

**“Application of Neural Network in developing Virtual Analyzer of  
Reformate Research Octane Number”**

By

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2164

Dissertation submitted in partial fulfillment of  
the requirements for the  
Bachelor of Engineering (Hons)  
(Chemical Engineering)

JANUARY 2005

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1) Motor Fuels -- Testing  
2) CHE -- Thesis

# **CERTIFICATION OF APPROVAL**

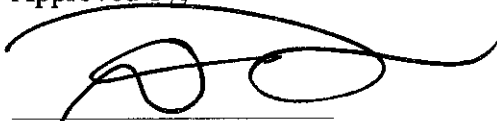
## **Application of Neural Network in developing Virtual Analyzer of Reformat Research Octane Number**

By

Zurairhan Selina Bte Suharin

A project dissertation submitted to the  
Chemical Engineering Programme  
Universiti Teknologi PETRONAS  
in partial fulfillment of the requirement for the  
BACHELOR OF ENGINEERING (Hons)  
(CHEMICAL ENGINEERING)

Approved by,



(Nooryusmiza Yusoff)

UNIVERSITI TEKNOLOGI PETRONAS  
TRONOH, PERAK  
JANUARY 2005

## **CERTIFICATION OF ORIGINALITY**

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.



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(ZURAIHAN SELINA SUHARIN)

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*Application of Neural Network in developing Virtual Analyzer of  
Reformat Research Octane Number*

by

*Zuraihan Selina Suharin*

**ABSTRACT**

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The interest of this Final Year Research Project covers the topic of *Application of Artificial Neural Networks for developing virtual analyzer for petroleum quality, Research Octane Number*. In general, the work deals with the potential application of neural network technology to Research Octane Number of Reformat estimation. This is done by presenting the system with a representative set of examples describing the problem, namely pairs of input and output samples; the ANN will then extrapolate the mapping between input and output data. The trained network was able to accurately and efficiently estimate the Research Octane Number at a given time. Statistical analysis was also conducted to verify if the key variables for estimating the Research Octane Number are suitable for network training. The selected key variables in predicting Research Octane Number are, feed flow rate, recycle flow rate, coil outlet temperature of furnace and equivalent temperature bed of reactors.

1068 sample data points are used for modeling the Research Octane Number which then are divided selectively into three sections; training, validation and testing data. For this case study, Backpropagation Network and Levenberg Algorithm are used. To evaluate the performance of the neural network model, the trained network was simulated using data that the network has not been trained before. The optimum configuration for the network is 2 hidden layers which 16 and 4 neurons respectively with R-squared is equal to 0.75. The design of the model is described in depth and further improvement is done for increasing the R-squared, and the MATLAB source codes are included in appendices.

## ACKNOWLEDGEMENT

First and foremost, I would like to express my gratitude to Allah for giving me the strength, ability and courage to complete this Final Year Research Project. My deepest gratitude to Mr Nooryusmiza, my personal supervisor for his technical guidance, continuous support, brilliant ideas and suggestions and personal concern during the duration of this final year project.

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Last but not least, special thanks to my mother, Pn Salmah Abdullah for the emotional support throughout this research.

# TABLE OF CONTENTS

<b>CERTIFICATION</b>		<b>i</b>
<b>ABSTRACT</b>		<b>iii</b>
<b>ACKNOWLEDGEMENTS</b>		<b>iv</b>
<b>ABBREVIATIONS AND NOMENCLATURE</b>		<b>vii</b>
<b>CHAPTER 1:</b>	<b>INTRODUCTION</b>	
	1.1 Background of study	1
	1.2 Problem statement	2
	1.3 Significant of the Project	2
	1.4 Study Objectives	2
	1.4.1 The relevancy of the project	2
	1.4.2 Feasibility of the Project	3
	1.5 Research Octane Number	3
<b>CHAPTER 2:</b>	<b>LITERATURE REVIEW AND THEORY</b>	
	2.1 Neural Network Reformate Research Octane Number	5
	2.2 Functionality	5
	2.2.1 Layers	6
	2.2.2 Neurons	6
	2.2.3 Connections	7
	2.2.4 Weight and Biases	7
	2.2.5 Recall	7
	2.2.6 Transfer Functions	8
	2.2.7 Learning	8
	2.2.8 Neural Network Types	9
	2.3 Neural Network Learning using Back Propagation	10
	2.4 Learning Rule and Levenberg-Marquardt Optimization	11
	2.5 Process Overview	12
	2.5.1 Feed Quality	15
	2.5.2 Reactor Temperature	16
	2.5.3 Recycle Gas Flow Rate	16
	2.5.4 Importants Inputs for Network	17
	2.6 Application on Process Engineering	18

<b>CHAPTER 3:</b>	<b>METHODOLOGY AND PROJECT WORK</b>	
3.1	Process Understanding	19
3.2	Finding the Most Useful Input	19
3.3	Selection of Training Data for Modeling	20
3.4	Training the Neural Network	21
	3.4.1 Selection of a Programming Language	21
	3.4.2 Matlab Basics	22
	3.4.3 Selection of Algorithm	23
	3.4.4 Computer Simulation on Modeling	23
	3.4.5 Design of the Appropriate Neural Network Topology	23
3.5	Case Study: Prediction of RON	25
<b>CHAPTER 4:</b>	<b>RESULTS AND DISCUSSION</b>	
4.1	Neural Network Model for Case Study	28
4.2	Comparison of Back-propagation and Neural Network Bayesian Regularisation	32
4.3	Comparison of Different Network Architecture	32
	4.3.1 Number of Neurons	33
	4.3.2 Transfer Function	34
	4.3.3 Training Algorithm	35
4.4	Comparison with Regression Methodology to Predict RON	35
4.5	Further Improvement Performance	37
4.6	Feasibility of Neural Network in Refinery	39
<b>CHAPTER 5:</b>	<b>CONCLUSION AND RECOMMENDATION</b>	40
<b>REFERENCES</b>		42
<b>APPENDICES</b>		43
	1. Detail Description of MATLAB Functions	
	2. Sample MATLAB Coding for Neural Network	
	3. Data set for case studies	

## **ABBREVIATION AND NOMENCLATURE**

- **COT** **Coil Outlet Temperature**
- **EIT** **Equivalent Isothermal Temperature**
- **F** **Furnace**
- **MON** **Motos Octane Number**
- **P** **Pressure**
- **RON** **Research Octane Number**
- **T** **Temperature**



# CHAPTER 1

## INTRODUCTION

### 1.1 BACKGROUND OF STUDY

Inferential measurement, modeling and control are very important in ensuring product to quality. This technique has long been part of process control and many simple but useful inferential variables have been identified first via plant data by process and technical personnel. Inferential variables are operating parameters which are identified to give high impact to the quality, and then it will be used in building a model to predict the required process quality.

Control engineers are now using more complex mathematical methods for developing inferential models such as linear and nonlinear model. In general, the process world is nonlinear but we can often get by linear approximation, because linear model building is generally easier. Meanwhile nonlinear models require more potent development tools and are generally difficult. Somehow, both methods are applicable but several characteristics must be looked at such as reliability and feasibility of the model to the process control.

The theme of this research is to seek possible ways of using Artificial Neural Network (ANN) analysis for building a model prediction for Research Octane Number of Reformate. ANN has seen an explosion of interest over the last few years, and is being successfully applied across an extraordinary range of problem especially in process control engineering. Moreover, ANN is also known for its ability to model nonlinear system and their inherent noise-filtering abilities. The true power of neural network lies in their abilities to represent both linear and nonlinear relationship and to learn these relationships directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contain non-linear characteristics.

## **1.2 PROBLEM STATEMENT**

The general objective of this project is to use ANN modeling for predicting Reformate Research Octane Number (RON) in the refinery. In detail, the concern is also to determine variables that are greatly impact to the RON, so they can be used in correlation between the input variables and output quality product. Thus, in order to condone the task, it is a fundamental to equip basic knowledge and familiarization of ANN tools software and its application to the refinery industry.

## **1.3 SIGNIFICANCE OF PROJECT**

By identifying the key variables affecting to RON, the model will then be used in process control and monitor the product specification with lab test conducted in refinery. Subsequently, it would also allow a better understanding of the identified input variables and its correlation to RON. Optimization methods would be formulated so that the model is able to be used at its fullest potential, leading to a better process control methods instead of relying only to the lab test.

## **1.4 STUDY OBJECTIVES**

The specific objectives for this research comprise the following;

1. To gain understanding on the theory and to familiarize of with MATLAB Neural Network Toolbox.
2. To determine the influencing factors (i.e. inputs) to the Reformate Octane Number.
3. To study the relationship exists between influencing factors (i.e. inputs) and observed behaviors (i.e. outputs).
4. To predict RON from reformer unit process variables to meet product specification (lab test) and reduce quality giveaway.

### **1.4.1 The Relevancy of the Project.**

The project is an opportunity for me to utilize the knowledge and obtained during the industrial internship regarding refinery operation. From the university's perspective, the project will be an extension to the previous study using non-linear regression method. It

will provide an alternative framework for development of prediction model for refinery Reformate RON.

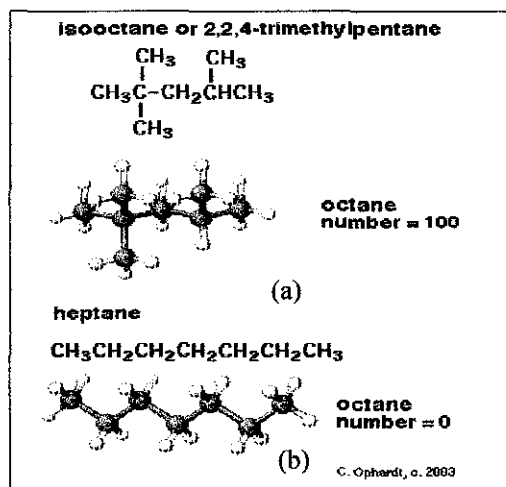
#### 1.4.2 Feasibility of the Project within the Scope and Time Frame.

The scope of the project is viable for completion in a one-semester research project. Approximately one-third of the duration was spent on studying the fundamentals, principles, applications and method of implementations of neural network modeling, another one-third on understanding the processes to be modeled, and the final one-third for actual computer modeling work.

#### 1.5 Research Octane Number.

Gasoline's octane rating is simply a measurement of the fuel's ability to resist engine knocking. It does not refer to a substance or the quantity of energy or power in the fuel. More correctly, an octane rating is often called as an "octane-knock index". Knocking can occur when using fuel with too low an octane rating for the engine, and severe knocking can cause engine damage. The higher the octane number of petrol, the greater is the resistance to knocking. Petrol grades are given two measures of octane rating, RON and MON (Motor Octane Number). RON is an indicator of petrol's antiknock performance at lower engine speed and typical acceleration condition. For example 92 regular premiums and 97 premiums have RON at 92 and 97 respectively.

The octane number is determined by comparing the characteristics of a gasoline to isooctane (2, 2, 4-trimethylpentane) and heptane. Isooctane is assigned an octane number of 100. It is a highly branched compound that burns smoothly, with little knock. On the other hand, heptane, a straight chain, unbranched molecule is given an octane rating of zero because of its bad knocking properties.



**Figure 1.1 (a) Isooctane (b) Heptane**  
(From C. Opherdt, c.2003)

The neural network approach to predict the Research Octane Number is a straightforward approach. The Research Octane Number Reformat data is extracted from the powerformer unit is presented to the network. The network, by proper design, self organizes and generalizes its own performance data. This process is referred to as “network learning”. When a sufficient amount of data are presented to the network, the network will become “trained network” capable of inferring the RON. The discussion of the neural network training techniques utilized will be presented in Chapter 3 and 4.

## CHAPTER 2

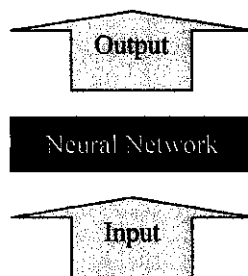
### LITERATURE REVIEW AND THEORY

#### 2.1 NEURAL NETWORK REFORMATE RESEARCH OCTANE NUMBER

Artificial Neural Network is computational models broadly inspired by the organization of the human brain. The most important features of neural network are its abilities to learn, to associate, and to be error tolerant. Unlike the conventional problem solving algorithm, ANN can be trained to perform particular task. This is done by presenting the system with a representative set of examples describing the problem, namely pairs of input and output samples; the ANN will then extrapolate the mapping between input and output data. After training, the neural network can be used to recognize incomplete or noisy data, an important feature that is often used for prediction, diagnosis or control purposed. Furthermore, neural network have the ability to self-organize, therefore enabling segmentation or coarse coding data.

#### 2.2 FUNCTIONALITY

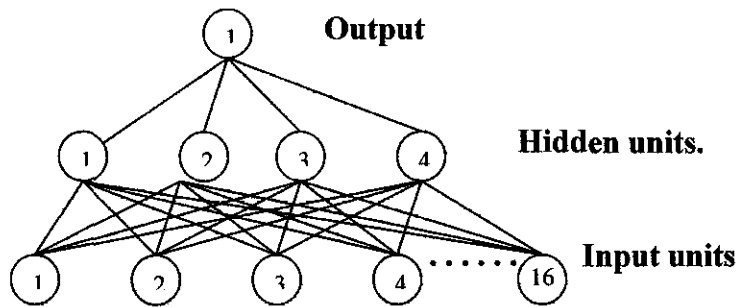
At the most abstract level, a neural network can be thought of as a black box, where data is fed in on one side, processed by the neural network which then produces an output according to the supplied input [Candill 1992]. Although a neural network can usually process any kind of data, e.g. qualitative or quantitative information, the data fed into the neural network should be preprocessed (e.g filtered, transformed) to enable faster training and better performance. In fact, the selection, preprocessing, and coding of information is one of the main issues to deal with when working with neural networks. Figure 2.1 shows the functionality of the neural network.



**Figure 2.1 Neural Network as a black box.**  
*(From Neural Network Aided Fuel Consumption modeling by Wing Hong Cheung)*

### 2.2.1 Layers

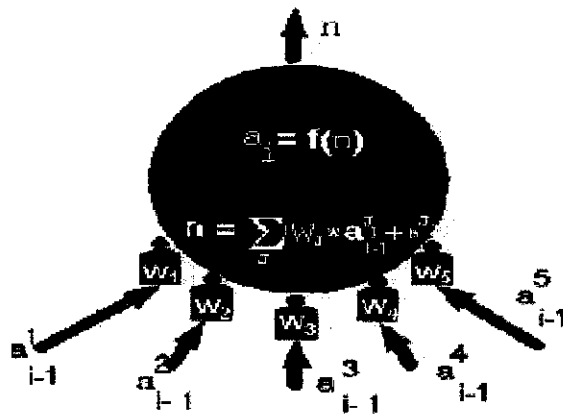
A closer look at the black box reveals that its interface to the outside world consists of an input layer and an output layer of neurons. The neurons are the processing units within the neural network and are usually arranged in layers [Allaxander 1989]. The information is propagated through the neural network layer by layer, always in the same direction. Besides the input and the output layer there can be other intermediate layers of neurons, which are usually called hidden layers. Figure 2.2 illustrates the simplified architecture of neural network.



**Figure 2.2 General Architecture of the Neural Network for this case study, 16-8-1.**  
*(From Neural Network Aided Fuel Consumption Modeling by Wing Hong Cheung)*

### 2.2.2 Neurons

A neuron collects information from all preceding neurons relative to the flow information and propagates its output to the neuron in the following layer. The output of each preceding neuron ( $a_{r-1}$ ) is modulated by correspondent weight ( $w_j$ ) and bias ( $b_j$ ) before affecting the activity of the neuron. This process is realized by the formula  $n_i = w_i a_{r-1} + b_j$ , where  $n_i$  represent the activity of the neuron. This activity is then modified by transfer function and become the final output  $a_i = f(n_i) = f(w_i a_{r-1} + b)$  of the neuron [Dayhoff 1990]. This signal is then propagated to the neuron of the next layer. Figure 2.3 depicts this process.



**Figure 2.3 A Single Neuron.**

*(From Neural Network Aided Fuel Consumption Modeling by Wing Hong Cheung)*

### 2.2.3 Connections

Connections are the paths between neurons where all the information flows within the neural network. Very often the neurons of two succeeding layers are fully interconnected, but there might still exist additional connections going to further or even missing connections between certain neurons.

### 2.2.4 Weight and biases.

One of the most important aspects of neural networks is the storage of information [Khanna 1996]. Each connection is equipped with an individual weight and bias that modifies the signal flow on the respective connection. The weight works as a factor by which the output of the preceding neuron is multiplied. The bias works as a fine adjustment by which the product of weight and output from the preceding layer is added. This mean that information is stored and distributed within a neural network and even minor destruction of some of the weights and biases will have a larger effect of learned information.

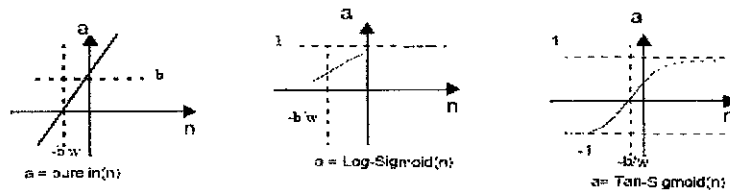
### 2.2.5 Recall

The phase when neural network applies the information acquired during the learning phase is called the recall phase. The recall always starts by applying an input patter to the input layer of the neural network [Khanna 1996]. Each of the input neurons holds a

specific component of the input pattern and normally does not process it, but simply sends it directly to all the connected neurons. However, before the output can reach the succeeding neurons, it is modified by the weight and bias on the connection. All the neurons of the second layer then receive modified (e.g. weighted and biased) input values and process them. Afterwards these neurons send their output to succeeding neurons of the next layer. This procedure is repeated until the neurons of the layer finally produce an output which is the neural network's answer to the presented input patterns.

