Prediction of Products Quality Parameters of a Crude Fractionation Section of an Oil Refinery Using Neural Networks

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ABSTRACT

Inferential analysis using neural network technology is proposed for an existing crude fractionation section of an oil refinery. Plant data for a three month operation period is analyzed in order to construct various neural network models using backpropagation algorithm. The proposed neural networks can predict various properties associated with crude oil productions. The simulation results for modeling Naphtha 95% cut point and Naphtha Reid vapor pressure properties are analyzed. The results of the proposed work can ultimately enhance the on-line prediction of crude oil product quality parameters for crude fractionation processes.

1. INTRODUCTION

In response to demands for increasing oil production levels and more stringent product quality specifications, the intensity and complexity of process operations of oil refineries have been exponentially increasing during the last three decades. To alleviate the operating requirements associated with these rising demands, plants designers and engineers are increasingly looking into the implementation of various intelligent control methodologies[1], [5]-[8].

Presently, in majorities of oil refineries, products samples are collected once or twice a day (based on the type of analysis to be performed) and supplied to the lab for analysis. If the lab results do not satisfy the specifications within an acceptable tolerance, the product has to be reprocessed to meet the required specification [4]. This procedure is costly in terms of time and dollars, because an off-specification product has to be routed to a holding facility, then the process is tuned before any further processing takes place. To resolve this problem, a continuous on-line method of predicting products stream properties that are consistent with and pertinent to column operation is needed.

In general, On-line analyzers can be strategically placed along the process vessels to supply the required product quality information to multivariable controllers for fine tuning the process. However, on-line analyzers are very costly and maintenance intensive. To minimize the cost and free maintenance resources, other alternatives methods should be considered.

In this paper, supervised NN architectures are proposed in order to generate inferential products properties predictors for improvement of current operation of the crude fractionation section of the oil refinery. Specifically, Artificial neural network has been implemented for the following product properties:

1) Naphtha 95% Cut-Point;
2) Naphtha Ried Vapor Pressure.

In this paper, only Naphtha 95% cut-Point parametr is discussed. The detail work for NN implementation of this parameter as well as other Crude oil properties for Crude Fractionation can be found in [9], [10].The proposed artificial neural network models predict products qualities well within the specified error goals in both training and verification phases. Various implementation issues such as model building, model data analysis, effects of neurons distribution on training, and model robustness are also discussed.

2. Building of Neural Network

The mathematical algorithms developed to model neurons can be adapted for many useful predictions in processing plants. The complexity of the pattern to be recognized dictates the complexity of the algorithm required. Some very useful "predictions" can be made in processing plants using algorithms whose coefficients are "discovered" through training [2].

Initial process variable selection is not critical, almost anything upstream of the measurement point could be useful. As many process variables should be included as can be handled. The training process will automatically

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determine which are important and which can be deleted from the calculation. For example, the process variables shown in Figure 1 are selected to predict Reid Vapor Pressure in the bottom of a stripper column. Their relative importance, determined by neural network training, is shown in Table1. If those process variables chosen initially do not give the required accuracy of prediction, less important variables should be dropped and other parameters added.

3. Data Analysis

3.1 Data Collections

The first step in data analysis, is to ensure that all column parameters are collected properly. Unavailable data due to transmitter downtime or calibration at the time of data collection should be identified. Since artificial neural networks require that all model parameters be available all the time, unavailable data for any of the parameters forces the elimination of the complete data set that is collected at that time. This includes lab data which is not collected at the scheduled sampling time. The definition of a complete data set is all process parameters plus one lab value. Lab analyzed properties(95% cutpoint, sulfur content, freeze point, etc.) were analyzed individually to generate neural network models.

Once a complete set of parameters is collected, the neural network model can then be used to do a complete data analysis. The neural network model allows the user to specify which data set will be used for model building (teaching phase), and which for model verification (testing phase). A statistical method can be used to eliminate a suspected bad lab data. The main assumption of the statistical method is that there has to be a correlation between model inputs (process parameters) and model output (lab value).

