NEURAL NET-BASED INFERENTIAL QUALITY CONTROL ON A CRUDE UNIT

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ABSTRACT

The paper aims at describing an application of virtual sensors successfully implemented on a crude unit in the Raffineria di Milazzo refinery. The quality predictions are obtained employing state -of-the-art neural network technology, seamlessly embedded in the existing distributed control system.
After a brief overview about project goals and process details, a description of the implementation stages and the hardware and software architecture will be given. The last section provides hints about the first operative results and future perspectives.

INTRODUCTION

Highly complex processes mostly characterize modern industrial plants. The complexity stems from the number of inputs and outputs, the frequent occurrence of delays, the inherent process non -linearity and from the high degree of interconnection between the various process units (heat regeneration, recirculation, etc.). Computer-based process control is now widespread; year after year, more plants are controlled using Distributed Control Systems (DCS), able to provide easy and powerful tools for process control, data monitoring and collection.
All the data easily collected can be used to improve process control by means of process modeling. A process model, able to predict process behavior, is a very valuable tool for process analysis, monitoring, control and optimization.
The capability of turning many, often unused, data into a small subset of very useful information is one of the essential reasons, for the impressive spreading of models in process automation [12].
Neural Networks technology, which is based on a data -driven approach to modeling problems, can be a very useful and powerful tool for real-time process control. This technology has entered the mainstream of data modeling in the last ten years. The applications are numerous and in wide ranging fields, from finance, to pattern recognition, to chemistry, to signal processing, to fault detection. In the refining and chemical industries typical applications of interest are products formulation (rubber, plastic, polymers, adhesives, gasoline, etc.), interpretation of complex measures (NIR spectra, etc.), emissions monitoring, online process control and optimization (for examples, see [2], [9], [10], [13], [14] and [15]).
Neural networks belong to a special branch of nonlinear regression modeling. As the name implies, they are related to the human nervous system. The flow of data through the equations that make up a neural network is best described through an illustration, as in Figure 1. Input data enter at the bottom layer. Each input variable is mapped to the central or "hidden" layer node, where the most important calculations take place.

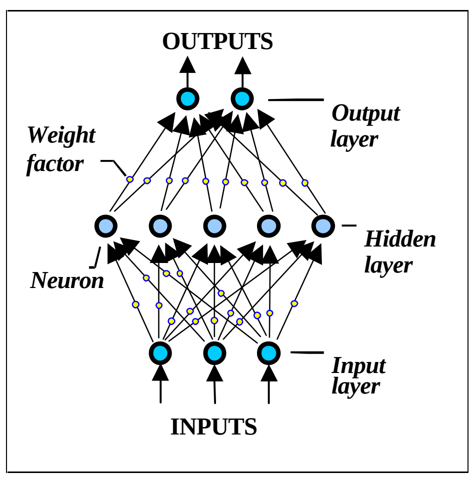

Figure 1 - Neural Network Structure

The outputs are then formed by combining the outputs of the last hidden layer. Depending on the application's complexity requirement more than one hidden layer may be used.

All inputs to the hidden nodes are combined in a weighted sum. Each node in each layer has a different set of input weights. These weights are analogous to the model coefficients in a regression model. The weighted sum is then used as the input to the S shaped sigmoidal function in order to compute the output value.

Schematically the main advantages of Neural Nets can thus be summed up:

- they do not require any prior detailed knowledge of the process behavior (though knowledge at a phenomenological level may be very useful)
- they do not need to be planned
- they can be trained through the simple presentation of examples
- they are efficient in computation terms.

Although neural network have demonstrated tremendous capability and performances, their use and application may be tricky and must be driven by expertise and a well sounded development procedures, in order to avoid failures and disappointment ([3], [11]).

PROCESS DESCRIPTION

Crude Unit, plant scope is to distillate the incoming crude oil, in order to separate the feed into a number of hydrocarbon streams of different composition.