### 2.2.6 Transfer Functions

Transfer functions are the processing units of neuron. These functions can be linear or non-linear. Three of the most common transfer functions are depicted in Figure 2.4.



**Figure 2.4 Typical Transfer Function**  
*(From Neural Network Aided Fuel Consumption Modeling by Wing Hong Cheung)*

### 2.2.7 Learning.

The phase when sample patterns of a certain problem are presented to neural network is called the training phase. During training, the weight and biases of the neural network are adjusted. Depending on the type of the neural network and on the problem it is going to solve, either a supervised or an unsupervised method can be used for adapting the weights [Beal 1992]. In both cases however, every training starts with a recall where the input is propagated through the neural network and its neurons change their activity accordingly. A supervised training is typically chosen when the mapping of input to output patterns is desirable. This requires that the output to a given input is known at the same time instants.

After the recall phase, the output of the neural network is compared to what the resulting output pattern should be. The observed difference is used to adapt the weights and biases.



The adaptation of the weights starts at the output neurons and continues downward toward the input layer. The weight and bias adaptation for one pattern often does not correct the neural network's faulty response completely, but improves it. Then the next input pattern is chosen and the whole process is repeated until the overall response of the neural network is satisfying. It is important to define the point where the training is terminated, because sometimes it is possible to over-train a neural network. Namely, at some point the neural network starts to memorize exactly the training examples to new patterns presented during recall. An unsupervised training is chosen when the neural network has to classify data on its own. In this fashion the neural network distinguish certain classes by using the interdependency it detects within the data. Some of these neural networks are even able to reorganize themselves, e.g. by recruiting new neurons to represent unknown patterns or new classes

### **2.2.8 Neural Network Types**

There are hundreds of different neural network types that can be classified in various ways, e.g. in the way they are trained (supervised or unsupervised, or reinforced), how the information flow in the network is organized (feedback or feedforward), how the topology is built (static or self organizing). Another way to classify neural network is by distinguishing between the training algorithms that are used to adjust the weights. In this case, the number of different training algorithms is even larger than the number of neural network types [Khanna 1995].

The typical steps for creating a neural network application are:

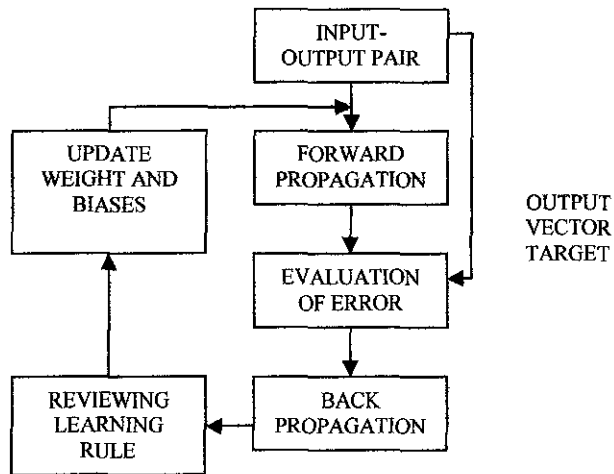
1. Analysis of the problem and collection of all available data.
2. Analysis of the collected data.
3. Choice of the neural network type that is capable of solving your problem.
4. Selection of the most important features that will be used.
5. Coding of information, using the result of the data analysis.
6. Separation of data basis into training, validation and testing set.
7. Design of the appropriate neural network topology, choice of neurons.

8. Functions and basis decision about the amount of neuron to be used each layers.
9. Training of the neural network and monitoring its performance on the validation and testing set.
10. Optimization of the neural network by changing the topology, the amount of neurons, and the neuron functions.

### **2.3 NEURAL LEARNING USING BACK-PROPAGATION.**

One of the most powerful uses of a neural network is a function approximation. Neural network are computing systems which can be trained to learn a complex relationship between input variables and target data sets. Neural nets employs Parallel Distributed Processing (PDP) composed of interconnecting simple processing nodes. Neural net techniques have successfully applied in various fields such as linear and/or non-linear function approximation, control systems and image processing. As discussed in previous section, the learning process is the most important part of the entire process. The objective of the learning process is to train the network so that the application of a set of inputs produces the desired or at least a consistent set of outputs. During training the network weights gradually converge to value such that each input vector produces the desired output vector.

A learning cycle starts with applying in an input vector to the network, which is propagated in a forward propagation mode which ends with an output vector. Next the network evaluates the errors between the desired output vector and the actual output vector. It uses these errors to shift the connection weights and biases according to a learning rule that tends to minimize the error. This process is generally referred to as “error back-propagation” or back-propagation for short. The adjusted weights and biases are then used to start a new cycle. A back-propagation cycle, also known as epoch, in neural network is illustrated in Figure 2.5. For a finite number of epochs the weight and biases are shifted until the deviations from outputs are minimizes.



**Figure 2.5 Back Propagation cycle.**  
*(From Neural Network Aided Fuel Consumption Modeling by Wing Hong Cheung)*

## 2.4 LEARNING RULE AND LEVENBERG MARQUARDT OPTIMIZATION ALGORITHM

As stated in the previous section, the neural network learning process is actually an iterative process which minimizes the error between the output and the targets by shifting weights and biases toward the optimum. This process can be achieved by applying the Levenberg-Marquardt algorithm. The Levenberg-Marquardt algorithm is based on two optimization techniques, the steepest descent algorithm is based on the first order Taylor series expansion, and the Newton's method is based on the second order Taylor series.

The advantages of using this type of algorithm is that, it is appear to be the fastest method for training moderate-sized feedforward neural network (up to several hundreds weights). It is also has a very efficient MATLAB implementation, since the solution of the matrix equation is built in function. So its attributes become more pronounced in a MATLAB setting.

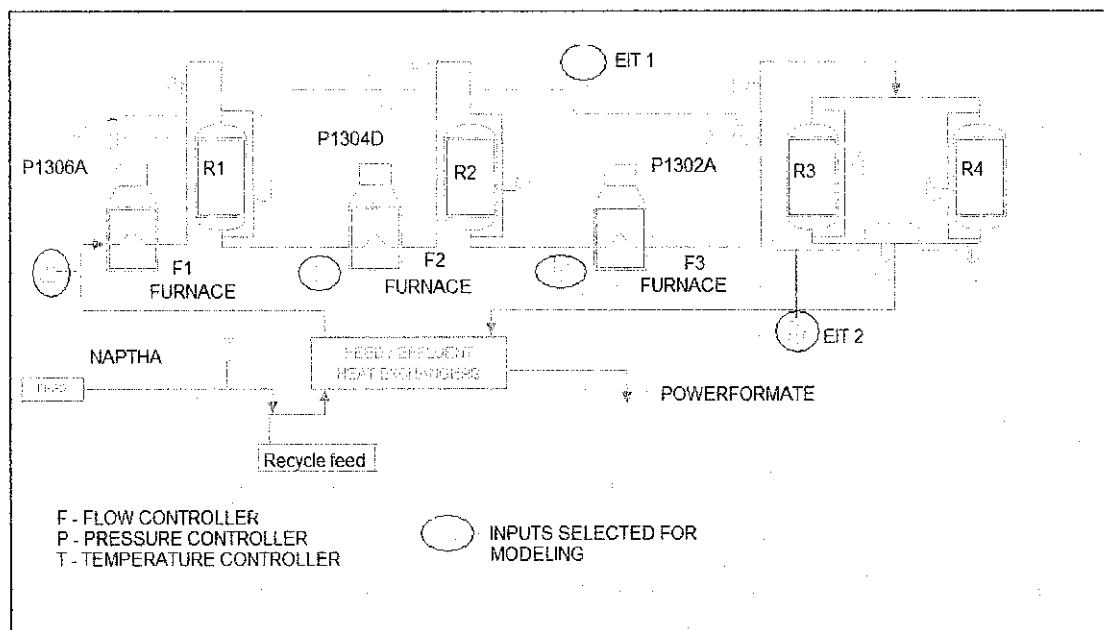
## 2.5 PROCESS OVERVIEW

For this case study, the reaction is subjected to the condition of the temperature that is employed in the powerformate unit, which will later provide the required product octane. Unfortunately, the desulfurized light and heavy naphtha fractions of crude oils have very low octane numbers, 40 to 60 Research Octane Number (RON). Catalytic Reforming uses heat, moderate pressure and fixed bed catalysts to turn naphtha, short carbon chain molecule fraction, into high-octane gasoline components - mainly aromatics to increase the percentage of low –octane components.

The hydrocarbons compounds that constitute heavy naphtha are classified into four different categories: paraffins, olefins (a very low percentage of olefins occur in the heavy naphtha from crude), naphthenes and aromatics. In lieu of a complete course in organic chemistry, simplistically the paraffins and olefins are compounds with straight or branched carbon chains, whereas the naphthenes and aromatics are carbon rings. The paraffins and naphthenes are saturated hydrocarbons. Saturated means that they have a maximum number of hydrogen atoms attached to the carbon atoms. The olefins and aromatics, however, are unsaturated hydrocarbons because the compounds contain carbon atoms that are double bonded to other carbon atoms. The straight saturated compounds exhibit very low octane numbers, the branched, saturated compounds exhibit progressively higher octane numbers.

Catalytic Reforming uses a precious metal catalyst (platinum supported by an alumina base) in conjunction with very high temperature to reform the paraffins and naphthenes into high octane components. Sulfur is poisonous to the catalytic reforming catalyst, which requires the virtually all the sulfur to be removed from the heavy naphtha through Hydrotreating prior to Catalytic Reforming reactors- olefins are converted to paraffins, paraffins are isomerizes to branched chains and to a lesser extent to naphthenes, and naphthenes are converted to aromatics. Aromatics compounds are essentially unchanged. The resulting Reformate product stream from catalytic reforming has a RON from 96 to 102 depending on the reactor severity and feedstock quality. The dehydrogenation reactions which convert the saturated naphthenes into unsaturated aromatics produce

hydrogen. This hydrogen available for distribution to other refinery processes which consume hydrogen.

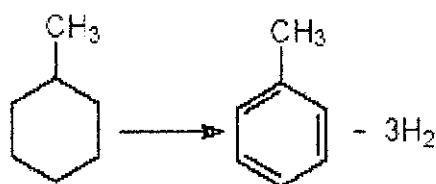


**Figure 2.6 Catalytic Reforming unit**

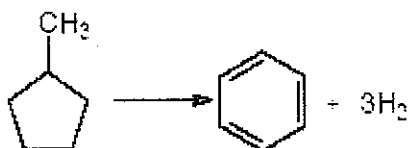
Catalytic reforming involves the naphtha fraction in vapor state over catalysts at 450-500°C and 10-55 atm, in the presence of hydrogen. The most common form of reactor is the 'Platforming' type introduced by Universal Oil Products (UOP). In this process the catalyst is held in two fixed-bed adiabatic reactors (R1 and R2) which are coupled in series and the other two (R3 and R4) in parallel; reaction is carried out at 25-40 atm with hydrogen to hydrocarbon feedstock ratio of 5-10:1. The feedstock is heated in the furnace (F1, F2 and F3) to 450-550°C before being fed to the reactors. The process is endothermic and as the temperature of the gas stream falls it may require reheating on exchangers. The catalysts involved are dual function where they have acidic and hydrogenation-dehydrogenation properties. They are normally platinum catalyses hydrogenation-dehydrogenation reactions and the alumina acid catalyzed rearrangement. Rheum is sometimes used as promoter. Figure 2.6 illustrates the process overview in the catalytic reforming unit.

Several chemical processes occur in reforming and are illustrated in Figure 2.7 (i to iv).

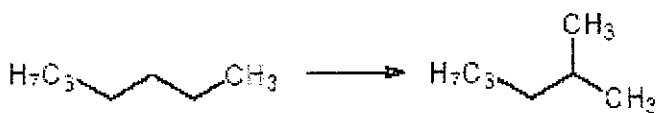
i. Dehydrogenation of cyclohexanes to aromatics



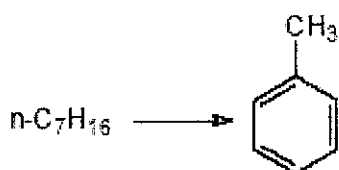
ii. Dehydroisomerism of cyclopentanes



iii. Isomerism of alkanes



iv. Dehydrocyclisation of alkanes



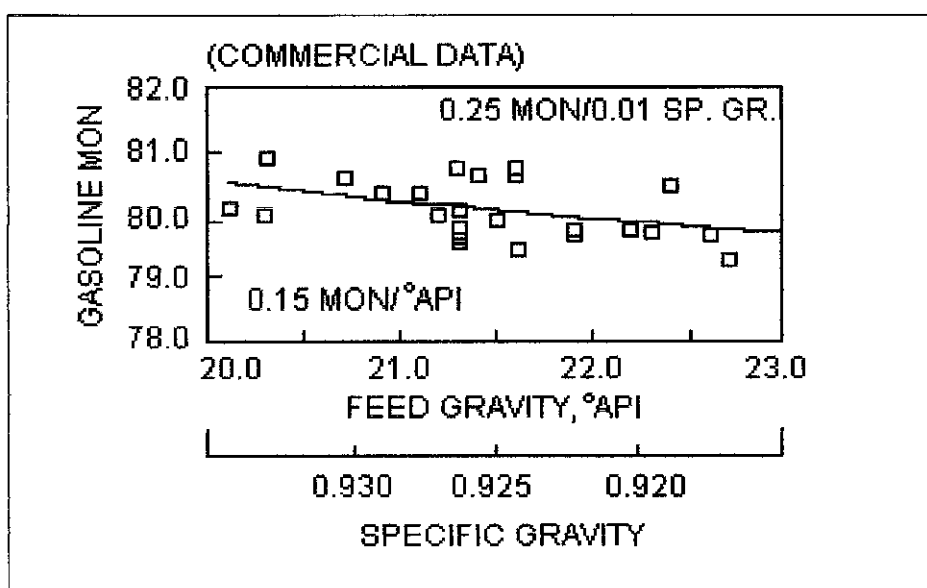
**Figure 2.7 Chemical Processes in Catalytic Reformer unit.**  
(From Atkins/Carey, *Organic Chemistry*)

During the recent past, refiners have been forced to increase the octane number of the gasoline to meet the impacts of lead phasedown regulations, volatility reductions regulations and growth in consumption of unleaded premium and mid-grade gasoline grades. There are numerous options available to refiners for enhancing octane from the catalytic reformer unit. These involve operational and catalyst changes. On the operational side, changes in reactor temperature, conversion level, gasoline end point, recycle rate and feed quality have impacts on Research Octane Number and Motor Octane Number. Research octane uses an industry-standard, single-cylinder test engine run at 600 rpm with an inlet-air temperature of 100°F. Motor octane numbers (MON) are

generated with this same test engine operating at 900 rpm with inlet air at 300°F. Typically, Research octane numbers are typically 8 to 10 numbers higher than Motor octane numbers, since higher inlet air temperatures will increase an engine's tendency to detonate. Operational changes can result gains of up to 3 RON and 1 MON. Catalyst selection can also enhance octane up to 3 RON and 1 MON depending on the base catalyst and octane level. There are several operating variables that affect most the value of RON and MON such as feed quality, reactor temperature and conversion, their effects are as follows:

### 2.5.1 Feed quality

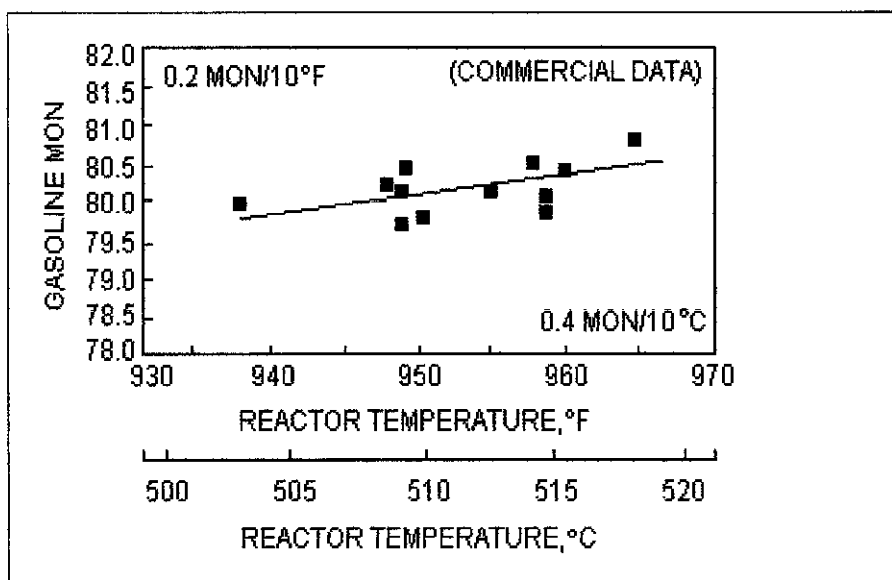
The hydrocarbon in the feed will influence octane in such when Napthenes feeds will dehydrogenate to olefins and aromatics in the gasoline boiling range and RON will increase. Moreover, when Paraffinic components are increase in feed, the paraffins in the gasoline will increase but RON and MON is reduced. It would be a highly desirable if the operator had total control of the type of the feeds processed in the catalytic reforming unit. In practice, that is not the case and in most refineries operators have limited capability in controlling gas oil quality.