3.2 Elimination of Bad Lab Values

Bad lab values can be identified as follows: The neural network model is given three data sets for model verification (out of 180 data sets), and the rest of the data sets are used for model building. All data sets are switched between model verification mode to model building mode until all data is tested. At any point during the above process, if any of the three model verification points fall outside the Lab repeatability, the degree of deviation from repeatability is recorded. At the end of this analysis, all deviant points are completely removed from model building. Thus it can be established that all remaining data sets conform to the general trend of the correlation.

As a final step, each of the deviant points is again individually added to the model and tested as a verification point by itself. If this point still fall outside Lab repeatability, then it is permanently eliminated. Otherwise, the point is returned to the model.

The elimination of data sets during this step do not necessarily reflect only bad lab value. It is possible that the lab analysis is done correctly, however, either the snap shot of the process values taken do not coincide with the time of sampling by operators, or the plant is not operating at steady state conditions at the time of samplin

3.3 Process Parameters Effect on Neural Network Prediction

All identified process parameters do not necessarily have an effect on each of the Lab values (properties). The final step of data analysis is to identify the most important process parameters that have a significant effect on the inferred analysis and eliminate those parameters which have little or no effect. Two methods can be used to perform the elimination process. The first is using engineering judgment to realize which process parameters can have little or no effect on the model. An example of this is removing all naphtha stabilizer parameters when the network is being used to model diesel sulfur.

The second method is utilizing the neural network model itself. The neural network program can generate an analysis of the final weights given to each of the process parameters to fit the data. This method of elimination, however is not as straight forward as one might expect. The neural network model relies more on process parameters with a large degree of variance. It is possible that the most important parameter that affects a particular lab data keeps the same value in all the generated data sets. Such a parameter will be ignored by the neural network program. Thus elimination should not include variables which from an engineering point of view should have a contribution on the inferred analysis.

4. Simulation Results

The central objective of the presented work herein, is to eliminate the dependency on laboratory and on-line sample analyzers for sampling of product qualities by implementing neural networks technology to predict those qualities to meet the more stringent market

specifications. In this paper, modeling of the naphtha 95% cut point property is presented using backpropagation algorithm. Various configurations, in terms of the number of hidden layers and the number of hidden neurons, have been tested. Due to space limitation, the details and graphs for simulation experiments are not presented herein, and can be found in [9]. For Naphtha 95% cut points, 85 data sets were analyzed. Each data set consists of 33 process variables as inputs to the model and one product quality (naphtha 95% cut point) as an output. A total of 52 data sets were used in the training phase and 15 data sets were used in the verification phase. At the first phase, the Naphtha 95% cut point property is simulated using backpropagation algorithm with a single hidden layer consists of 5 neurons. Table 2 summarizes the results of the simulations.

It can be noticed that in the training phase the models perform well, however, in the verification phase all the tested models could not predict with enough accuracy. It is suspected that the neural network models are memorizing the relationship between the inputs and the output since they are trying to adhere to a very small error goal in the training phase.

It is important to prevent the neural network model from memorizing the input/output relationship. A neural network with enough hidden neurons given enough iterations and a very small error goal will actually memorize a given relationship between model inputs and outputs. In other words; A network memorizes relationships between outputs and inputs when the model building points are allowed to conform to a degree much less than lab repeatability. It means that an acceptable sum squared error goal in the training phase should generate a degree of accuracy very close to lab repeatability.

Table 3 shows a summary of the simulation results. In Figures 2-6 the simulation results for four different structures are presented. The detail of the simulation experiments can be found in [9]. The best model architecture (in terms of better prediction in both training and verification modes) consisted of eight neurons in one hidden layer. Both hidden and output layers use sigmoidal activation functions as the nonlinear element for their neurons. The model is trained to achieve an error goal of 0.1. The sum squared error goal in the verification mode is 0.097.