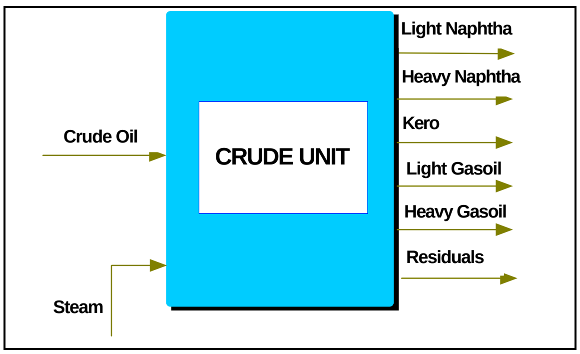

Figure 2 – Unit Inlet/Outlet Streams

The Crude Unit where this application took place has a processing capability up to 8 millions of ton of crude oil, with heavy crude, even if its normal throughput is lower.

The feed, always made of a blend of different crude oils, may be classified in 3 different types, based on the chemical/physical features: high sulfur content, medium sulfur content and low sulfur content. Each feed type is stored in different locations at different temperature.

The unit is able to separate the feed into 6 different outlet streams, here listed from lighter to heavier, as described in Figure 2:

1. *Light Naphtha* (**BL**)
2. *Heavy Naphtha* (**BP**)
3. *Kero* (**KERO**)
4. *Light Gasoil* (**GAL**)
5. *Heavy Gasoil* (**GAP**)
6. *Residuals* (**RA**)

All the product streams are sent to downstream conversion units, whose actual requirements fix the Crude Unit operating targets and constraints.

The Unit is composed by of the following process sections:

§ furnace F-1
§ fractionator C-1
§ stripper C-2
§ stabilizer C-3
§ splitter C-4

The crude oil feed, divided into 2 parallel lines, is pre-heated by some heat exchangers, which use a few process streams (product extractions and pumparound flows), as warm flow. Desalting is performed in 2 desalter units.

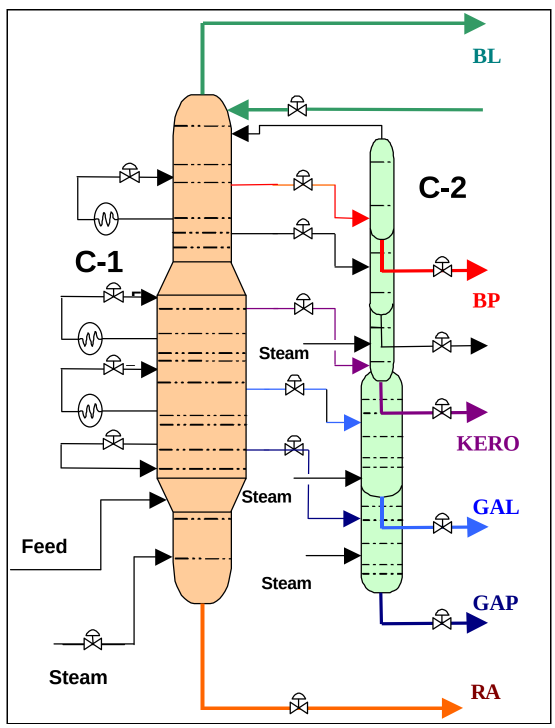

Figure 3 - Fractionator C-1 and Stripper C-2

The furnace is structured in four lines, each one temperature controlled, which merge in a single line before entering the fractionator C-1.
The column C-1, made of 55 trays, is designed to perform the distillation of the feed into the different hydrocarbon products streams. The thermal profile is provided by means of 3 pumparound circuits (from above PAS, PAM and PAI) where heat is removed using heat exchangers and air coolers. A liquid recycle is placed around the flash zone in order to improve the column separation capability between GAP and RA. The stripper C-2 receives its feeds from column C-1 its scope is to extract volatile components from the product extractions coming from column C -1 by injecting steam.
The stabilizer C-3 and the splitter C-4 process the Light Naphtha (BL) coming from the fractionator overhead.
The unit is equipped with an Infi90 DCS, commissioned in 1998 and connected to a powerful Plant Information Management System, able to record and store all the meaningful process data.