**Figure 2.8 Effect of Feed Gravity on MON**  
*(From [www.refiningonline.com](http://www.refiningonline.com))*

### 2.5.2 Reactor temperature:

Reactor temperature is the easiest parameter for the operator to control and, compared with other variables, has the greatest impact on the RON and but less impact for MON. RON changes as a function of the reactor temperature were obtained from commercial units and illustrated in Figure 2.9. Based on the pilot plant and commercial data it shows that this type of parameter has a significant effect on Reformate octane sensitivity.



**Figure 2.9 Effect of Reactor Temperature on Octane**  
(From [www.refiningonline.com](http://www.refiningonline.com))

By understanding the process, the next major task is to determine the appropriate inputs without complicating the network model. According to refinery engineers, the most common parameters that they use to control RON is only by controlling the temperature of the reactor and also the temperature of coil outlet temperature of every furnaces before letting the heavy naphtha going inside the reactor.

### 2.5.3 Recycle Gas Flow Rate

The recycle gas improves the gasoline octane by approximately 0.3 MON for 10-20% increase in the combined feed ratio. This method is not practiced often since it reduces fresh feed capacity of the unit. The  $\Delta\text{MON}/\Delta\text{RON}$  ratio for this variable is approximately 0.6.



#### 2.5.4 Important inputs for network.

The important properties of determining the RON in this case study is complies with the theory above, and discussed below:

- **Equivalent Isothermal Temperature (EIT) 1 and 2.**

EIT is stands for Equivalent Isothermal Temperature. This tag is a single temperature presenting all the bed temperature in the group reactors. This is something of an average temperature where rate of reaction is being accounted for in the calculation. EIT 1 is controlling the bed temperature in reactor 1 and 2. Meanwhile EIT 2 is for reactor 3 and 4. Controlling EIT gives better control of the RON as compared to controlling Coil Outlet Temperature (COT) in the furnace. At the same COT, the bed temperature profile could vary when the feed quality changes. The changes in bed temperature profile indicate changes in rate of reaction, which affect the RON quality. But at the same EIT, COT is adjusted to makeup for the bed temperature variation and maintains a steadier rate of reaction. This then, takes care indirectly the feed quality changes effect on RON.

- **Coil Outlet Temperature (COT) for F1, F2, F3**

COT is stands for Coil Outlet Temperature in the furnace. This parameters is indicating the how much the heat duty that transferred to the reactor for catalytic reforming reaction. Temperature measurement at the outlet of each pass is used as a guide for adjusting the flow rates of each pass as well as for calculating the process heat duty. It is also recommended to measure the temperature of process fluid at the outlet of each pass in the radiant and convection sections which help in calculating the process heat duty split between the radiant and convection sections

- **Recycle gas**

The catalyst inventory is therefore divided among a number of fixed beds. Reaction temperatures are controlled by introducing part of the recycle gas as a quench medium between beds.

- **Feed rate.**

Since the feed quality data is not available due to limited of data, feed flow rate is used. The control objective in the catalytic reforming unit is to regulate the reactor temperature at a desirable set point value in the presence of disturbances such as changes in feeding flow rates which this can change the reactor temperature.

## **2.6 APPLICATION IN PROCESS ENGINEERING**

In process engineering, neural network has been applied in various problems, such as process identification, inferential property prediction and model-based control strategy development. Various papers and studies have been published regarding the use of neural network modeling in refinery optimization. Barsamian and Macias (199) in their work on inferential property predictors studied the use of Neural Network to produce non-linear property correlation such as for boiling point, flash point, freeze point, Reid Vapour Pressure, asphalt penetration, yield and octane number prediction.

## **CHAPTER 3**

### **METHODOLOGY AND PROJECT WORK**

This chapter outlines the procedures used to develop the model for estimating Research Octane Number using given data in the refinery. The general approach as well as means and methods that were used to achieve the goals of this thesis are outlined through the following steps:

#### **3.1 PROCESS UNDERSTANDING**

The first step in designing a neural network is to study and understand the process to be modeled. This is start by determining the input/output problem. The type of input/output mapping will have an impact on the type of network as well as network architecture that is suitable for modeling the process. For refinery optimization problems, the input/output mapping generally falls under the function approximation classification, where the objective is to predict the value of certain parameters, given the values of the other parameters that are known to have impact on the output. Sufficient understanding on the nature of the process, as well as the characteristics of the inputs and outputs are necessary prerequisites before proceeding to the next step.

#### **3.2 FINDING THE MOST USEFUL INPUT.**

Not all data points collected from the plant information system are equally useful in model building. Engineering judgments are needed to exercise some judgment in selecting data, which will produce the model that predicts the real world process with the greatest accuracy.

Only significant variables are used in modeling Reformate RON. A model is most reliable when built using the smallest number of useful variables. The measured output property is usually related not to single process variable, but too many. However, including many input variables that are unrelated to the output will reduce the accuracy of the model. As a model builder, only those inputs that contribute to the model's ability to predict the output, while making sure that to not overlooked any critical variables. Once

the useful keys are at a preliminary set of potential input variables, stepwise-regression model is done and reject the least useful predictors.

### **3.3 SELECTION OF TRAINING DATA FOR MODELING.**

Models of plant processes are usually built using data from a set of plant data. To develop a good model, it is ensured to have enough good data points for building the model (training), validation and testing data. For neural network, it requires more data points, depending on the number of hidden nodes in the model. But, keep in mind that not all the collected data points will be valid ones. One of the first things that must be done is to eliminate or filter any bad data point (outliers) from the building process.

Secondly, for the model to be reliable, it must be validated and tested using data different from that used to build it. General practice dictates that to reserve one-third of the collected data for validating the model

An assumption must be made in order to ensure that the data points are valid for building the model. There are:

- For this case study, a set of data points are used in order to predict the RON value in the lab. Usually, the lab test will be conducted approximately at 6:00 am in the morning. To predict the RON lab test, the data points must be extracted at the same time as the lab test is conducted. Sometimes, due to residence time error, there would be a slightly changes in the time schedule of conducting the test. To avoid this problem, the lab test that conducted within the plus and minus half hour from the exact time of conducting the lab test is accepted.

### **3.4 TRAINING THE NEURAL NETWORK.**

#### **3.4.1 Selection of a Programming Language**

The implementation of neural networks can be expedited with the use of commercially available software. Examples of these are Neural Forecaster, WinCrain and Neuralyst. Another approach is to code networks in high level computer programming languages such as C or PASCAL. Programming in MATLAB could be considered an intermediate approach for experimenting with neural networks. This approach lies closer to the programming approach than it does to the prewritten, commercial-software approach.

Programs that were developed in MATLAB to perform neural net computation will enable us to perform the following task:

1. Network training/learning.
2. Testing and evaluation of trained network.
3. Implementation to calculate RON.

For any given problem, the data will be split into learning (training) set, validation set and testing set. Each network configuration is also trained under two conditions; early stopping and without early stopping. Early stopping is another method used to improve generalization. In this method the data divided into training, validation and testing sets. The training data is used for computing the gradient and updating the weights and biases. The error of the validation data is monitored during training process. When then network starts to overfit the data, the error of the validation data set will increase. Training stopped when the validation data error increases for a specific number of iterations, and the weight and biases at the minimum of the validation error are returned. The program will require the user to give the following:

1. The number of inputs.
2. A value for the learning coefficient.
3. The number of processing elements (neurons) in the hidden layer and output layers.
4. The maximum number of cycles (epochs) for each run.

### 3.4.3 Selection of Algorithms.

Based on one of the studies using a demonstration package provided by MATLAB, Levenberg-Marquardt algorithm are found to be the most efficient and reliable means to be used for this study [Mathworks 2003]. Table 3.2 shows a comparison of the three most popular supervised algorithms. These numbers are based on MATLAB Version 6.5 being run on my computer.

**Table 3.2 Comparison of different types of algorithm**

<b>Function</b>	<b>Technique</b>	<b>Time</b>
TRAINBP	Back-propagation	185s
TRAINBPX	Fast Back-propagation	30
TRAINLM	Levenberg-Marquardt	10s

### 3.4.4 Computer simulation on modeling

The next stage is computer simulation of the various network configurations to determine which configuration results in the best model for the process. The sample coding for creating, training and simulating the network is included in Appendix 2. The trained network is simulated using the validation and testing data to see how well it can predict the RON from inputs it has not seen before. The different architecture will be compared and evaluated based on the following criteria:

- R-squared value.
- Size of the network, i.e number of neurons in hidden layers.
- Comparing data of 30 days moving average.

### 3.4.5 Design of the Appropriate Neural Network Topology

The design of the appropriate neural network topology involves the following steps [Dayhoff 1990]:

1. Choosing the appropriate neurons' function (transfer function).
2. Basic decision about the amount of neurons to be used in each layer.

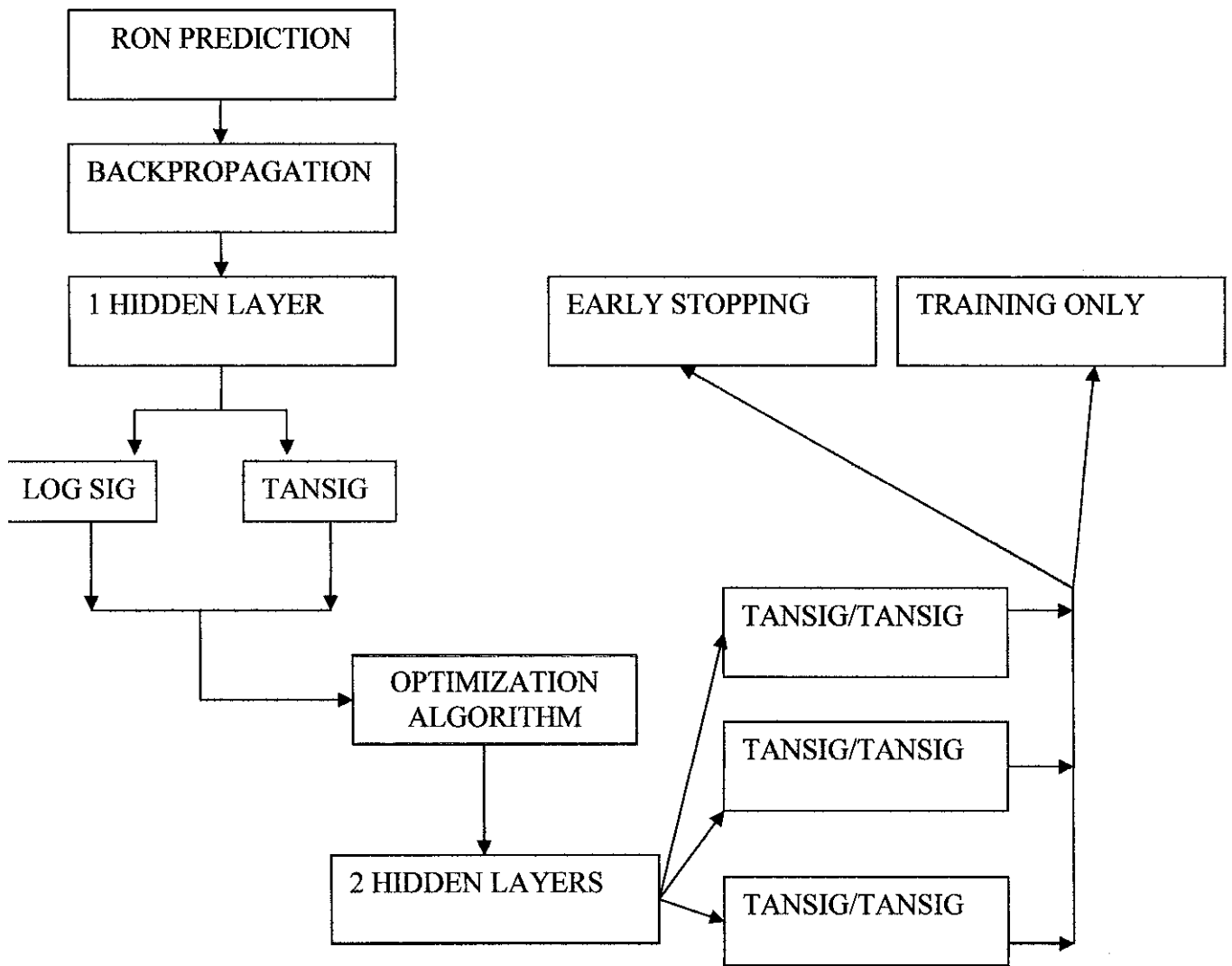
### 3. Selecting the amount of hidden layers.

Function approximation is one of the most powerful uses in neural networks. Typically, two or three layer network is sufficient to approximate any function with a finite number of discontinuities. In order to gain an insight as to how topology affects the output, tangent sigmoid, logarithmic-sigmoid and pure linear neuron (transfer function) were selected for further investigation. Moreover, the amount of neurons each layer depends on the complexity of the target function. If there are not enough neurons in each layer, the output will not be able to fit all the data points (under-fitting). On the other hand, if there are too many neurons in each layer, oscillations may occur between the data points (over-fitting).

Therefore, topology study must be conducted in order to find the most appropriate architecture for this project. Note that there are an infinite amount of combinations between the number of neurons and layers. For this reason, some typical architecture is considered as candidates for this project. Training inputs for this part of the plant data are 344 data points selected from the 1032 data points selected from the catalytic reforming unit and then tested, validated and generalized with another 688 data points selected from the same source. The selection of data points in each type of data is done in every three data points. Meaning that, data for the first day is allocated for training data, data second day is for validation data and third day is for the testing and same configuration to the next three sample points.

Results are evaluated based on the number of R and R-squared. Meanwhile the output, which means the target (RON) of the neural network are taken from the lab test.

From the framework development of neural network, a set of possible network configuration to model the case studies is obtained and summarized in Figure 3.3.



**Figure 3.3 Framework Developments.**

### 3.5 CASE STUDY: PREDICTION OF RON

The objective of the model is to predict Research Octane Number obtained from catalytic reforming unit using temperature properties such as EIT, COT and also recycle gas and feed flow rate as inputs to the model. For this case study, the data used is the same data that was used in the non-linear regression study, which was obtained from Refinery XYZ. There is 1068 data sample of data point and the division is done selectively. For modeling the RON, the input vectors are listed as below:



1. EIT 1 (Bed temperature calculation for Reactor 1 and 2)
2. EIT 2 (Bed temperature calculation for Reactor 3 and 4)
3. COT 1 (Coil Outlet Temperature for Furnace 1)
4. COT 2 (Coil Outlet Temperature for Furnace 2)
5. COT 3 (Coil Outlet Temperature for Furnace 3)
6. Recycle Gas Flow rate.
7. Feed Flow rate.

From the bivariate analysis, it was found that the EIT1 and EIT2 have the highest correlation value of R. The result of the bivariate analysis is summarized in Table 3.4.

**Table 3.4 Bivariate analysis**

<b>Input vector</b>	<b>Correlation coefficient</b>
EIT1	0.4
EIT2	0.4
COT1	0.35
COT2	0.3
COT3	0.2
REC/GAS FLOW RATE	0.2
FEED FLOW RATE	0.2

Incorporating the concept of prior knowledge regarding to the process, the inputs elements to be included in the network chosen based on consideration of the catalytic reforming process and engineering judgments, i.e. what are the properties that are expected to affect the RON of Reformate strongly? According to the engineer of Refinery XYZ, the RON in the refinery is commonly control by using the temperature parameters in the catalytic reforming unit. Theoretically, recycle gas flow rate and also the feed flow rate do affect the RON. The complete data sets for training, validation and testing are included in Appendix 3.

## CHAPTER 4

### RESULT AND DISCUSSION

The network performance was determined by comparing the R-squared between the actual and outputs and outputs predicted by the network for the training, testing and validation data .The r-squared value can be interpreted as the proportion of the variance in y attributable to the variance in x. It is the most popular measure of fit in statistical modeling. There is a natural appeal for a measure that can be computed for a fitted model, takes values between 0 and 1, and becomes larger as the model “fits better”. The equation for the Pearson product moment correlation coefficient, r, is:

$$r = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \sum(y - \bar{y})^2}}$$

R-squared,

$$r^2 = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \sum(y - \bar{y})^2}}$$

x and y = data points,  $\bar{x}$  and  $\bar{y}$  = mean of data x and y respectively.

There are three data set, 2001 data, 2002 data and 2003 data set. To facilitate the comparison between the data, R-squared is computed. For each data set, the network configuration that gives the highest R-squared is selected as the best model for the problem. For the best models selected as the best network configuration for each data set, the results also represented in the form of predicted versus actual outputs. If the model is able to predict the outputs perfectly, the plot will have about R-squared 0.8 and upward. Otherwise, the points will deviate far from the actual output. Error analysis was also

conducted to find the absolute error as well as maximum deviation between the actual and predicted in order to design the automatic bias updating for the model predicting the outputs.