5. Conclusions and Discussion

In this paper, various neural network architectures are proposed for the prediction of products quality of an oil refinery. The important parameters involved in acquiring valid data sets are considered. Close attention is paid to selecting the model inputs and the effects of such selection was discussed in detail. Finally, Naphtha 95% cut point was successfully modeled using Neural Networks.

After the generation of the neural network models, they may be used on-line by utilization of the algorithm on the central processing computer system of the oil refinery. Using the model on-line is straightforward except for one point of caution. The network was trained within a specific range for the different process variables and the lab data. It is important to realize that while neural network models are excellent interpolators, they can be bad extrapolators due to the non-linearity of the correlation generated. It is, therefore, important to check process parameters being used in the prediction and make sure that these parameters fall within the range that was used to create the model. As the variability in plant operation increases, and the network window expands, the generation models can become more reliable.

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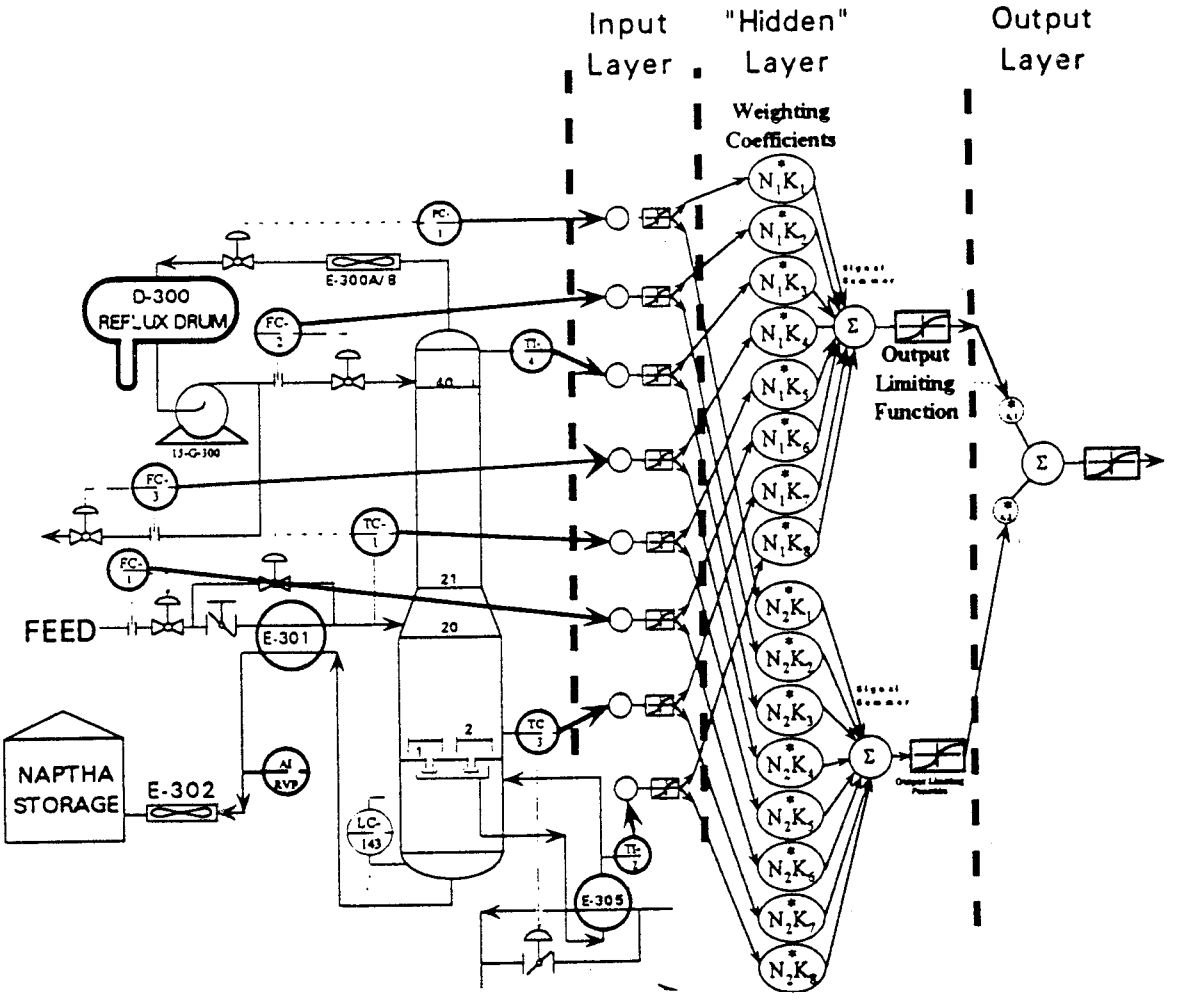

