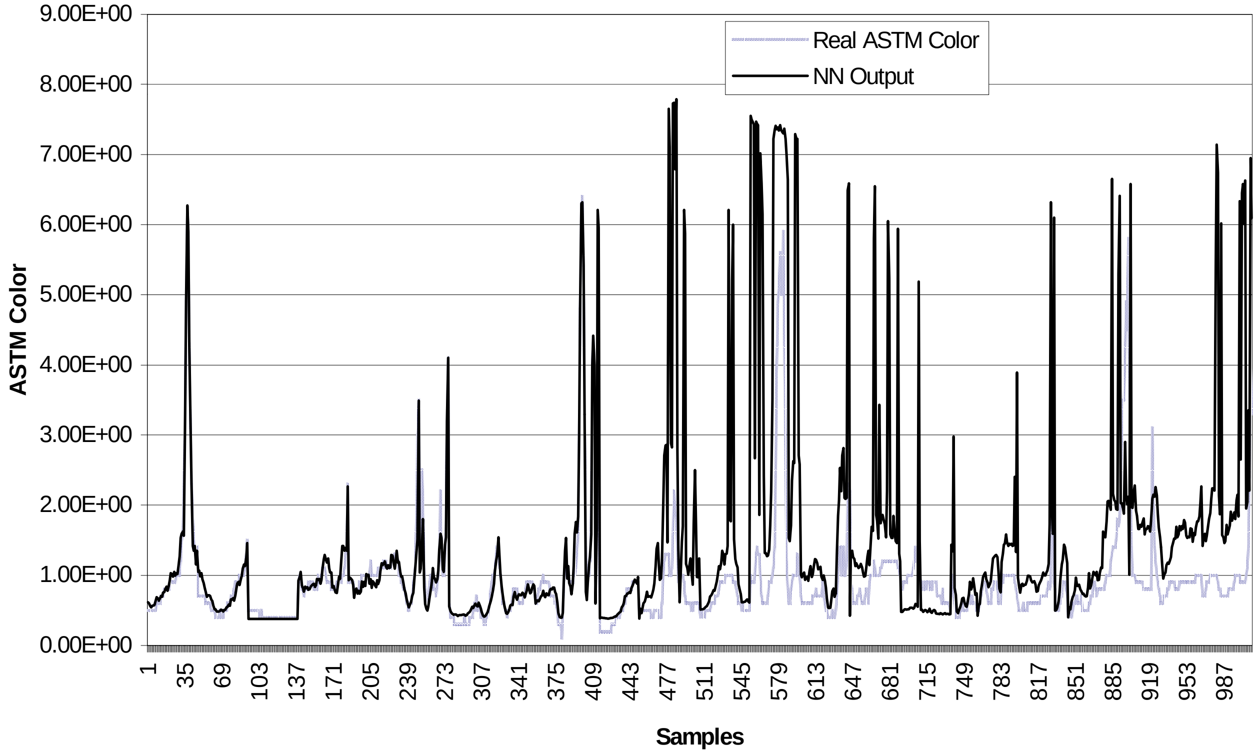

Fig. 5 – Inference of a NN considering an autoregressive model and using a standard training.

Initially we could see that the curve gave a much better approximation for the data with which it was trained, but the inference was rather poor in validation (it showed excessive peaks). This is very inconvenient when we need to use the inference as an indication since it makes the operator strangle the extraction unnecessarily. When analyzing a trained net, we observed very high values in certain weights, which were responsible for the errors. We then used a training technique that penalizes the high weights. Thus, we obtained a net that behaved more adequately regarding the peaks but it lost a lot of information regarding the standard value of the color. These results are shown in figure 6.