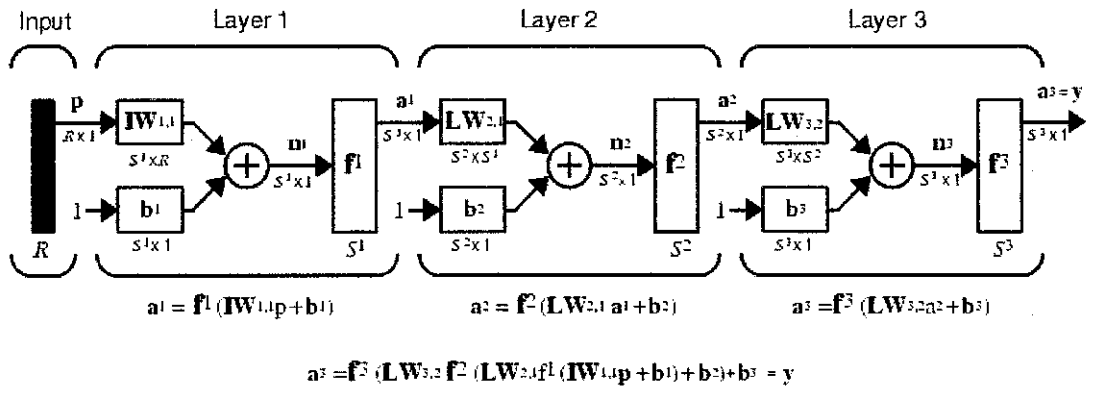
Thirty days moving average of the predicted and actual RON is also computed in MATLAB. This approach is to show the average value of a predicted and actual RON over a period of time. When calculating a moving average, a mathematical analysis of the RON average value over a predetermined time period is made. Moving averages are one of the most popular and easy to use tools available to the technical analyst. They smooth a data series and make it easier to spot trends, something that is especially helpful in analyzing the case study. The equation for 30 days moving average is:

$$a(t_j) = \frac{1}{2k} \sum_{i=j-k+1}^{j+k} s(t_i)$$

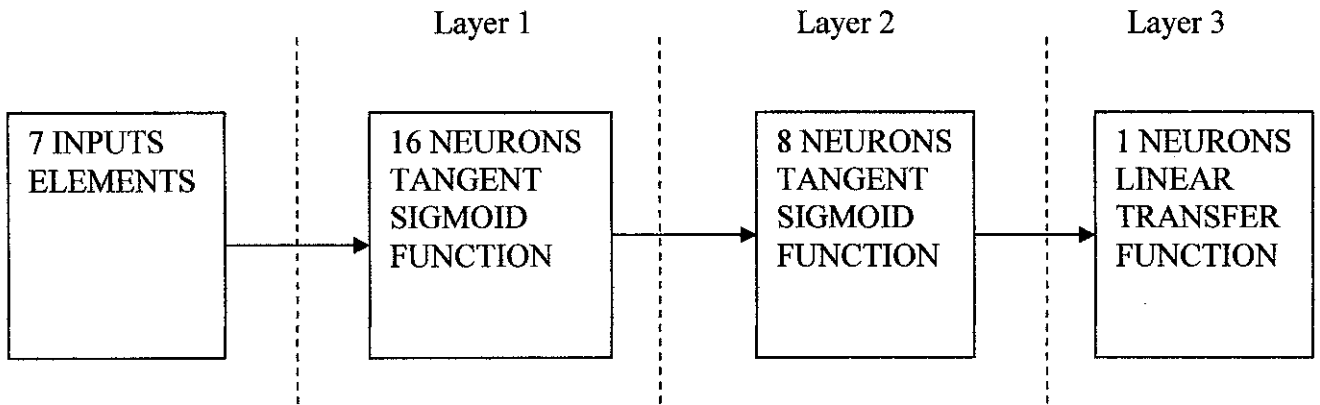
k= 15, j=15..... 329, a = 30 days average, s<sub>ii</sub> = data point

#### 4.1 NEURAL NETWORK MODEL FOR CASE STUDY

The modeling process for case study was done using a single network with 7 inputs and 1 output. Various network architecture, as depict in Figure 3.3, were tested and simulated in MATLAB then to select the network which gives the highest value of R-squared. For this case, the architecture of network that gives the highest R-squared is from data 2003 which then is selected as training data. The configuration of the network built from 2003 data is a feedforward network with two hidden layers, 16-4-1 neurons architecture, tangent-sigmoid transfer function on both hidden layers, Levenberg-Marquardt learning algorithm, with early stopping. The network architecture is shown on figure 3.5.



**Figure 4.1 Neural Network Architecture for case study.**



**Figure 4.2 Simplified Neural Network Architecture for case study.**

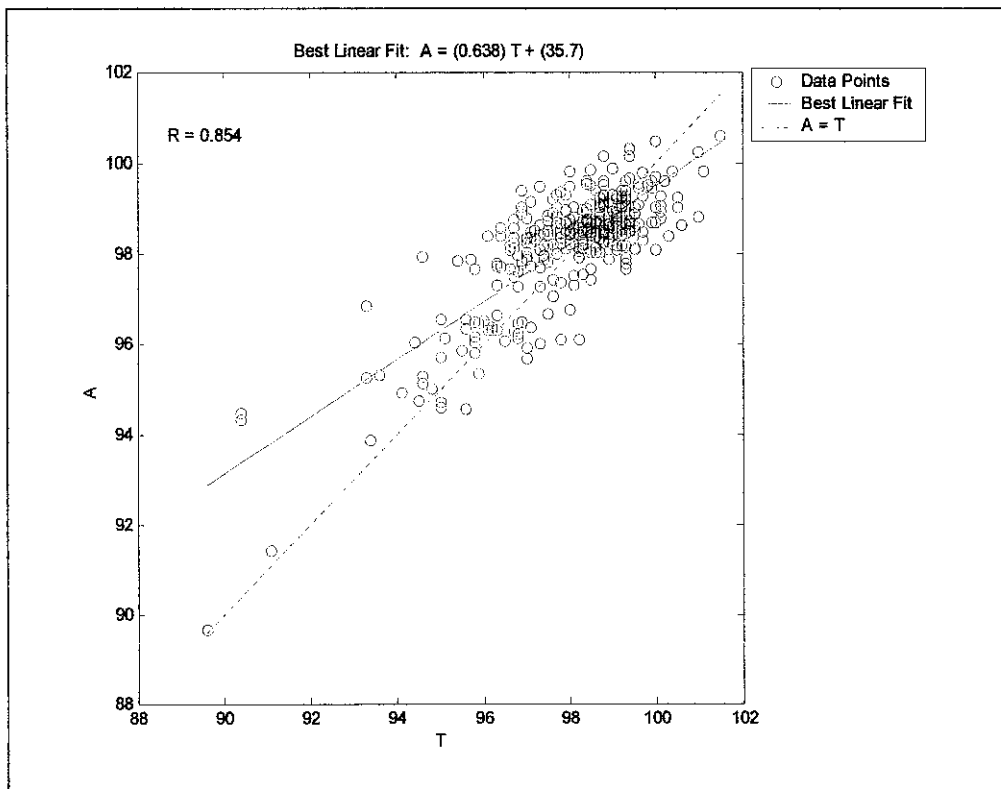
It is found that when network is simulated using training data, the R-squared is larger when the network trained using early stopping compared to without early stopping. The advantage of using early stopping is the network will have a better generalization for predictive capability when faced with data it has not seen before. To illustrate this, below is the comparison between early stopping and without early stopping for the optimum network.

**Table 4.3 Comparison of R-squared**

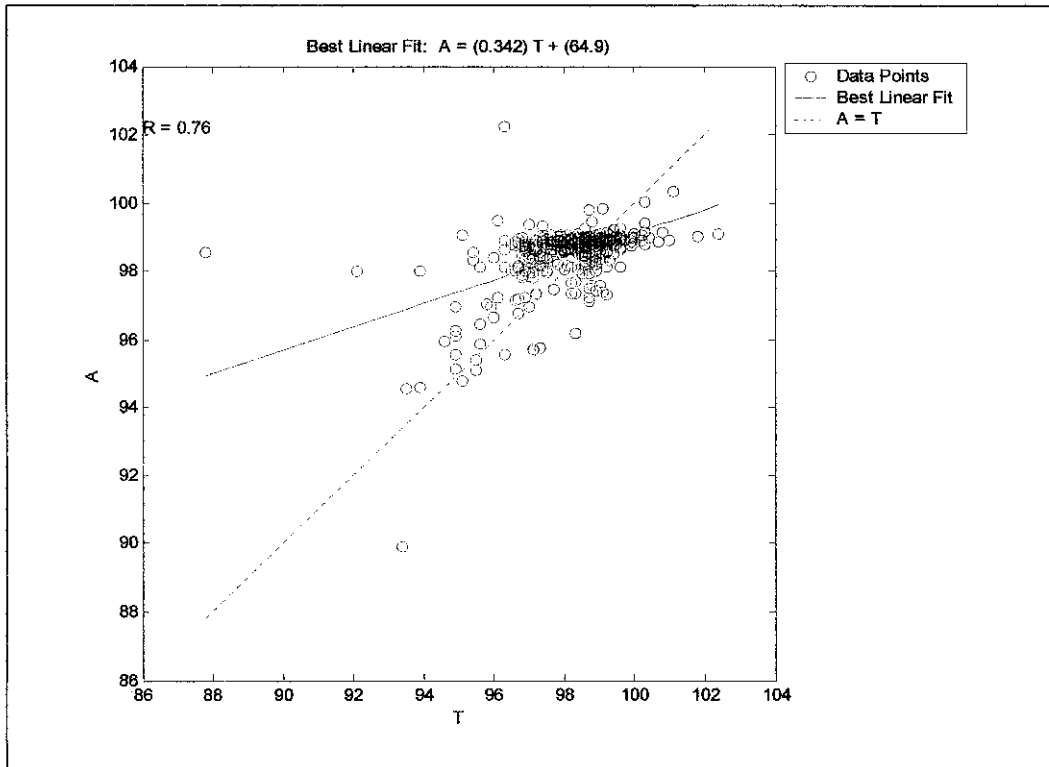
Network	R-squared
Early stopping	0.734
Without early stopping	0.18

Based on the R-squared comparison in Table 3.7, it is seen that using early stopping for building the model will significantly improve the prediction.

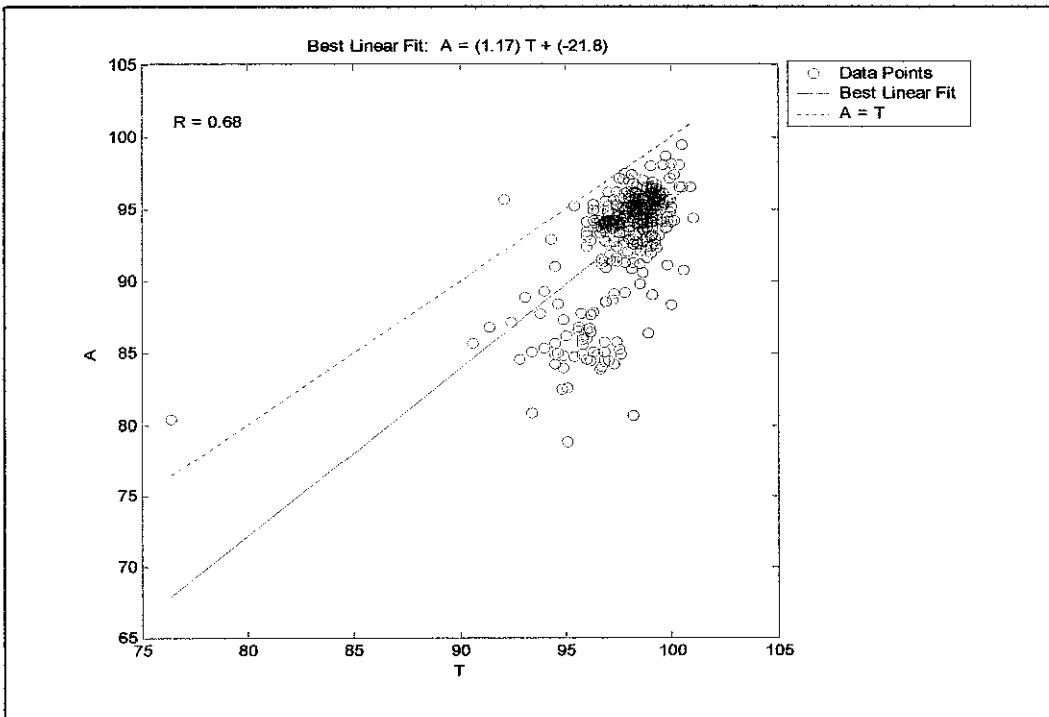
The plots of actual RON and predicted RON are shown in Figure 3.8, 3.9 and 3.10. The straight line; red color represents the ideal situations where the predicted output is equal to the actual output. From the graphs; blue color line, it is seen that the prediction is not so good though it is actually the best model achieved for this case study. The unsatisfactory prediction for RON is due to the fact that the time delay and fluctuating of the temperature parameters in the catalytic reforming. R-squared for training data is 0.834, followed by validation data is 0.76 and testing data is 0.68.



**Figure 4.4 Data for 2003 (Training Data)**



**Figure 4.5: Data for 2002 (Validation Data)**



**Figure 4.6 Data for 2001 (Testing Data)**

## 4.2 COMPARISON OF BACKPROPAGATION AND NEURAL NETWORK TO BAYESIAN REGULARISATION

For the case study, a multiple layered feedforward network with early stopping gives a better prediction than Bayesian regularization for the same network architecture ( same number of hidden layers, number of neuron and transfer function). Table 4.7 show the comparison between the results obtained using Backpropagation network with early stopping and Bayesian regularization, for the same network configuration as selected before:

**Table 4.7 Comparison of Backpropagation to Bayesian Regularization**

Case study	R-Squared	
	Early stopping with Levenberg-Marquardt	Bayesian Regularization
RON	0.77	0.39

Early stopping with Levenberg-Marquardt and Bayesian regularization are both optimization techniques for improving the generalization capability of the network. One of the common problems that must be avoided is when the network is over fitting the training data. One advantage of Bayesian regularization is that it provides a measure of how many network parameters (weight and biases) are being effectively used by the network. For this case, the R-squared values are not very significant, so Bayesian regularization should also be considered as good option for the model.

## 4.3 COMPARISON OF DIFFERENT NETWORK ARCHITECTURE

For the case study, networks with 2 hidden layers perform better than networks with 1 hidden layer in terms of R-squared performance. The disadvantage of having the two hidden layer, however lies in terms of the time required for the solution to converge due to increase number in biases and weights. However, this difference in convergence time

is almost negligible, especially if the network is simulated in a computer with high memory capacity.

#### 4.3.1 Number of neurons.

The optimal number of neurons is selected on trial and error basis using topology table. The goal is to find the optimum value of R-squared with minimum number of neurons when the network is simulated using the test and validation data. For this case study, the network configuration tested starts from 4 neuron, and increased consecutively by 4 neurons each time. When it comes to 2 hidden layers, the second hidden layer is remaining constant but the first hidden layer will start from 4 neuron and increase consecutively by 4. As the number neuron is increased from 4 to 8, R-squared for training, testing and validation is increased. However, when the neurons increase after a certain point, the R-squared value for the training, testing and validation data continue to decrease. This indicate that when the size of the network become too large, the network is no longer generalizing the function but not likely to fitting the data.

The number of neurons selected for the network architecture is where the R-squared is optimum. This illustrated by Table 4.8 which shows the R-squared for different number of neurons and hidden layers. For this case, the result shows that when the first hidden layer is having 16 neurons, the R-squared value is quite high. A further analysis has been done with maintaining 16 neurons for the first hidden layer but for the second hidden layer the configuration will start from 1 neuron and increase consecutively by 1 neuron each times in order to find the optimize value for R- squared. This illustrated by Table 4.9.

**Table 4.8 The effect of Number Neurons on Network Performance for training data (2003) in topology table analysis.**

<b>Architecture</b>	<b>R-squared for training data</b>
8,1	0.2978
16,1	0.3882
24,1	0.4379
8,8,1	0.502
16,8,1	0.6728



24,8,1	0.0359
8,16,1	0.2296
16,16,1	0.7012
24,16,1	0.0705
8,24,1	0.3295
16,24,1	0.7175
24,24,1	0.304

**Table 4.9 The effect of Number Neurons Performance for training, validation and testing data.**

Architecture	R-squared Training	Validation	Testing
16,2,1	0.5352	0.3131	0.5129
16,4,1	0.734	0.44	0.55
16,6,1	0.2015	0.2335	0.3022
16,10,1	0.7	0.1484	0.3072
16,12,1	0.3512	0.3811	0.1154
16,14,1	0.6271	0.2704	0.2450
16,18,1	0.481	0.4	0.035
16,20,1	0.5688	0.2186	0.2542
16,22,1	0.574	0.034	0.212

The optimal value for R-squared is obtained by maintaining the first hidden layer to have 16 neurons and varied the number of neurons in the second hidden layers. From the result, it is shown that, the best network architecture for the model is 16, 4, and 1.

#### **4.3.2 Transfer function**

Theoretically, for network that uses Backpropagation algorithm for updating the weights and biases, the type of transfer function used for the layers must be a sigmoid function. As mentioned in Chapter 3, the tangent sigmoid transfer function squashes the inputs to nonlinear range -1 to 1, while log sigmoid to range from 0 to 1. From the modeling studies it is observed that choice of transfer function between the log sigmoid and tangent does not affect the network performance too much.