Figure 1: Process Variables Selection in the Stripper Column

FEED FLOW RATE	F-1	4 %
REFLUX FLOW RATE	F-2	8 %
OVERHEAD PRESSURE	P-1	6 %
FEED TEMPERATURE	T-1	13 %
REBOILER RETURN TEMPERATURE	T-2	27 %
TRAY 2 TEMPERATURE	T-3	36 %
COLUMN TOP TEMPERATURE	T-4	5 %
DISTILLATE FLOW RATE	F-3	2 %

Table 1: Relative Importance of Process Variables Determined by Neural Network Weights.

Hidden neurons	Training Phase				Verification Phase	
	Error goal	Iterations	Final SSE	Max. Error degree F	Final SSE	Max. Error degree F
5 BP	0.01	10000	0.045	7.84	0.45	11.59
5M	0.01	10000	0.031	1.57	0.22	7.92
5	0.01	3180	0.01	2.17	0.28	5.49
8	0.01	4563	0.01	1.35	0.25	3.29
10	0.01	2088	0.01	1.83	0.27	7.95
8-4	0.01	4302	0.01	1.33	0.14	4.81

Table 2: Initial Simulation Results for Naphtha 95% Cut Point

Hidden neurons	Training Phase				Verification Phase	
	Error goal	Iterations	Final SSE	Max. Error degree F	Final SSE	Max. Error degree F
5	0.1	374	0.1	3.21	0.091	4.17
	0.3	196	0.3	6.61	0.432	13.76
8	0.1	238	0.1	2.87	0.097	3.29
	0.05	681	0.05	1.8	0.111	3.99
	0.01	5686	0.01	1.37	0.161	4.7
12	0.1	385	0.1	3.18	0.117	4.87
	0.05	1237	0.05	1.7	0.145	5.79
5 - 2	0.1	269	0.1	3.03	0.098	5
	0.2	211	[illegible]	3.81	0.127	5.45

Table 3: Simulation Results for Naphtha 95% Cut Point

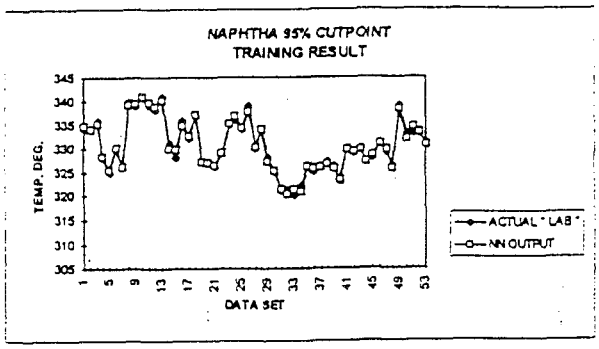

Figure 1 : Final absolute error values during training phase
(hidden layer neurons=5, error goal=0.01, maximum error=1.57 degree F)