The fractionator column can produce the distillated streams with various plant configurations. In particular, the overhead features two different possible configurations:

- *Case 1*- BL extraction directly from overhead and BP extraction from top side draw
- *Case 2*- BP and BL are both extracted from the overhead and then separated downstream by means of the splitter C-4.

In order to cope with the two different configurations, which are associated with very different thermodynamics profiles, 4 neural networks were developed. The first two nets estimate BP and BL qualities for Case 1, the other two nets estimate BP and BL qualities for Case 2.
In summary, the project scope has been to develop 6 neural nets-based inferential sensors, able to estimate product qualities in terms of 95% ASTM for the following streams:

1. *Light Gasoil* (**GAL**)
2. *Kero* (**KERO**)
3. *Heavy Naphtha (**BP**) Case 1*
4. *Light Naphtha (**BL**) Case 1*
5. *Heavy Naphtha (**BP**) Case 2*
6. *Light Naphtha (**BL**) Case 2*

PROJECT EXECUTION

The project execution has been divided into 3 major stages: data collection featuring also data analysis and pre-processing, neural network development and neural network on-line implementation.

DATA COLLECTION

It is straightforward that for a data-driven technology such as the neural one, the availability of a powerful and reliable instrument for the acquisition of that sort of raw material such as data, is a decisive factor
Data collection was performed using a Plant MIS connected to the plant DCS. The process data have been taken from an historical database, as one-hour average of measured process data. The laboratory analyses, to be used as training examples for the 95% ASTM values were extracted from the laboratory database. The laboratory analyses recalled from the laboratory database were linked to the relevant process measurement in order to produce one record for each analysis available.
Direct data collection has also been performed by means of *WindowView Data Collection*, an ABB Automation package designed to allow easy data acquisition and management from the company's own DCSs or through devoted DDE protocols.

NEURAL NETWORK DEVELOPMENT

The data collected and opportunely sorted out, have been then used inside of *Infi Neural Net*, an ABB proprietary product able to deploy neural networks-based control strategy into company's own DCS architecture [4]. Infi-Neural Net off-line development toolkit, is based on *Process Advisor®*, a devoted software package for designing, training and validating systems based on Neural Networks. The software is licensed by *AI Ware Co.* (now part of *Computer Associates Inc.*) and supported by a reference list with over 400 industrial applications [1].

Neural Networks for the 6 different streams were trained as independent nets, each one with one hidden layer. Inputs were chosen among relevant process measurement, like temperatures, pressures and flows. A set of records (around 15% of the total data set) was used for each neural network in order to validate the neural model using separate and independent data. As an example, Fig. 4 shows the prediction results on the Kero test-set.

The neural nets were finally validated using separate new data sets coming from the plant, available few days before the commissioning began. Some of the most interesting statistical parameters for each neural net are described in Table 1 (signal/noise ratio is given by standard deviation/reproducibility).

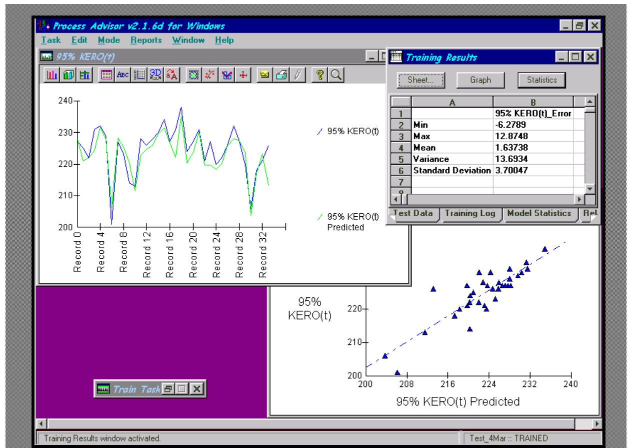

Fig. 4 – Prediction Results on Kero Test-set

	R^2 - train	R^2 - test	f-test	Signal/ Noise
GAL	92.78	93.57	13.29	5.36
KERO	82.25	74.57	9.10	1.87
BAP	96.22	83.20	4.24	1.57
BALS	87.62	93.69	12.18	5.83
BAFS	82.85	73.86	5.35	1.15
BATS	80.65	73.22	4.78	2.26