### **4.3.3 Training algorithm**

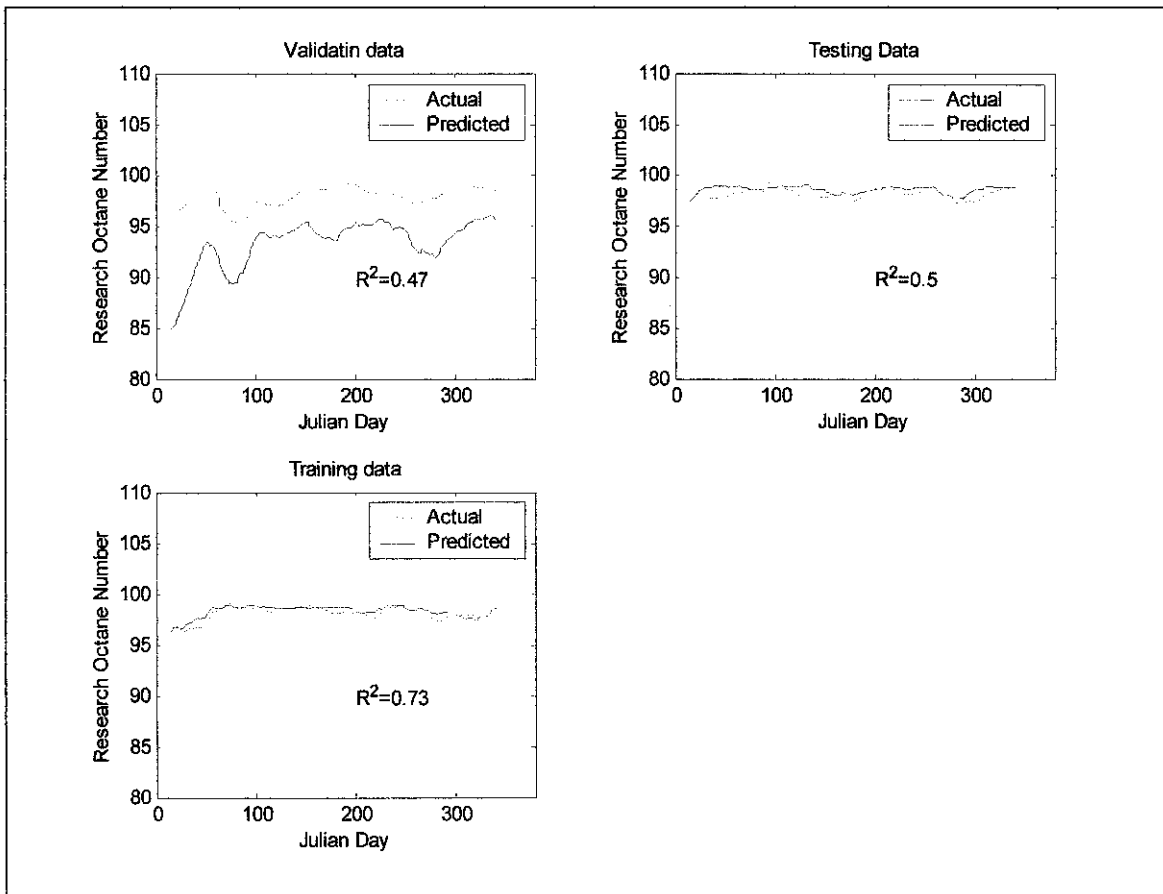
For this case study, the choice of which algorithm to be used does affect the network performance very much in terms of R-squared value. However, the effect is more on the time required the network to converge. It is observed that for most network tested, the Levenberg-Marquardt learning algorithm gives the fastest convergence, which has been mentioned in Chapter 3.

## **4.4 COMPARISON WITH REGRESSION METHODOLOGY TO PREDICT RON**

As mentioned before, a plot of 30 days moving average is done in order to see the trend of the actual output of RON and the predicted output from neural network. It is to see how fit the model is to the actual RON on daily basis. The are three subdivision and each data consist of 356 data points, which is training data, validation data and testing data.

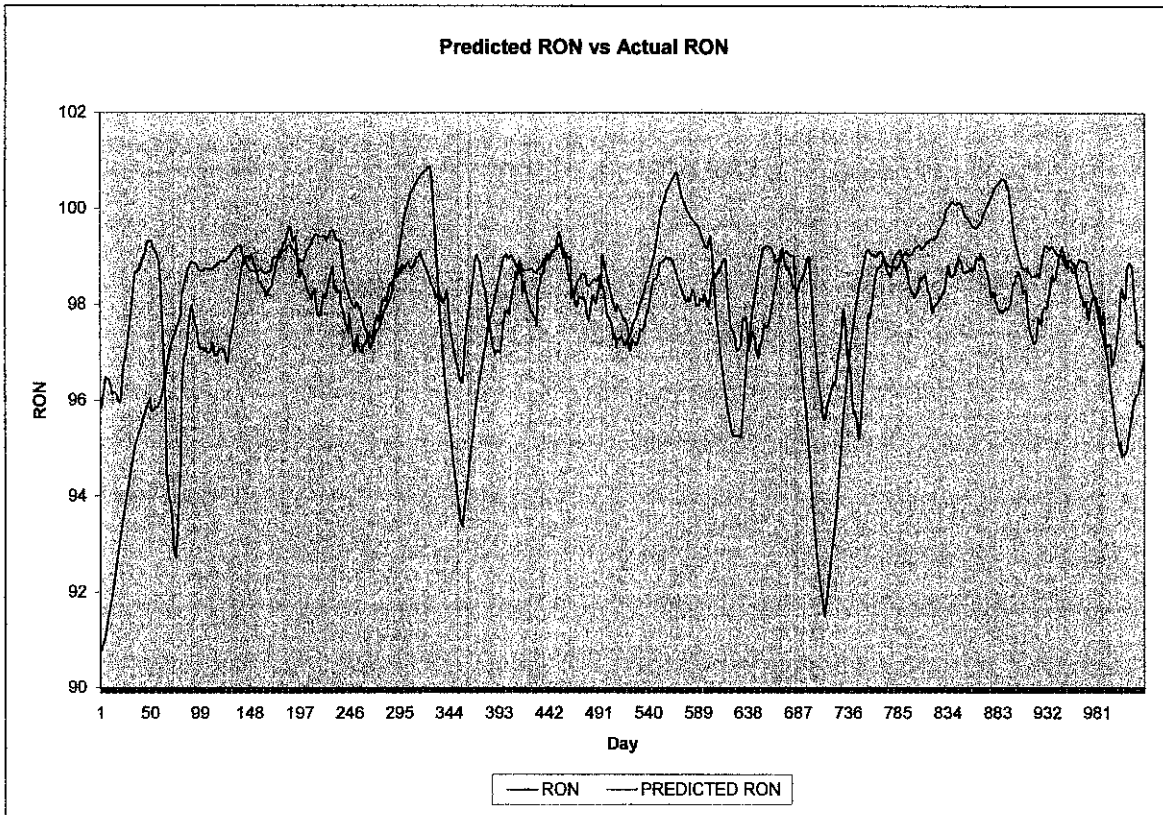
From the graph, it is show that, when the R-squared is getting higher, the error between the actual and predicted RON is getting smaller and smaller. Moreover, if we are to look at testing data and the validation data, R-squared is quite low and large deviation between the actual and predicted value. Somehow, if we look carefully to the predicted value in testing and validation trend, it is having approximately the same trend but the problem is that it is deviated far from the actual value due to error. If the error can be reduced, the predicted value can be push up or down to get as close as possible to the actual RON. This matter will be discussed in the next section.

Training data is having a highest R-squared, 0.73 because the modeling is built by using this data, followed by validation data, 0.5 and testing data is 0.47. The 30 days moving average of neural network is depict in Figure 4.9.



**Figure 4.9 Neural Network of RON for 30 days moving average  
(Before updating the model)**

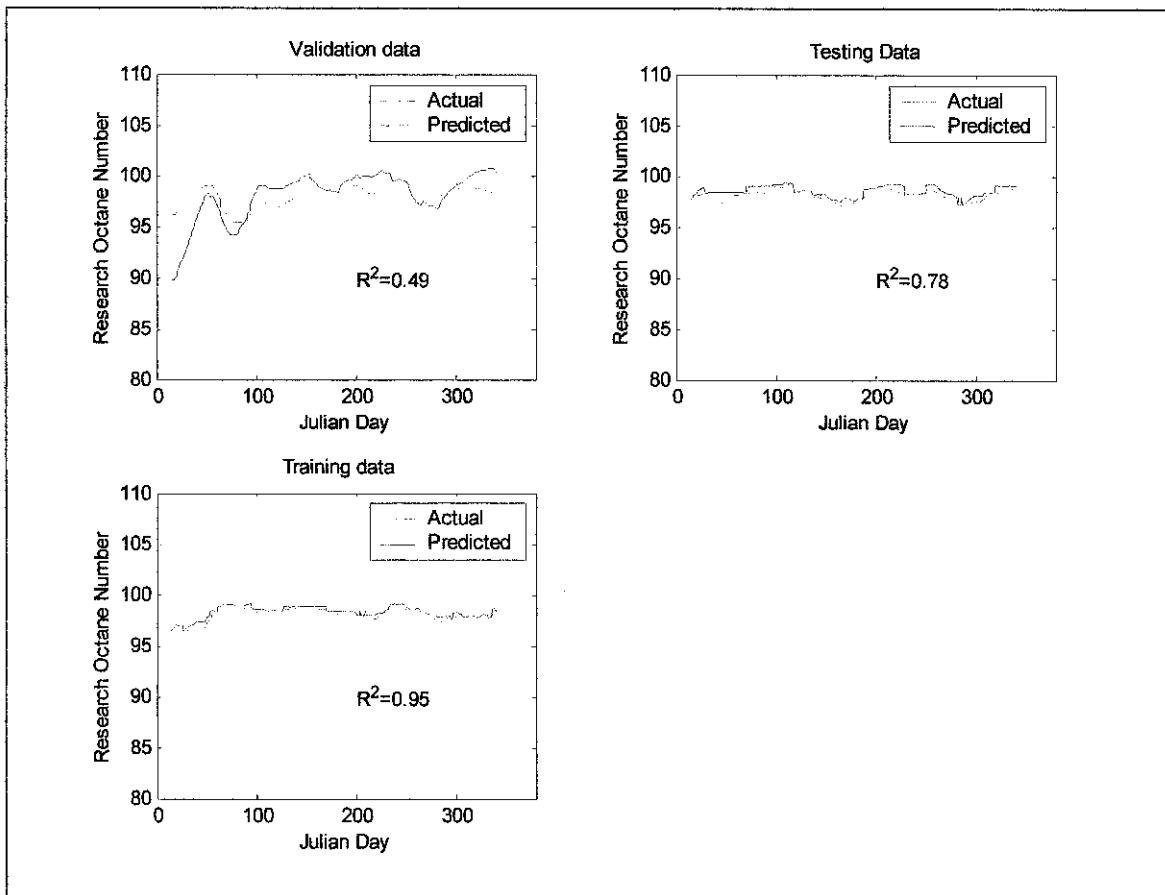
A comparison with regression method is done in order to justify that neural network methodology is better to modeling predicting the RON. Same approach also applied in regression method, where a 30 days moving average analysis is used to see how smooth the trend predicted RON to actual RON. The graph is depicting in Figure 4.10. The graph is showing a poor correlation between the actual and predicted RON. Thus, neural network analysis approach is more reliable than regression method.



**Figure 4.10. Predicting RON using Regression method.**

#### 4.5 FURTHER IMPROVEMENT PERFORMANCE

In order to improve the performance of the network, one method is introduced in order to reduce the error between the actual RON and predicted RON. The method is called automatic bias updating (Error analysis). The bias updating is a suitable method since it will calculate the average of previous data set and update the predicted output if the deviation between the predicted and actual is larger than the average deviation. The terminology of the improvement, automatic bias updating is easily illustrated in figure 4.11. A comparison has been made with Figure 4.9, before-update model. From Figure 4.11, as the automatic bias updating is applied in the model, the R-squared is increased and the deviation between the actual and predicted RON is reduced. However, the trend is not so good in validation data. Table 4.12 summarized the R-squared value before updating and after updating the model.



**Figure 4.11 Neural Network of RON for 30 days moving average  
(After updating the model)**

**Table 4.12 Comparison of R-squared for each type of data**

<b>Data set</b>	<b>R-squared before update</b>	<b>R-squared after update</b>
<b>Training data</b>	<b>0.73</b>	<b>0.95</b>
<b>Testing data</b>	<b>0.5</b>	<b>0.78</b>
<b>Validation data</b>	<b>0.47</b>	<b>0.49</b>

#### **4.6 FEASIBILITY OF NEURAL NETWORK MODELING FOR REFINERY**

In general, the results obtained for the case study above is not very satisfactory. However, the result is improved by implementing the automatic bias updating approach. I was elected to use the approach due to my experience while doing my industrial internship in Refinery XYZ and see the approach works well in updating the inferential analyzer.

As stated in the objectives, the main goal of the project is to understanding the Neural Network methodology. The aim is to get to know well the theoretical background and the fundamental principles of neural network, its method of implementation, as well as how the results should be interpreted and to get the best model for predicting the RON. As such, the results then will be studied so a further improvement can be introduced.

As in the case in most modeling method, if the model output does not predict the actual result very well, the cause can be traced to either one of two factors. The first factor is probably the mismatch between the process characteristics and the modeling approach itself. For example, the regression method would be a linear modeling technique to model a process that inherently non linear for this case of study. The second factor is related to the degree to which the characteristics of the process are accurately represented the model. This problem can be known as the residential time problem in the refinery. Since the RON lab test on Reformate sample is usually conducted at 6:00 am, there would some a delay time when extracting the process plant data from the plant. There would be slightly changes in the time, for example, the test is conducted at 6:03 am but the data extracted for the modeling is on 6:00 am.

These two factors mentioned must be looked carefully when determining the most suitable model and modeling approach on solving the problem.

## **CHAPTER 5**

### **CONCLUSION AND RECOMMENDATIONS**

The study has achieved its objective on developing the model for predicting Reformate Research Octane Number. Moreover, a framework has been built in order to focus on aspects such as data gathering, input selection, and architecture of the network, learning algorithm, transfer function, network training and finally the network simulation. The methodology is applied for the problem on predicting RON.

The network created and design by using MATLAB software. To determine if the performance of the mode, the trained network was simulated using a set of data from testing and validation data. The output of the data is then compared by using R-squared value. The optimum network obtained for this case study is having R-squared value for 0.73 (before updating) and it has increased when bias updating is applied to the network to 0.95.

For this case study, a further improvement of the network has been implemented by using automatic bias updating. The R-squared is increased as the bias updating method is introduced to the system. Several conclusions can be drawn based on the results obtained. The network also perform worse when asked to predict the output for validation data whose input values do falls within the range of the training data. On the other hand, when presenting a data, which is the testing data (who is close to specific data set which the network trained) the network predict the output better and greater accuracy.

As a conclusion, the case study has shown that, there is a potential of neural network in predicting RON in the refinery. A weighed consideration of the limitations of neural network will allow for a formulation of better model and accuracy.

## RECOMMENDATIONS FOR FUTURE WORK

Future study on application of neural network modeling for inferring of RON in a refinery could focus on several aspects, as follows:

- Integration of neural network model into plant's Advanced Control strategy. The neural network could be used to monitor process data available from Distributed Control System (DCS) to get inferential property predictions for properties that hard to measure on-line such as composition, freeze point and etc. which will translate to saving in terms of time and cost from reduction in lab analysis or use of analyzer or use of online analyzer.
- Study on the inversion property of neural network. The inversion process takes a neural network that maps input to output and invert it. The inverted will give a set of inputs necessary to achieve a desired output.



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# APPENDIX

## Appendix 1: Detail description of MATLAB functions.

### 1. newff

**Purpose** Create a feed-forward Backpropagation network.

**Synopsis** net = newff (PR, [S1 S2...SN1], {TF1 TF2...TFN1}, BTF, BLF, PF)

**Description** net = newff (PR, [S1 S2...SN1], {TF1 TF2...TFN1}, BTF, BLF, PF) takes,

PR – R x 2 matrix of min and max values for R input elements.

Si – Size of ith layer for N1 layers.

TFi – Transfer function of ith layer

BTF – Backprop weight/bias learning function

PF – Performance function

### 2. trainlm

**Purpose** Trains a feed-forward network with Levenberg-Marquardt Algorithm.

**Description** A function which employs the Levenberg-Marquardt Algorithm in training the weights and biases to map the input vectors. Training continues until the error goal is met or until the number of epochs. The variable  $\mu$  determines whether the learning progresses according to Newton's or gradient descent methods. Here is the Levenberg-Marquardt rule for updating parameters (such as weight and biases):

$$\Delta W = (J^T - \mu I)^{-1} J^T e$$

where J is the Jacobian Matrix, as discussed in Chapter 2. Note that as the  $e$  gets large the  $J^T J$  term becomes negligible and learning progresses according to  $\mu^{-1} J^T e$  becomes a gradient descent method. Whenever a step is taken with increasing error,  $\mu$  is increased until a step can be taken without increasing error. However, if  $\mu$  becomes too large no learning takes place (i.e  $\mu^{-1} J^T e$  approaches zero). This occurs when an error minima has been found. This is why learning stops when  $\mu$  reaches its maximum value.

### 3. **sim**

**Purpose** Simulate a neural network.

**Synopsis**  $[Y, Pf, Af] = \text{sim}(\text{net}, P, Pi, Ai)$

**Description** Sim simulated neural networks.  
 $[Y, Pf, Af] = \text{sim}(\text{net}, P, Pi, Ai)$  takes,  
net – Network.  
P - Network inputs.  
Pi – Initial input delay conditions, default = zeros.  
Ai – Initial layer delay condition, default = zeros.  
and returns,  
Y – Network outputs.  
Pf – Final input delay conditions.  
Af- Final layer delay conditions.