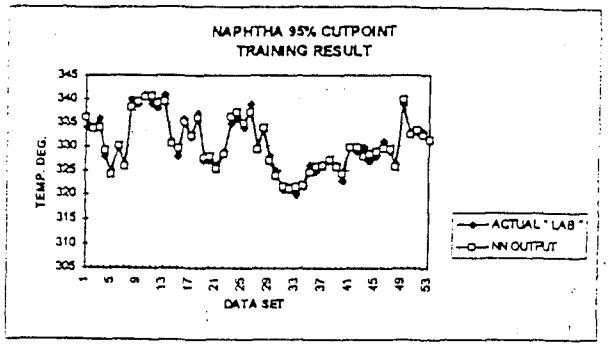

Figure 3: Final absolute error values during training phase
(hidden layer neurons=5, error goal=0.01, maximum error=2.17 degree F)

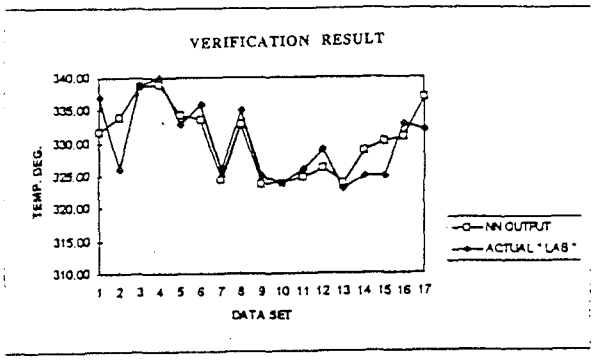

Figure 2: Final absolute error values during verification phase
(hidden layer neurons=5, error goal=0.01, maximum error=7.92 degree F)

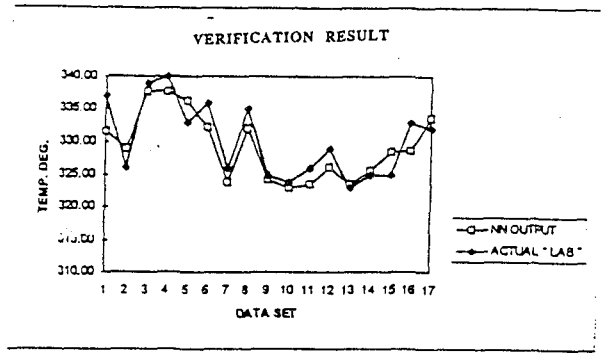

Figure 4: Final absolute error values during verification phase
(hidden layer neurons=5, error goal=0.01, maximum error=5.49 degree F)

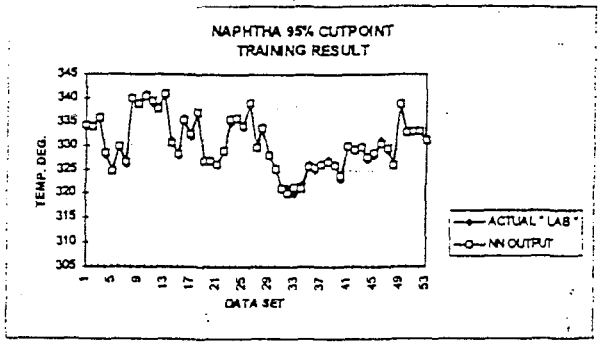

Figure 5: Final absolute error values during training phase
(hidden layer neurons=8, error goal=0.01, maximum error=1.35 degree F)

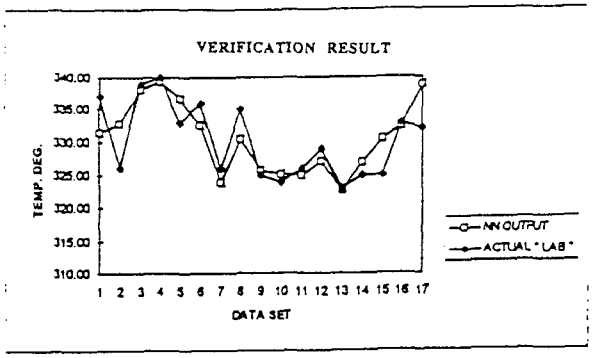

Figure 6: Final absolute error values during verification phase
(hidden layer neurons=8, error goal=0.01, maximum error=6.82 degree F)