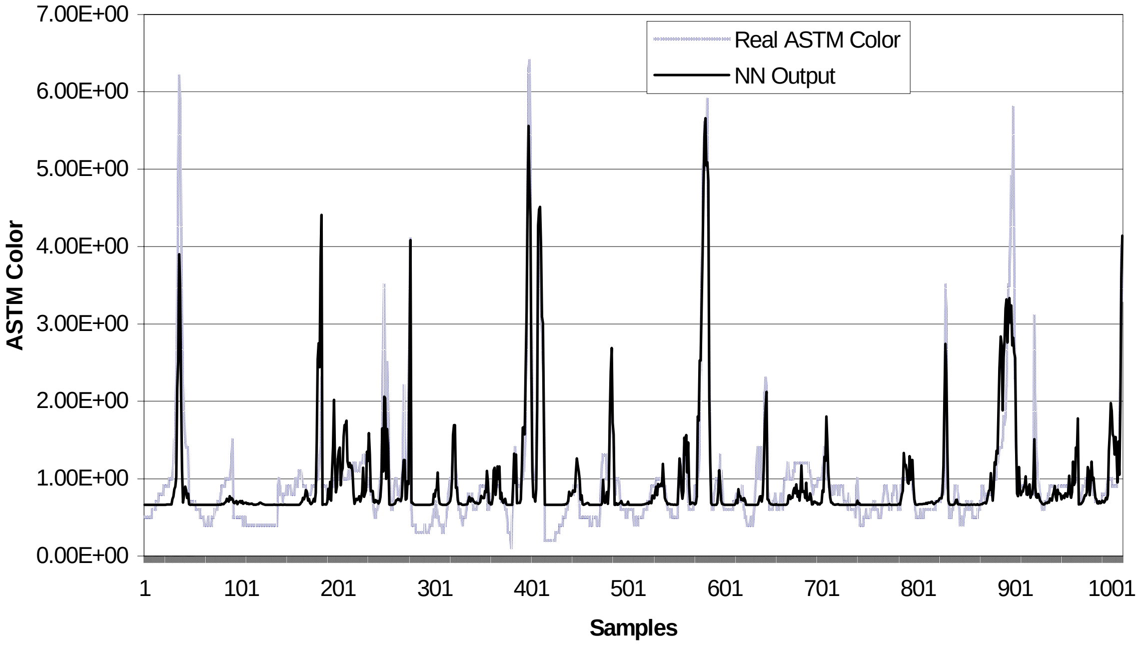

Fig. 6 – Inference using an autorregressive model, with an excessive penalization of big weights.

To solve this problem we chose a compromise solution taking into account the limitation of the mean error and the penalization of the excessive weights, thus obtaining general improvements. The approximation obtained is shown in figure 7 and the error for each sample is shown in figure 8.