### 4. **init**

**Purpose** Initialize neural network.

**Synopsis**  $\text{net} = \text{init}(\text{net})$

**Description**  $\text{init}(\text{net})$  returns neural network net with weight and bias values updated according to the network initialization function.

### 5. **premnmx**

**Purpose** Preprocess data so that minimum is -1 and maximum is 1

**Synopsis**  $[\text{pn}, \text{minp}, \text{maxp}, \text{tn}, \text{mint}, \text{maxt}] = \text{premnmx}(\text{p}, \text{t})$   
 $[\text{pn}, \text{minp}, \text{maxp}] = \text{premnmx}(\text{p})$

**Description**  $\text{premnmx}$  preprocesses the network training set by normalizing the inputs and targets so that they fall in the interval  $[-1, 1]$ .  
P-  $R \times Q$  matrix of input (column) vectors  
T –  $S \times Q$  matrix of target vectors.  
And returns,  
PN –  $R \times Q$  matrix of normalized input vectors  
 $\text{minp}$  –  $R \times 1$  vector containing maximum for each P.

TN – S x Q matrix of normalized target vectors.

Mint – S x 1 vector containing minimum for each T

maxt – S x 1 vector containing maximum for each T

## 6. postmnmx

**Purpose** Postprocess data which has been preprocessed by premnmx

**Synopsis** [p,t] = postmnmx (pn,minp,maxp,tn,mint,maxt)

[p] = postmnmx (pn,minp,maxp)

**Description** postmnmx preprocess the network training set which was preprocessed by premnmx. It converts the data back into unnormalized units.

Postmnmx takes these inputs,

PN – R x Q matrix of normalized input vectors

minp – R x 1 vector containing maximum for each P.

TN – S x Q matrix of normalized target vectors.

Mint – S x 1 vector containing minimum for each T

maxt – S x 1 vector containing maximum for each T

And returns,

P- R x Q matrix of input (column) vectors

T – S x Q matrix of target vectors.

## 7. logsig

**Purpose** Log sigmoid transfer function.

**Synopsis** logsig(n)

**Description** Log-sigmoid is a function used to map a neuron input from the interval  $(-\infty, \infty)$  into interval  $(0, 1)$ . The log-sigmoid is a differential function, which makes it suitable for neurons being trained with Levenberg-Marquardt algorithm. The following is the log-sigmoid equation applied to each input element:

$$\text{Logsig}(n) = \frac{1}{1+e^{-n}}$$

## 8. tansig

**Purpose** Tangent-sigmoid transfer function.

**Synopsis** tansig(n)

**Description** A tan-sigmoid function, used to map a neuron input from the interval  $(-\infty, \infty)$  into interval  $(-1, 1)$ . The tangent-sigmoid is a differentiable function, which makes it suitable for neurons being trained with Levenberg-Marquardt algorithm. The following is the tangent-sigmoid equation as it applied to each input element:

$$Tansig(n) = tanh(n)$$

## 9. purelin

**Purpose** Linear transfer function.

**Synopsis** purelin(n)

**Description** Purelin is the simplest transfer function a neuron can have is the pure linear transfer function, which simply passes a neuron's input vectors on to its output, being altered only by the neuron's bias, which is added to it.

## Appendix 2: Sample MATLAB Coding for neural network.

%Use of Neural Network to develop commercial predictors for Research Octane Number for Reformat

%Data loading

%Data 2001, Data 2002, Data 2003

load Data01.dat

load Data02.dat

load Data03.dat

%DAY/Year for modeling basis

Jday = Data01(:,1)';

%Training set (2001 data)

p01= Data01(:,2:8)';

t01= Data01(:,10)';

[pn01,minp01,maxp01,tn01,mint01,maxt01]= premmmx(p01,t01);

val01.P=pn01;

val01.T=tn01;

%validation set (2002 data)

p02= Data02(:,2:8)';

t02= Data02(:,10)';

[pn02,minp02,maxp02,tn02,mint02,maxt02]= premmmx(p02,t02);

val02.P=pn02;

val02.T=tn02;

%Testing set (2003 data)

p03= Data03(:,2:8)';

t03= Data03(:,10)';

[pn03,minp03,maxp03,tn03,mint03,maxt03]= premmmx(p03,t03);

```

test03.P=pn03;
test03.T=tn03;

%setup network
net= newff(minmax(pn03), [16 4 1], {'tansig','tansig','purelin'},'trainlm');
net.trainparam.goal=1e-5;
net.trainparam.epochs=350;
randn('seed',19873490957);
%with early stopping
net=init(net);
net = train(net,pn03,tn03,[],[],val01,val02);

%simulate network
%2001
an01 = sim(net,pn01);
a01 = postmnmx(an01,mint01,maxt01);
figure (2)
[m01,b01,r01] = postreg(a01,t01);
RSQ01=rsq(a01,t01)

%2002
an02 = sim(net,pn02);
a02 = postmnmx(an02,mint02,maxt02);
figure (3)
[m02,b02,r02] = postreg(a02,t02);
RSQ02=rsq(a02,t02)

%2003
an03 = sim(net,pn03);
a03 = postmnmx(an03,mint03,maxt03);
figure (4)

```



```
[m03,b03,r03] = postreg(a03,t03);
```

```
RSQ03=rsq(a03,t03)
```

```
%30 day moving average for model
```

```
%a: output/predicted RON
```

```
%t: inputs/key variables(COT,EIT. Recycle Flowrate and Feed Flow rate)
```

```
k=15
```

```
t01w= zeros(356,1); t01w(:,1)=nan; a01w= zeros(356,1) ; a01w(:,1)=nan;
```

```
t02w= zeros(356,1); t02w(:,1)=nan; a02w= zeros(356,1) ; a02w(:,1)=nan;
```

```
t03w= zeros(356,1); t03w(:,1)=nan; a03w= zeros(356,1) ; a03w(:,1)=nan;
```

```
%data 01
```

```
for j=15:341
```

```
    t01w(j)= sum (t01(j-k+1:j+k))/(2*k);
```

```
    a01w(j)= sum(a01(j-k+1:j+k))/(2*k);
```

```
    t02w(j)= sum (t02(j-k+1:j+k))/(2*k);
```

```
    a02w(j)= sum(a02(j-k+1:j+k))/(2*k);
```

```
    t03w(j)= sum (t03(j-k+1:j+k))/(2*k);
```

```
    a03w(j)= sum(a03(j-k+1:j+k))/(2*k);
```

```
end
```

```
%R-squared value
```

```
RSQ01w= rsq(a01(15:326),t01(15:326))
```

```
RSQ02w= rsq(a02(15:326),t02(15:326))
```

```
RSQ03w= rsq(a03(15:326),t03(15:326))
```

```
figure (5)
```

```
subplot(221),....
    v=axis;
alp= 2.5;
bet= 5;
xpos=alp*v(2) + (1-alp)*v(1);
ypos=(1-bet)*v(4)+ bet*v(3);
plot(Jday,t01w,'g', Jday, a01w),...
    xlabel('Julian Day')
    ylabel('Research Octane Number')
    title('Training Data')
    legend ('Actual','Predicted')
    axis([0 380 80 110])
    text(200,90,['R^2=' num2str(RSQ01w,2)]);
```

```
subplot(222)
v= axis;
alp= 2.5;
bet=5;
xpos=alp*v(2) + (1-alp)*v(1);
ypos=(1-bet)*v(4)+ bet*v(3);
plot(Jday,t02w, 'g', Jday, a02w),...
    xlabel('Julian Day')
    ylabel('Research Octane Number')
    title('Validation Data')
    legend ('Actual','Predicted')
    axis([0 380 80 110])
    text(200,90,['R^2=' num2str(RSQ02w,2)]);
```

```
subplot(223)
plot(Jday,t03w, 'g', Jday, a03w),...
```

```
xlabel('Julian Day')
ylabel('Research Octane Number')
title('Testing Data')
legend ('Actual','Predicted')
axis([0 380 80 110])
text(200,90,['R^2=' num2str(RSQ03w,2)]);
```

```
%for bias updating
```

```
%bias updating is to improve the
```

```
a1=(sum(a01)/length(a01))-(sum(t01)/length(a01));
```

```
if a1<0
```

```
    a1=a1*-1;
```

```
else
```

```
    a1=(sum(a01)/length(a01))-(sum(t01)/length(a01));
```

```
end
```

```
a2=(sum(a02)/length(a01))-(sum(t02)/length(a01));
```

```
if a1<0
```

```
    a2=a2*-1;
```

```
else
```

```
    a2=a2;
```

```
end
```

```
a3=(sum(a03)/length(a03))-(sum(t03)/length(t03));
```

```
if a1<0
```

```
    a3=a3*-1;
```

```
else
```

```
    a3=a3;
```

end

%Automatic bias-updating. Automatic bias updating is to make the predicted values  
%to approach the target values as close as possible. However the bias updating is  
%still using the neural network model as a basis to push up or pull down the  
%predicted RON to its desired value. Below is an example on how to obtain the value  
%for bias updating.

%a : output/predicted value from neural network.

%t : target value/actual value.

%b : bias updating value

% b= mean(a)-mean(t), if mean(a)- mean(t)>b, then a = a - b

% if mean (a)-mean(t)<b, then a = a + b

k=15

t01w= zeros(356,1); t01w(:,1)=nan; a01w= zeros(356,1) ; a01w(:,1)=nan;

t02w= zeros(356,1); t02w(:,1)=nan; a02w= zeros(356,1) ; a02w(:,1)=nan;

t03w= zeros(356,1); t03w(:,1)=nan; a03w= zeros(356,1) ; a03w(:,1)=nan;

for j=15:341

%bias updating for data2001

t01w(j)= sum(t01(j-k+1:j+k))/(2\*k);

a01w(j)= sum(a01(j-k+1:j+k))/(2\*k);

if sum(a01w(j))/length(t01w(j))-sum(t01w(j))/length(a01w(j))>a1%

a01w(j)=sum(a01(j-k+1:j+k))/(2\*k)-a1;

else

a01w(j)= sum(a01(j-k+1:j+k))/(2\*k)+a1;

end

```

%bias updating for data2002
t02w(j)= sum(t02(j-k+1:j+k))/(2*k);
a02w(j)= sum(a02(j-k+1:j+k))/(2*k);

if sum(a02w(j))/length(t02w(j))-sum(t02w(j))/length(a02w(j))>a2
    a02w(j)=sum(a02(j-k+1:j+k))/(2*k)-a2;
else
    a02w(j)= sum(a02(j-k+1:j+k))/(2*k)+a2;
end

```

```

%bias updating for data2003
t03w(j)= sum(t03(j-k+1:j+k))/(2*k);
a03w(j)= sum(a03(j-k+1:j+k))/(2*k);

if sum(a03w(j))/length(t03w(j))-sum(t03w(j))/length(a03w(j))>a3
    a03w(j)=sum(a03(j-k+1:j+k))/(2*k)-a3;
else
    a03w(j)= sum(a03(j-k+1:j+k))/(2*k)+a3;
end

```

```

end

```

```

%R-squared for new model (after bias updating)

```

```

RSQ01w= rsq(a01w(15:326),t01w(15:326))

```

```

RSQ02w= rsq(a02w(15:326),t02w(15:326))

```

```

RSQ03w= rsq(a03w(15:326),t03w(15:326))

```

figure (6)

```
subplot(221),...
    v=axis;
alp= 2.5;
bet= 5;
xpos=alp*v(2) + (1-alp)*v(1);
ypos=(1-bet)*v(4)+ bet*v(3);
plot(Jday,t01w,'g', Jday, a01w),...
    xlabel('Julian Day')
    ylabel('Research Octane Number')
    title('Training Data')
    legend ('Actual','Predicted')
    axis([0 380 80 110])
    text(200,90,['R^2=' num2str(RSQ01w,2)]);
```

```
subplot(222)
v= axis;
alp= 2.5;
bet=5;
xpos=alp*v(2) + (1-alp)*v(1);
ypos=(1-bet)*v(4)+ bet*v(3);
plot(Jday,t02w, 'g', Jday, a02w),...
    xlabel('Julian Day')
    ylabel('Research Octane Number')
    title('Validation Data')
    legend ('Actual','Predicted')
    axis([0 380 80 110])
    text(200,90,['R^2=' num2str(RSQ02w,2)]);
```

```
subplot(223)
plot(Jday,t03w, 'g', Jday, a03w),...
```

```
xlabel('Julian Day')
ylabel('Research Octane Number')
title('Testing')
legend ('Actual','Predicted')
axis([0 380 80 110])
text(200,90,['R^2=' num2str(RSQ03w,2)]);
```

Appendix 3: Case study data set.  
Testing Data

Day	COT1	COT2	COT3	EIT1	EIT2	Recycle Flow rate	Feed flow rate	Actual RON(OUTPUT)
1	453.4	452.8	453.4	490.4	472.4	355.0	335.1	93.4
2	455.3	454.1	455.3	490.4	474.4	357.3	335.5	94.6
3	455.4	454.3	455.4	490.4	474.5	357.5	335.7	94.5
4	457.3	453.9	457.9	490.4	474.8	357.6	335.1	94.9
5	452.5	452.9	453.5	490.4	473.1	358.8	337.0	94.5
6	453.7	455.6	454.8	490.4	472.1	343.8	327.8	94.8
7	454.7	456.6	455.8	490.4	471.8	330.4	322.2	95.1
8	459.7	458.0	457.2	490.4	476.2	336.5	326.1	96.7
9	460.4	458.7	458.0	490.4	478.6	339.3	330.8	96.8
10	460.5	458.8	458.0	490.4	478.9	339.8	332.0	97.5
11	460.3	458.6	457.8	490.4	479.3	341.0	333.3	97.4
12	459.4	457.7	456.9	490.4	478.4	340.1	332.6	96.8
13	457.8	457.0	455.3	490.4	475.8	333.6	328.1	95.4
14	458.3	457.6	455.8	490.4	476.4	333.4	326.7	96
15	458.1	457.4	455.6	490.4	476.2	332.9	326.3	96.2
16	459.2	459.1	458.8	490.4	477.6	348.0	332.6	96.6
17	461.3	460.6	460.2	490.4	478.7	334.4	326.3	97.3
18	461.2	460.4	460.0	490.4	478.7	334.4	327.3	96.8
19	462.6	461.8	461.5	490.4	479.8	335.9	329.1	97
20	461.9	461.1	460.7	490.4	479.4	331.4	325.2	96.8
21	461.5	460.8	460.5	490.4	478.3	331.9	326.9	94.5
22	462.3	461.3	461.2	490.4	478.9	342.7	330.8	94.9
23	464.2	463.1	463.1	490.4	481.6	341.2	332.1	96.5
24	464.6	463.5	463.4	490.4	481.6	340.7	331.2	95.8
25	464.5	463.4	463.4	490.4	482.1	342.4	333.4	96.3
26	465.2	464.1	464.1	490.4	484.7	349.1	336.0	96
27	465.0	463.9	463.9	490.4	485.0	350.4	337.9	95.8
28	465.6	464.5	464.5	490.4	485.9	351.1	337.2	96
29	465.7	464.2	464.5	490.4	485.7	350.5	336.8	96.1
30	465.9	464.8	464.8	490.6	486.3	351.3	337.4	95.6
31	466.8	465.2	465.7	491.1	487.6	353.6	339.7	96.2
32	466.4	464.8	465.3	492.2	487.7	354.4	339.5	96.2
33	466.5	464.8	465.4	492.2	487.7	355.0	340.3	95.6
34	468.1	466.5	467.0	492.5	490.7	358.8	345.0	96.9
35	470.2	468.5	469.1	493.8	493.0	360.3	345.7	98.5
36	472.0	470.4	470.9	498.4	495.8	365.0	351.5	99
37	473.4	470.5	472.3	499.7	498.0	366.2	351.5	99.1
38	473.0	470.1	471.9	499.0	495.7	365.5	351.7	98.8
39	472.5	470.2	471.3	499.2	494.3	364.6	351.6	96.7
40	472.9	471.0	471.8	500.5	496.3	368.2	354.1	99
41	469.6	473.4	469.9	500.7	493.0	368.3	357.0	97.2
42	471.6	471.9	472.1	498.6	494.8	372.2	359.2	98.6
43	474.2	471.1	473.4	498.6	499.3	376.9	364.5	98.4