Table 1 – Main Statistical Results for Each Training

It appears quite clearly, from the above table, the correlation between the f-test value and the signal/noise ratio: obviously the better is the latter, the better is the former. This result is pretty important because it proves the goodness of the models: the mismatch present in the predictions comes almost completely by the inherent uncertainty present in the data.

Neural Network Implementation

While the more rewarding features for an off-line development environment are user-friendliness and powerful analysis capabilities, the on-line environment needs to be reliable, fast and very well-integrated with existing base automation.

The on-line Infi Neural Net engine resides inside a MFP (Multi Function Processor) control module located into a standard DCS cabinet. This solution makes it possible to benefit from a natural and direct communication channel, absolutely necessary in order to avoid excessive installation and maintenance problems (see Figure 5). This approach has already proved his efficiency in a number of process control applications (see for example [5], [6], [7] and [8]).

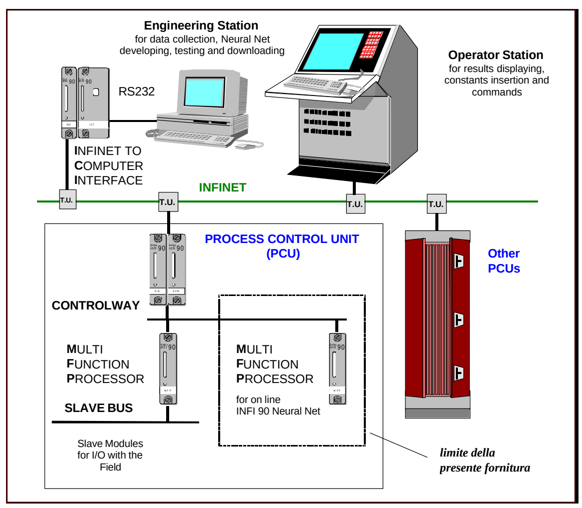

Figure 5 - Architecture of INFI 90 Neural Net HW

An important feature of the Infi Neural Net architecture lies in the fact that one single MFP is capable of hosting up to 6 different Neural Nets. That means that once the software licenses and the hardware card necessary for the first application have been acquired, the client can implement up to other 5 real-time totally different applications.

A module, devoted to on-line estimation of the product qualities was added to the plant DCS. The module contains the neural network calculation engine, the data files containing the neural networks

configurations and some block-based logics able to perform on-line data pre-processing and filtering; these tasks will be better described in the following paragraph.
The download procedure was performed using a devoted proprietary soft ware tool, named *Infi-Neural Net Download*, which allows easy and effective downloading

Input Measures Processing

The Neural Network estimator employs a set of process measures as inputs. All inputs undergo a pre-processing procedure in order to identify abnormal values, filter fast dynamics and provide the system functionality even in degraded conditions.
The pre-processing is made of the following stages:

- Input data moving-average filtering
- Consistency check (on the typical operating range)

When a bad quality or an inconsistency happens on a variable, a digital signal is issued, so to provide an alert on the operator console.
When an input is not available (for example for a sensor failure), the last good value is kept. As an alternative the operator is allowed to perform a manual update of the input value, acting on some specially designed displays on the operator console. This action is automatically inhibited, when the sensor reading is valid, so to prevent undesired manual substitution for correctl y working sensor. After a sensor failure when the input variable comes back to normal status, the fail-back procedure is disabled and the neural estimator is fed with the actual value from the field.