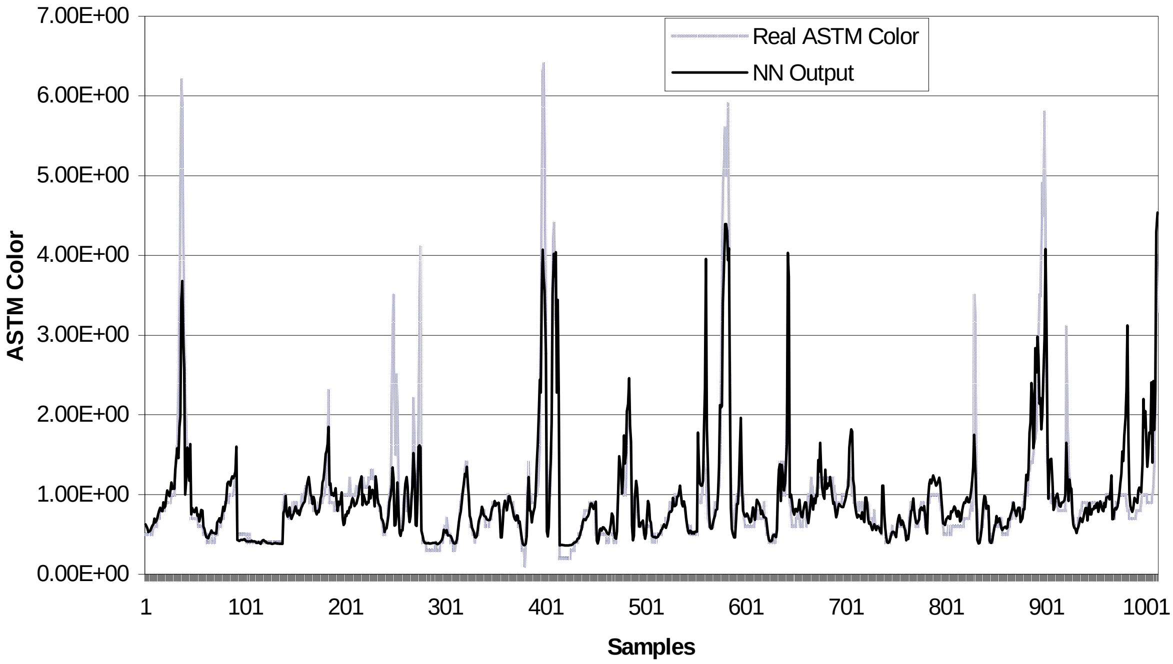

Fig. 7 – Inference achieved taking into account earlier experience. This NN was implemented on line in the plant for final validation.

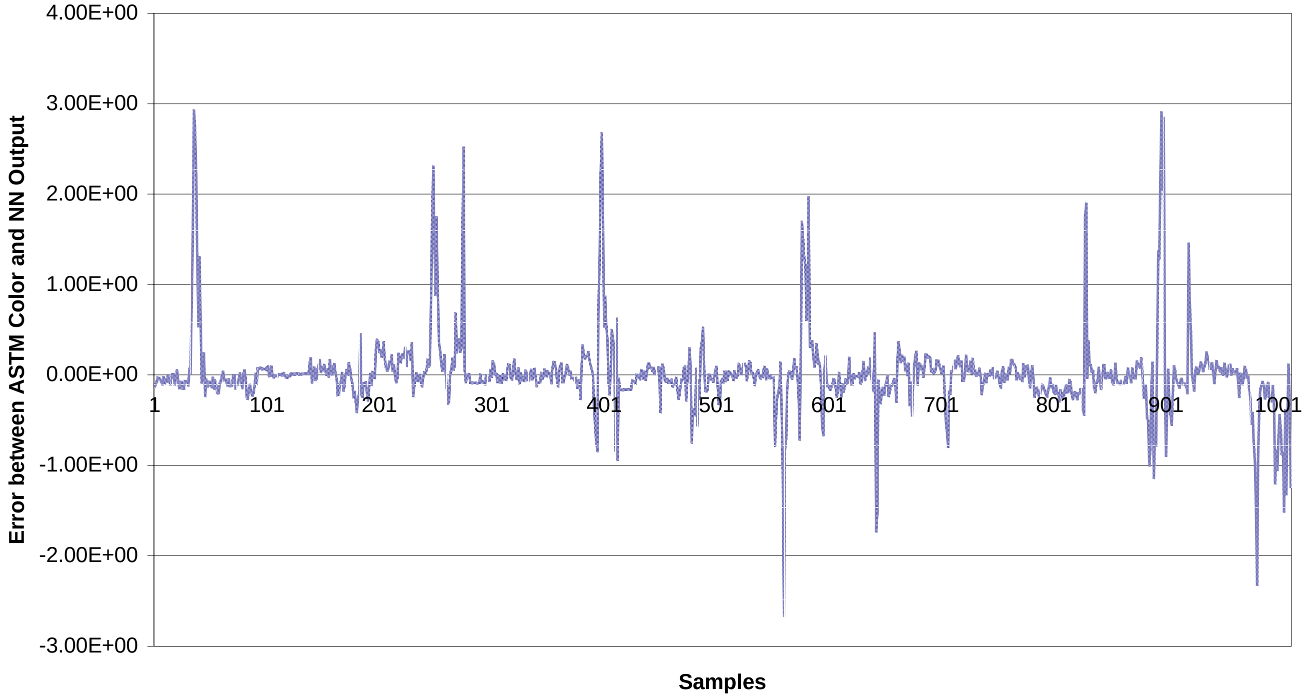

Fig. 8 – Error of the approximation achieved with the NN of Fig. 7.

We implemented this net in a PC connected to the historic of the plant to compare the results inferred with the actual results obtained in the laboratory. In order to do this we ran an algorithm that simulates the net with the information obtained in the plant. The data acquired were logged while disturbances were introduced to the plant to cover a wide range of color. Simultaneously we sampled as explained before.