44	474.4	471.2	473.7	500.1	499.8	377.8	365.8	98.9
45	474.6	471.1	473.7	504.8	499.6	376.9	364.5	98.5
46	475.6	471.5	474.4	504.0	503.0	376.7	363.9	99.7
47	475.5	473.8	474.3	504.0	502.3	377.7	364.2	99.2
48	476.4	472.9	475.2	504.0	501.8	377.3	362.7	99.2
49	476.0	474.1	474.8	504.0	501.7	376.1	363.9	99.3
50	475.9	473.4	474.8	504.0	501.4	375.0	362.6	98.4
51	476.5	474.2	475.3	505.3	502.9	377.8	363.7	99.2
52	475.7	476.3	474.6	505.3	504.3	380.6	366.6	99.8
53	476.2	474.0	475.8	505.7	503.7	379.4	365.1	98.6
54	476.2	476.2	475.8	506.7	503.8	378.2	364.8	98.7
55	476.6	475.3	476.2	506.6	503.2	377.5	364.3	98.5
56	477.9	478.1	476.4	508.4	505.5	381.9	368.4	99.4
57	478.0	473.0	476.6	505.0	501.3	373.6	361.6	98.4
58	480.5	474.4	479.7	505.0	507.0	383.0	369.0	99.8
59	482.4	478.7	482.1	505.0	509.7	383.7	370.3	99.3
60	481.2	478.9	481.3	512.5	505.2	374.3	359.4	100.6
61	481.0	475.1	480.3	508.9	507.5	380.7	367.9	100.9
62	479.8	475.6	479.1	508.8	504.8	378.9	365.2	99.6
63	480.5	474.0	477.3	508.8	503.7	376.9	363.3	99.1
64	481.0	477.4	477.3	509.3	508.4	386.2	373.6	99.3
65	478.7	477.7	477.3	509.3	505.2	382.2	369.3	98.6
66	477.4	478.8	478.1	506.6	504.9	377.0	362.8	97.8
67	478.5	481.8	480.3	508.3	509.0	378.1	364.8	98.5
68	477.3	477.1	478.4	513.4	506.5	387.1	355.0	98.9
69	473.9	479.5	480.8	511.2	501.5	379.6	346.7	97.6
70	477.5	480.3	483.0	511.2	508.4	384.8	361.5	98.5
71	478.8	478.4	482.5	513.4	511.6	384.6	370.3	97.7
72	479.9	482.3	483.2	514.6	512.8	386.7	373.6	98.1
73	480.9	479.2	481.8	514.6	512.4	383.9	370.7	96.6
74	481.0	479.9	481.7	518.5	513.2	385.1	373.4	95.7
75	475.7	478.9	480.2	518.5	504.2	385.5	367.3	92.8
76	479.5	480.4	480.9	517.8	509.7	392.5	375.0	94
77	479.4	480.8	481.3	515.7	509.9	393.2	375.7	91.4
78	479.7	481.2	481.4	515.7	510.4	392.7	374.9	92.4
79	478.2	478.7	481.4	515.7	507.4	382.2	365.6	90.6
80	481.8	468.6	474.5	515.7	401.9	227.0	214.8	76.4
81	488.3	489.4	488.6	515.7	472.8	338.9	330.2	95.1
82	492.7	490.9	492.8	477.9	482.0	360.5	352.1	94.9
83	492.8	492.9	492.8	478.2	483.6	353.7	339.0	96.9
84	491.7	492.4	491.8	479.4	481.7	355.4	343.3	96.3
85	492.8	491.7	492.8	479.4	480.9	350.3	336.0	94.6
86	492.8	492.4	492.8	479.4	479.2	351.4	340.1	93.8
87	493.6	493.0	493.5	479.9	482.4	365.7	357.8	93.1
88	494.3	494.2	494.3	479.9	484.7	373.2	370.7	94
89	495.4	494.2	495.4	485.6	485.4	373.9	372.5	94.5
90	496.5	496.1	496.4	488.7	491.6	388.5	391.7	96.8
91	497.7	498.6	497.7	490.8	496.3	400.7	390.2	99.5
92	497.4	497.5	497.4	497.1	496.3	399.1	392.7	98.9
93	497.2	496.6	497.2	497.1	495.7	399.2	391.3	99.1
94	501.3	496.4	500.9	497.4	494.5	396.4	389.7	98.2
95	501.8	496.5	501.4	497.4	495.6	397.9	391.1	97.8

96	501.7	497.9	501.2	498.0	497.3	399.5	393.7	100
97	498.3	498.9	497.9	498.0	496.7	396.5	381.1	99.1
98	497.7	498.2	497.3	498.2	496.5	396.3	380.2	98.6
99	499.0	496.8	498.3	498.2	493.2	389.6	378.7	96.3
100	499.7	497.9	498.9	496.1	494.4	389.8	383.7	97
101	499.7	497.0	498.9	496.2	492.4	387.5	377.5	97
102	499.7	497.3	498.9	495.0	492.6	385.4	372.2	97.1
103	499.7	497.0	498.9	493.5	485.4	357.7	338.3	96
104	499.9	497.1	499.1	494.4	493.8	387.7	378.5	97.5
105	499.9	496.8	499.1	494.5	494.1	387.2	375.1	97.5
106	499.9	497.1	499.1	494.5	494.0	388.3	380.0	97.4
107	499.9	497.4	499.1	494.5	493.2	386.7	376.7	97
108	499.9	496.5	499.1	494.5	493.1	387.1	378.1	97.4
109	499.9	496.7	499.1	494.5	493.5	388.6	380.2	97.9
110	499.7	496.4	498.9	494.5	492.9	386.9	378.5	96.8
111	499.7	495.5	498.9	494.5	492.5	386.5	377.9	96.5
112	499.8	495.4	499.1	493.6	492.5	387.5	378.2	97.2
113	499.9	495.8	499.1	493.6	492.3	387.9	379.5	97.2
114	500.0	494.9	499.1	493.7	490.4	385.7	372.8	96.9
115	499.9	496.0	499.1	494.0	490.0	385.4	372.6	96.9
116	500.0	495.3	499.2	494.4	490.4	385.0	372.3	96.7
117	500.2	494.9	499.3	495.5	490.7	386.2	374.3	96.6
118	500.3	495.4	499.5	495.6	491.2	385.5	374.7	96.8
119	500.2	495.6	498.3	495.9	492.5	387.9	379.2	96.6
120	500.9	495.1	500.1	496.0	493.7	389.5	381.6	97.1
121	500.7	496.4	499.9	495.3	495.6	392.4	379.8	97.3
122	501.1	494.8	500.3	497.9	493.8	391.3	383.5	97
123	501.1	495.7	500.3	496.8	495.0	390.9	383.1	97.4
124	497.7	496.1	496.9	501.7	495.6	394.9	380.2	99.4
125	495.8	494.6	494.9	492.3	489.6	389.9	360.6	98.3
126	496.0	497.6	495.2	492.3	490.0	392.3	366.9	96.4
127	497.8	494.4	497.0	492.1	488.8	389.7	371.7	94.3
128	499.8	493.3	499.0	491.6	491.4	391.9	377.5	96.2
129	500.4	496.0	498.1	496.3	493.9	388.9	377.9	96.9
130	500.8	495.1	501.7	496.3	493.1	386.7	376.5	97.2
131	502.5	495.3	501.7	496.0	495.4	387.8	377.0	97.7
132	502.4	495.1	501.6	495.2	494.1	384.8	373.1	97.2
133	500.3	496.3	500.4	495.2	490.9	382.5	370.9	96.9
134	500.4	496.7	500.4	495.2	491.2	382.9	371.7	96.8
135	500.5	497.3	500.5	495.2	491.5	383.2	372.8	97
136	500.5	497.8	500.5	494.7	491.9	383.3	372.4	96.6
137	500.7	498.1	500.7	493.2	492.5	384.0	372.9	97.2
138	500.7	497.6	500.7	493.3	491.8	383.0	372.0	96.3
139	501.3	497.5	501.3	493.4	493.1	383.2	373.0	97.2
140	501.3	497.7	501.3	493.4	493.0	383.0	372.7	97.5
141	500.7	497.5	500.7	494.5	493.4	392.7	378.4	97.8
142	499.8	499.7	499.8	493.4	495.5	397.3	383.0	98.7
143	499.5	499.8	499.5	493.4	495.1	397.9	383.9	98.2
144	499.3	499.9	499.3	493.4	494.7	395.7	381.1	98.4
145	499.6	499.8	499.6	492.9	495.5	396.8	383.1	99
146	498.7	499.4	498.7	497.4	495.7	398.4	381.2	99
147	498.5	499.2	498.5	497.0	495.6	397.6	379.0	99.4

148	498.1	498.1	498.1	496.0	494.5	397.6	377.0	98.7
149	498.3	498.5	498.3	496.0	494.8	394.4	377.0	99.2
150	498.3	497.8	498.3	493.7	493.6	391.7	376.5	98.3
151	498.3	499.9	498.4	496.4	497.1	398.7	376.0	99.1
152	498.3	499.1	498.3	496.1	496.2	396.6	374.9	99.4
153	498.3	498.4	498.3	495.0	495.2	395.3	377.1	99.3
154	498.3	497.8	498.3	495.3	495.2	394.5	377.5	99.1
155	498.2	498.2	498.3	495.0	494.9	394.8	377.1	98.6
156	498.5	499.6	498.5	495.3	496.5	397.3	377.1	99.5
157	500.2	498.9	500.8	496.4	495.4	391.4	377.5	97.9
158	501.6	498.6	501.6	496.1	497.7	395.6	384.2	98.2
159	501.7	500.9	501.6	500.7	503.5	407.1	384.4	100.4
160	501.0	496.7	501.0	500.8	500.5	406.2	386.2	98.8
161	501.5	497.8	501.5	500.3	499.0	393.7	383.1	99.2
162	501.8	496.6	501.8	498.6	497.3	390.7	381.3	98.3
163	501.8	500.6	501.8	497.3	502.9	401.6	377.5	100.1
164	500.9	497.8	501.7	496.8	497.8	403.5	378.3	98.6
165	501.1	497.6	501.9	496.8	495.5	398.2	369.5	97.7
166	500.7	501.5	501.5	496.8	491.8	387.0	350.6	97.8
167	499.5	498.1	500.3	496.8	493.0	397.5	369.8	98.3
168	500.6	499.5	501.0	497.3	497.3	397.7	380.7	98.5
169	480.8	478.7	483.3	498.7	457.7	363.6	358.3	98.2
170	490.5	486.8	491.8	498.7	481.9	374.7	371.2	96.9
171	491.6	491.4	492.8	493.9	487.0	377.3	377.3	98
172	492.3	492.9	493.5	479.6	487.5	377.2	377.6	97.8
173	494.3	493.6	495.5	483.1	492.1	382.3	381.7	98.3
174	494.0	492.9	495.2	487.3	492.9	383.0	385.3	99.1
175	493.8	494.1	495.0	489.1	491.4	381.0	378.7	98.5
176	494.4	494.5	495.6	487.7	491.6	381.2	378.5	98.8
177	495.8	494.5	497.0	485.8	490.6	378.8	367.4	97.9
178	497.8	495.4	499.0	487.5	494.5	381.9	375.8	98.3
179	499.3	496.4	500.5	492.5	499.1	385.9	375.5	98.7
180	499.5	495.9	500.7	493.8	498.6	385.3	372.7	98.9
181	499.4	496.0	500.5	493.8	497.9	384.5	378.5	98.5
182	499.4	495.8	500.5	493.8	497.7	385.1	383.0	98.4
183	500.1	496.0	500.9	495.0	498.3	387.1	385.8	99.1
184	499.9	494.5	500.5	494.5	495.9	384.1	382.8	98.8
185	500.4	495.2	501.1	495.2	499.9	386.3	379.0	99.3
186	500.3	493.9	501.8	495.4	501.5	391.8	388.8	98.7
187	500.5	496.5	502.5	497.0	503.9	394.6	389.0	99.2
188	500.7	495.0	502.3	500.0	504.4	396.8	389.2	100.4
189	499.5	496.0	501.2	500.0	502.6	398.4	388.8	99.9
190	499.3	495.5	500.7	499.2	500.9	396.5	384.8	99.4
191	499.8	492.7	501.4	492.3	494.7	383.9	376.9	98.8
192	500.5	492.1	503.2	497.5	494.5	390.3	381.8	99
193	501.4	496.0	503.2	497.5	502.3	395.2	392.3	99.2
194	502.0	494.9	503.7	498.2	501.3	391.3	382.0	99.9
195	501.5	496.9	503.1	500.0	501.3	392.5	387.4	99.9
196	501.4	494.3	503.9	499.1	497.8	387.5	376.5	99.3
197	501.6	494.4	503.9	499.4	498.2	387.4	379.6	98.4
198	501.7	491.4	502.1	499.4	502.4	392.5	382.9	100.1
199	501.2	494.0	501.7	499.8	504.5	405.8	380.1	100.5

200	500.7	499.0	501.1	501.7	507.4	416.4	387.2	100.5
201	500.9	495.2	500.9	504.0	497.9	364.0	345.3	99.8
202	499.0	496.6	499.0	496.1	496.1	305.1	420.7	99.1
203	498.9	497.4	498.9	493.5	493.1	301.0	414.1	99
204	500.2	494.2	502.8	493.5	494.5	393.7	370.0	98
205	500.6	494.0	502.8	497.6	495.3	394.7	366.0	98.2
206	501.3	493.8	500.7	494.3	502.3	400.0	384.8	99.3
207	501.3	494.3	500.6	494.3	501.5	396.4	385.8	100
208	497.2	492.8	500.9	493.8	488.4	380.3	368.2	96
209	499.2	494.1	504.0	493.0	492.8	384.6	373.0	96
210	500.9	494.5	504.1	495.6	497.6	388.8	379.5	96.3
211	500.7	494.8	504.7	499.2	496.5	388.9	378.3	97
212	500.6	495.3	504.7	495.3	496.1	389.3	379.1	101
213	501.2	499.8	501.1	502.7	504.9	403.0	389.6	100
214	500.5	499.6	500.5	501.2	503.6	402.6	388.6	99.6
215	500.3	500.5	500.3	501.6	504.1	405.0	389.5	99.7
216	499.1	498.3	499.1	500.2	497.2	397.4	380.2	99.1
217	500.1	496.1	500.1	495.0	496.8	392.0	382.0	97.6
218	499.9	492.6	499.9	495.0	494.1	388.9	378.1	97.4
219	498.8	495.3	498.9	495.0	493.5	390.4	375.7	97.1
220	499.3	497.8	499.3	494.6	495.1	392.4	380.2	97.5
221	501.7	501.8	501.3	494.9	491.5	416.7	309.2	99
222	501.7	500.9	501.3	491.9	494.6	303.0	425.7	98.8
223	499.7	497.4	501.5	500.0	500.6	308.7	433.8	95.4
224	502.1	499.0	501.7	499.3	496.2	368.9	345.2	98.4
225	501.0	495.5	502.2	497.3	500.3	372.6	353.3	96.3
226	501.7	497.8	500.9	500.9	498.1	367.6	350.0	97.8
227	502.0	496.8	501.6	499.0	500.2	368.8	351.2	97.1
228	502.7	497.6	502.3	503.7	496.8	392.5	390.9	97.4
229	501.5	497.6	502.0	498.6	500.3	394.7	392.1	98.5
230	502.1	499.1	502.1	495.8	499.2	388.6	389.2	98.9
231	502.1	498.5	502.1	503.6	503.1	401.1	394.1	99.3
232	502.5	497.1	502.9	503.5	501.7	392.0	390.9	98.2
233	502.8	498.5	503.4	503.5	504.3	393.2	393.0	99.6
234	501.7	497.9	502.9	502.2	499.6	386.6	384.1	99.4
235	502.5	498.5	502.9	502.2	504.7	394.2	392.4	99
236	503.1	499.9	503.7	502.7	505.9	394.1	394.0	98.4
237	502.7	498.9	503.8	504.3	503.7	392.4	392.4	98.3
238	503.1	499.2	503.9	504.3	504.5	394.7	395.7	97.9
239	503.8	499.2	503.9	504.3	505.9	394.1	393.7	99
240	504.1	497.4	503.9	504.6	506.1	392.8	389.0	98.5
241	504.5	497.1	504.9	504.3	506.5	394.7	392.9	98.7
242	505.0	498.0	504.9	505.7	510.7	399.0	388.6	98.6
243	504.2	497.8	505.1	510.0	506.3	384.8	372.2	98.8
244	504.9	501.0	505.1	508.7	506.6	372.5	357.3	99.2
245	504.6	499.9	505.1	504.7	505.0	371.2	356.5	92.1
246	504.9	499.8	505.1	504.7	505.4	371.8	357.0	98.9
247	504.9	498.0	505.1	505.9	501.2	371.7	351.8	99.3
248	505.0	497.5	505.1	509.6	501.2	370.2	352.0	98
249	504.8	497.4	505.1	505.2	500.0	368.2	348.7	99.1
250	505.4	498.0	505.3	491.9	501.6	370.2	349.3	99.1
251	505.2	500.3	505.3	491.9	504.6	371.7	355.4	98.8