Estimation Processing

In order to reduce errors caused by systematic model mismatches, the property predictions provided by the neural estimators are biased with a factor produced by a statistical process control based procedure (named SPC Bias Update, see [7] for details). The SPC Bias Update employs fresh in formation coming from the daily lab analysis to provide an on-line automatic calibration mechanism, able to compensate for equipment drifts, model mismatches or random unmodeled disturbances. The bias is statistically processed to avoid that possible wrong analysis results coming from the lab cause the predictions to be away from the real value for long periods.
Each neural estimate is added with its own bias factor, updated with the same frequency of the lab analysis (once a day for the Crude Unit). The update occurs when the lab analysis is available, and the updated bias factors are then used until the next laboratory analyses are available.
The SPC Bias Update procedure is easily managed by operators through an especially devoted display.

First Operative Results

The 95% ASTM product qualities predictors have been commissioned in January 2000, although some of them had to be considered just as preliminary releases due to the reduced amount available for training & test. The first results have been quite encouraging for the soft sensors which have undergone the complete procedure of training, test and validation on a large amount of data, able to provide accurate and reliable quality estimates.
As an example, Figure 6 shows the comparison between predicted and measured quality on the Light Gasoil stream over a 5 week-long period. The average % absolute error, defined as in (1) is about 1.23 with a standard deviation of 1.10.

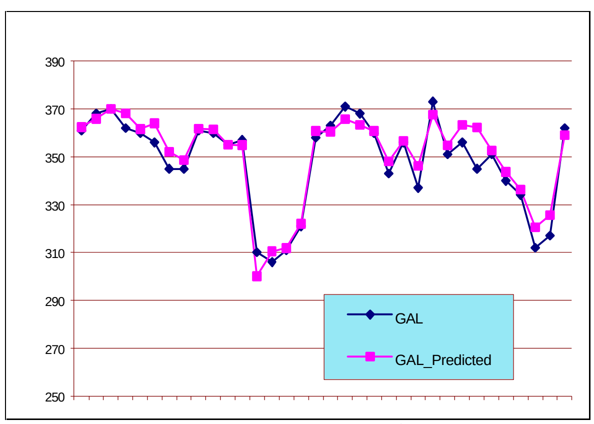

Figure 6 – Lab Measures vs. Prediction for GAL Stream over 5 Week-long period

Quality predictions on other streams show similar performances, notwithstanding the lowest signal/noise ratio. The inferential sensors accuracy is still improving as the size of the available data base increases. As soon as the property predictions prove consistently their reliability, they will be used in closed-loop so to reduce operator's burden and to guarantee more effective and stable process operation.

The good results obtained have moved the refinery to start a new project to extend the neural network-based inferential sensors to a twin crude unit.

$$\bar{\varepsilon}(\%) = 100 * \frac{1}{N} \sum_{i} \frac{\sqrt{(X^{i}_{est} - X^{i}_{meas})^2}}{X^{i}_{meas}} \quad (1)$$

CONCLUSIONS

Neural net-based product quality estimation, described in this paper, provides a valuable tool to make available real-time information on actual operation performances. This allows control room people to keep the process closer to pre-defined production objectives and to identify disturbances and possible minor failures before they cause costly plant upsets. Neural net-based predictions on 95% points have average discrepancies, respect to what provided by laboratory analysis, of ± 3 °C (slightly bigger for the heavier products, slightly smaller for the lighter). This is a very good result, being the ASTM D86 methodology characterized an inherent reproducibility of about $\pm 3 \div 4$ °C.

The neural approach has proved the following extra benefits:

1. Capability to use on-line laboratory results to perform auto-calibration procedures;
2. Capability to use new process information to both increase prediction accuracy and extend effective performances over new operative modes;
3. Reduced life-cycle cost compared to both a hardware analyzer and a first-principle software sensor.

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