The results of this comparison are shown in figure 9.

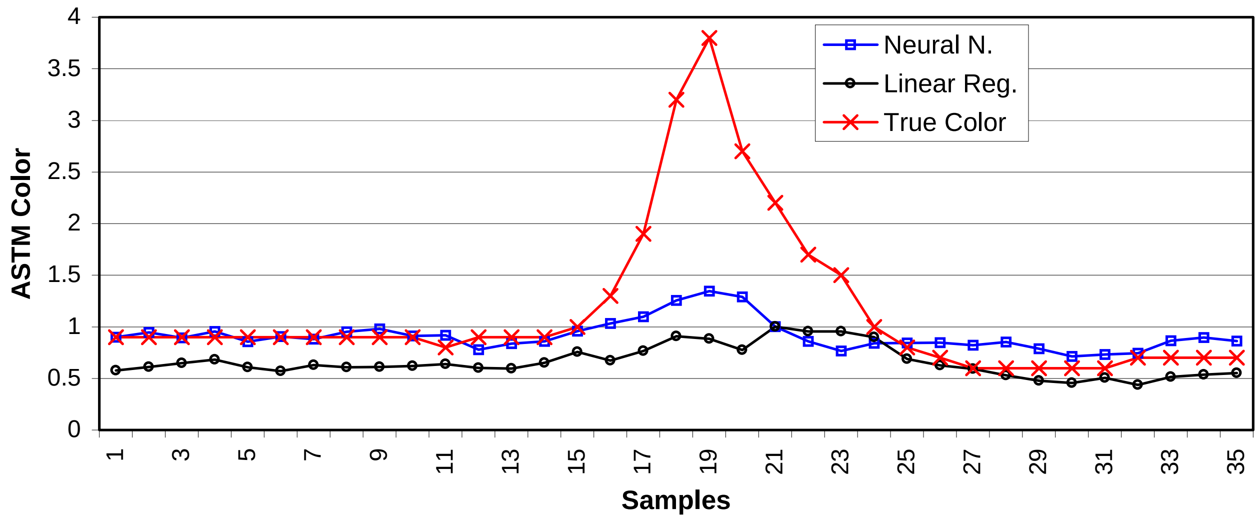

Fig. 9 – Approximation of the NN (☐) compared with the true ASTM color of the Gas Oil (x) and a Linear Regression (O).

Observing these curves, we can initially think that both approximations are quite similar, however, if we analyze them more deeply we can observe that the NN has a better behavior. We can assure this because for small values the inference is very good, better than linear regression (a previously and a first approximation to the problem of inference the ASTM color). When the peak appears the NN starts following this peak immediately, the same occurs when the peak comes down again. This behavior is very important if we want to use this inference as a control variable.

Conclusions

1.- In this work we presented not only experimental results of inference of color based on NN, but also the process of designing the net. This, we believe, is very useful as a starting point for future work in this area. For us, this stage is the first of a plan that includes a more robust inference to allow an optimum control of the extraction of gas-oil.

2. NN has shown to be a very efficient means to infer properties of products in chemical processes. However, they are not always enough on their own for this type of application. The development of the inference must be preceded by a thorough analysis of the process, such as the one needed for this project.

3. The NN requires a great number of input-output samples to obtain good results. In our case this could only be achieved with an on line colorimeter. Another possibility is having a wide data history that shows the exact extraction time of the sample. In the case of a product, which has a daily routine of sampling, this implies having many years of stored information without modifications in plant structure.

4. We observed that when the number of samples is insufficient the quality of the results obtained with NN is not significantly superior to other techniques. However, once this limitation is overcome the NN exhibits a better behavior.

5. Because of the impossibility of predicting color grades higher than 2.1 in ASTM-D1500 norm with different models and the corresponding analysis of the process by plant personnel, we identify the necessity of a single additional instrument that would allow us to indicate the level of the product in the collector. The reason is because of a sudden increase of the level of the product the color increases significantly. This happens in response to the decrease of the internal recycle under the collector of the light gas oil. This causes a deficient separation between the fractions that are responsible for the color increasing.

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