252	489.9	489.2	491.0	491.5	435.6	343.6	334.4	93.4
253	501.0	497.5	500.7	490.1	494.4	386.6	382.9	97.5
254	503.9	499.9	503.2	494.0	503.2	392.8	389.3	98
255	501.9	499.5	501.7	505.6	497.5	386.2	376.9	97
256	502.1	500.1	501.7	505.6	499.3	389.7	385.8	96.9
257	502.2	500.3	501.8	501.3	500.0	390.5	386.2	97.3
258	502.6	500.5	502.0	501.4	501.2	392.2	388.1	98.1
259	502.1	501.2	501.7	501.3	501.2	393.4	386.8	97.4
260	501.7	500.0	501.4	497.4	494.4	344.9	392.2	98.3
261	500.8	498.6	500.4	498.3	494.8	308.7	411.3	96.5
262	501.3	499.3	500.9	498.3	495.1	357.0	347.2	96
263	501.9	497.8	502.1	498.3	497.9	381.1	387.6	96.3
264	502.8	498.4	502.2	502.8	500.8	384.3	389.4	96.3
265	502.9	499.0	502.6	500.7	501.0	384.0	390.7	97.4
266	503.0	505.0	501.6	502.1	506.7	352.3	375.9	99.4
267	491.2	483.2	491.8	506.1	477.4	338.1	328.3	97.3
268	490.3	481.8	491.2	499.2	468.7	313.5	310.0	98.2
269	491.5	488.2	492.9	477.0	476.3	356.5	346.6	95
270	491.5	489.4	493.8	472.1	475.7	364.8	341.0	95.8
271	491.6	489.1	493.8	475.2	474.2	363.3	339.0	95.8
272	498.4	492.7	496.8	480.9	484.7	367.9	359.0	97.4
273	498.5	496.8	496.9	480.9	488.3	378.6	364.3	97.8
274	497.3	496.2	496.4	485.3	483.9	366.1	354.3	99.8
275	497.3	495.3	496.0	485.7	484.8	367.4	352.9	98.2
276	497.2	495.2	495.9	484.6	483.1	365.8	352.0	96.9
277	497.9	496.5	496.7	485.0	484.5	367.8	355.8	96.7
278	498.8	496.4	497.6	486.2	483.2	365.2	352.2	97.2
279	498.9	498.1	497.7	486.2	485.4	367.0	356.0	97.4
280	498.9	500.6	497.7	493.1	491.3	371.2	360.6	98.4
281	498.6	499.7	497.4	492.3	488.9	379.5	364.4	97.9
282	499.3	498.4	498.1	489.8	487.2	370.7	357.5	97.7
283	499.4	497.3	498.2	489.6	486.6	373.4	361.7	97.1
284	500.0	497.8	498.8	488.8	488.2	378.3	363.9	97.4
285	500.2	497.8	499.0	489.9	488.7	380.4	365.2	97.3
286	500.3	497.8	499.1	489.9	488.5	376.9	363.1	97.7
287	500.0	499.5	498.7	491.0	491.5	384.7	373.1	98
288	498.4	497.7	497.2	494.7	485.3	414.5	278.5	98.8
289	497.9	497.1	496.7	488.9	483.8	413.6	279.1	98.2
290	497.9	497.1	496.6	485.6	481.4	406.6	275.8	98.8
291	497.9	497.0	496.6	485.6	484.8	414.6	284.3	99
292	497.6	496.8	496.4	491.8	489.5	422.8	294.5	99
293	497.5	496.6	496.2	491.8	487.1	417.8	283.5	98.9
294	498.3	497.5	497.2	485.8	480.1	341.8	326.9	97.1
295	497.9	497.1	496.9	485.8	482.1	295.4	384.3	98.2
296	498.4	498.5	497.3	487.0	484.7	359.8	332.8	98.8
297	499.5	493.9	498.6	487.0	480.1	342.3	329.0	96.8
298	499.6	499.2	498.8	487.0	488.8	335.5	385.6	98.8
299	499.5	499.1	498.7	488.3	486.7	298.1	414.0	99.1
300	499.5	499.1	498.7	492.2	487.6	299.6	415.6	98.5
301	501.3	500.6	500.5	492.2	491.6	371.1	357.8	98.7
302	501.9	501.1	501.1	497.8	495.6	387.3	382.5	98.1
303	501.1	500.4	500.4	494.6	490.3	374.3	336.6	98.6

304	501.9	501.1	501.1	495.3	493.3	356.1	358.8	99.6
305	501.5	501.1	501.1	497.3	494.8	357.1	358.1	99.1
306	503.3	502.1	502.9	496.9	498.4	382.2	391.9	99.1
307	503.3	502.5	502.9	500.7	498.1	380.0	387.9	99.6
308	502.9	502.4	502.7	500.7	496.3	376.2	383.8	98.4
309	503.5	502.6	503.5	501.6	501.4	383.1	394.4	99.8
310	503.5	499.5	503.5	498.6	494.7	373.9	384.9	97.6
311	504.1	500.6	503.9	499.4	496.9	375.2	385.7	98
312	502.2	500.8	501.4	501.9	497.0	374.5	384.4	99
313	501.5	500.7	500.7	498.3	498.7	376.8	389.5	99
314	501.6	501.1	501.1	498.3	497.6	376.0	387.3	98.3
315	503.3	502.8	502.9	503.7	500.6	380.9	394.2	98.6
316	504.5	504.6	504.4	504.3	501.5	383.1	393.5	99.4
317	504.3	504.9	504.1	503.8	503.1	381.5	394.2	98.5
318	504.7	504.2	504.5	505.6	502.5	382.7	394.0	99.1
319	504.7	505.0	504.5	506.4	503.4	385.3	396.9	99.2
320	504.9	500.2	504.8	503.0	500.2	382.0	393.3	98.1
321	505.1	503.0	505.1	503.0	502.8	386.4	397.3	99.1
322	505.4	500.5	505.4	503.0	500.1	380.9	393.6	99
323	505.5	500.4	504.9	507.3	502.4	386.3	393.9	99.6
324	505.5	501.7	504.9	507.9	505.2	394.7	394.2	99.5
325	505.5	501.5	504.9	507.9	506.5	396.7	395.7	99.5
326	506.5	500.1	505.9	508.1	503.4	383.7	395.1	98.7
327	506.7	502.3	505.9	508.4	508.3	393.5	400.7	99.2
328	507.1	503.7	506.3	510.4	507.6	391.7	400.6	99.1
329	507.2	503.6	506.3	510.2	506.4	387.3	397.7	99.2
330	507.1	505.8	506.3	510.8	508.9	392.7	402.1	99.3
331	505.7	503.1	505.4	512.5	502.9	380.5	389.8	97.4
332	506.3	503.2	505.9	512.5	506.1	386.8	397.8	98.1
333	506.3	505.7	506.1	512.5	508.0	389.5	399.9	98.2
334	506.3	504.1	506.1	512.5	505.9	383.5	396.1	98
335	506.5	503.3	506.3	515.0	508.1	391.0	400.8	97.8
336	506.1	504.3	505.9	510.9	509.3	395.1	394.5	98.3
337	506.3	502.2	506.1	510.4	507.8	391.2	394.5	98.3
338	506.3	502.5	506.1	510.6	508.3	392.2	394.1	98.3
339	506.5	502.5	506.3	511.4	509.0	393.6	394.1	98.5
340	506.5	501.7	506.3	512.5	508.5	392.8	393.2	98.2
341	506.6	500.4	506.3	510.8	506.7	387.4	391.8	98.1
342	506.6	500.9	506.3	510.1	507.3	389.4	392.7	98.7
343	505.4	503.3	505.0	510.0	506.1	395.3	378.3	98.5
344	505.5	504.1	505.1	509.7	507.9	390.0	392.4	98
345	506.1	502.5	505.7	508.4	508.5	391.3	395.4	97.6
346	506.5	503.6	506.1	513.1	511.0	396.7	396.0	98
347	506.7	503.4	506.1	512.8	511.2	397.7	396.4	98.7
348	506.7	502.3	506.1	513.8	511.1	398.0	397.7	98.1
349	506.7	503.3	506.1	513.4	510.9	397.3	396.7	97.5
350	506.8	504.9	506.4	511.9	506.1	367.3	366.9	97.7
351	507.9	502.6	507.5	510.8	510.1	393.2	402.3	97
352	508.1	503.2	508.1	515.2	511.4	392.9	397.6	97.7
353	507.8	506.2	508.6	516.5	513.8	387.6	387.8	99.2
354	507.3	504.5	508.1	516.5	510.7	371.4	373.9	98.7
355	491.0	490.9	491.0	516.5	488.7	414.6	371.9	100

356	492.8	494.0	492.8	480.6	481.2	371.9	350.7	99.1
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## Validation Data

Day	COT1	COT2	COT3	EIT1	EIT2	Recycle Flow rate	Feed flow rate	Actual RON(OUTPUT)
1	448.938	448.955	448.9491	490.4338	474.9393	368.8183585	343.0458	95.1
2	452.078	452.0812	452.0984	490.4338	471.1206	351.6391774	337.9783	93.5
3	455.239	454.1152	455.2474	490.4338	474.8959	357.7237487	336.2314	94.6
4	454.617	456.5061	455.7242	490.4338	469.9426	326.5483149	319.7622	94.9
5	459.945	458.2577	457.4794	490.4338	477.3208	338.3246186	328.8809	97.1
6	458.138	456.919	455.6723	490.4338	476.3971	335.6578063	329.2106	96.3
7	459.515	458.8793	457.0467	490.4338	477.4182	335.8560979	328.8311	97.1
8	464.366	463.2626	463.2585	490.4338	482.4453	342.3479635	332.5265	95.6
9	465.033	463.9468	463.9457	490.4338	484.2443	349.4910911	336.7929	95.8
10	465.044	463.9531	463.9531	490.4338	484.6639	348.049478	336.6673	95.9
11	465.979	464.8772	464.8675	490.4338	486.0827	351.4591637	337.4664	96.1
12	467.401	465.783	466.2986	492.4503	489.3901	358.1130081	343.1681	96.9
13	471.302	469.6768	470.1854	497.9099	494.7189	364.258481	348.8631	98.7
14	472.702	469.9495	471.5773	499.7083	497.4117	364.5955334	350.4433	98.7
15	473.199	470.2609	472.0994	499.5211	497.9494	365.4426465	349.8874	99.2
16	472.893	471.0144	471.7777	500.5317	496.6412	368.8740605	353.8526	98.9
17	473.858	472.8527	473.1563	498.5856	498.2986	378.2188429	365.6794	98.9
18	474.545	471.2323	473.812	498.5856	499.7626	377.2381386	364.9434	98.7
19	474.452	471.0998	473.7013	504.8406	499.8981	377.8108882	365.51	98.8
20	475.402	471.2305	474.2402	504.0332	502.2679	376.1300253	362.8702	99.1
21	475.631	473.792	474.4408	504.0332	502.2981	376.5432596	363.2323	99.2
22	476.21	475.3604	475.7487	506.656	502.9218	376.9533399	364.6148	98.3
23	476.801	474.9842	476.4436	506.5562	503.544	378.5526012	365.0096	98.7
24	477.811	473.113	476.6093	507.5234	501.5007	373.6574884	361.0872	98.6
25	478.617	473.1521	477.1316	504.987	501.9238	373.5896467	361.373	98.7
26	477.425	471.4491	479.5291	504.987	499.992	375.1994447	364.1678	96.9
27	481.742	479.5258	481.7645	512.4915	508.9726	380.7135236	364.7595	101.8
28	480.997	474.9064	480.2768	508.8856	507.778	381.8841079	369.6753	100.3
29	480.348	475.4476	477.6694	508.5642	503.8045	376.3597798	361.9245	99.4
30	480.257	474.0473	477.3264	509.3427	504.453	378.9508548	365.5306	98.4
31	477.316	478.3321	477.8171	508.3752	505.5276	384.6057788	371.1308	97.9
32	479.005	481.5971	480.2815	506.5851	509.5954	379.5187271	365.9447	98.7
33	474.298	475.5745	478.7998	512.8628	503.3843	379.7138141	350.5914	96
34	474.495	478.6752	481.2971	511.249	501.7053	381.0828405	347.171	97.1
35	476.384	479.422	482.2826	511.249	504.75	383.6831504	352.7743	97.4
36	478.813	478.6134	482.5029	513.3985	511.3566	383.7902656	369.2423	97.4
37	478.824	479.9353	482.9963	513.6987	509.9621	382.2430209	368.2732	97.6
38	480.989	478.8492	481.7614	514.5992	512.4146	384.0587906	370.6016	97
39	481.003	480.7908	481.7577	515.5751	513.2144	386.0606314	373.9238	96.1
40	475.849	479.346	479.2933	518.503	504.5556	384.4881913	366.5963	92.1
41	499.348	498.4618	498.9344	498.0179	493.5405	390.710921	383.2171	98.2
42	497.651	497.6089	497.2524	497.9875	495.9646	395.7970569	378.4147	99
43	498.261	498.0382	497.4503	498.8359	497.0382	396.8354034	377.2503	98.4



44	499.665	497.7501	498.8622	496.1068	494.1711	389.2011715	382.9008	96.9
45	499.664	497.4142	498.8619	496.2221	492.6999	387.696868	378.6682	96.7
46	499.677	497.6538	498.8664	495.0212	492.6873	387.0636032	376.2717	96.9
47	499.817	496.7917	499.0068	488.964	488.1794	368.1998224	351.7402	97.4
48	499.864	497.2129	499.0652	490.3328	493.2042	387.2958956	378.9896	97
49	499.874	496.2712	499.0644	494.4392	493.6881	385.9965088	373.5902	97.5
50	500.268	495.4215	499.4637	495.4786	491.9164	387.7779136	379.3133	96.9
51	500.303	495.6562	499.3447	495.8953	492.8533	386.6307447	377.0039	97.7
52	500.808	493.9122	499.4125	496.0264	492.1423	387.5924778	377.3831	97
53	499.715	499.8042	498.9106	495.2611	499.6834	399.2485243	383.0213	100.2
54	501.082	494.9342	500.2762	497.8585	493.8853	390.0618069	381.7409	97.6
55	501.093	494.9046	500.2815	497.8585	493.7094	390.3203089	382.4314	97.7
56	501.066	497.8335	500.2945	496.8033	496.316	392.9770584	385.1458	97.7
57	498.729	499.6245	497.9028	501.6558	500.531	400.5516118	385.3406	102.4
58	496.282	495.237	495.4835	499.3067	491.7591	390.8917323	366.1471	98.1
59	495.862	496.7252	495.0431	492.2757	489.5775	393.9642581	365.9256	96.9
60	496.745	496.6357	495.9611	492.3245	491.01	395.1474172	368.0436	97.2
61	498.902	493.3666	498.0997	491.5883	489.43	389.2680483	373.6189	95.4
62	498.688	499.9185	498.6619	494.3568	497.4594	396.7001838	375.7488	100.3
63	498.264	499.1302	498.2582	496.436	496.1993	396.8985123	375.5869	99.2
64	498.275	499.0179	498.2672	495.0235	495.416	395.5045243	377.5216	99.3
65	498.265	497.9059	498.263	495.254	495.1703	394.1343029	378.1108	98.8
66	498.263	499.718	498.2575	494.9891	496.0898	395.7927	376.0425	98.8
67	498.484	500.8935	498.4673	496.4296	498	399.8452326	377.1652	100.4
68	501.039	498.9551	501.0531	496.1331	496.9656	395.5891528	383.5054	98.1
69	502.116	499.8629	502.1013	497.2724	500.9283	402.1726091	381.5312	99.6
70	500.609	498.1595	501.2803	500.7162	502.066	409.600279	387.8052	100.3
71	501.495	498.0485	501.4951	500.7931	499.068	394.9055327	383.0517	99
72	501.483	497.6266	501.4919	499.0185	498.8646	395.2734876	382.5737	99.1
73	502.127	501.2345	502.1026	497.2893	504.5277	406.0980323	382.8038	100.3
74	491.741	489.9797	491.1742	496.8421	468.7512	386.6395529	363.0068	87.8
75	501.074	498.2543	501.8899	496.8421	497.3936	401.5067073	372.3475	97.9
76	501.1	500.2262	501.8827	496.8421	488.9638	374.5463123	333.8319	98.2
77	500.183	498.3695	500.9844	496.8421	493.4165	396.8703499	368.5655	97.2
78	497.938	498.3456	498.551	496.8421	492.6419	397.2697004	375.0985	98
79	503.297	497.7623	503.697	498.6687	494.657	346.9577917	337.4238	98.3
80	489.848	488.6647	490.2521	498.6687	482.2467	371.804509	368.6628	97.2
81	491.603	490.8435	492.8117	498.6687	487.7139	379.1425867	379.2237	98.2
82	491.879	492.4727	493.0818	479.584	487.0574	378.1463628	376.316	98.2
83	493.601	493.1884	494.8153	483.0592	489.7272	378.7951123	380.5606	98.4
84	494.013	493.825	495.2339	487.2755	494.2602	382.2643846	387.4602	99.3
85	493.685	495.1598	494.9231	490.2092	491.9758	381.5075883	382.6944	99.1
86	494.429	494.6015	495.6363	487.696	493.2535	384.6530264	382.6161	98.6
87	495.128	493.9492	496.3498	487.2298	490.1166	379.2508479	367.5515	98
88	499.371	495.1661	500.5648	492.4719	498.9543	384.018278	373.6317	98.8
89	499.41	496.5902	500.6171	492.7987	499.5691	386.0622132	374.4845	99
90	499.434	496.1018	500.576	493.7789	498.2619	384.7717675	375.8361	98.6
91	499.416	495.6613	500.5013	493.8416	497.3623	385.8004814	386.5421	99
92	500.203	495.7917	501.0819	494.1333	498.2084	386.8395697	383.0028	99.6
93	499.83	495.0315	500.4713	494.8737	497.6401	385.964332	386.4877	99
94	500.183	494.7459	500.7853	494.4703	497.7768	385.3390408	383.6412	98.6
95	499.554	491.6306	501.0507	496.7978	496.4585	385.1512186	382.8693	98.6

96	499.3737	496.5552	499.4377	500.1593	496.0616	395.061	379.7184	97.6
97	498.9228	496.5255	498.8942	495.0191	494.8533	393.1635	376.753	98
98	499.2915	497.0512	499.2737	494.9198	494.8061	392.6153	379.7776	97.5
99	498.894	497.5185	498.9039	494.5037	494.6993	391.2523	379.6208	97.3
100	501.6691	502.6171	501.2913	491.8866	493.8879	345.3207	381.3724	99
101	501.6778	499.3925	501.2869	493.9127	497.8753	305.7798	429.2787	98.4
102	502.4296	501.7376	502.7951	498.5646	502.7313	396.446	392.3737	99.6
103	490.129	488.686	489.5793	497.8778	498.2054	392.335	390.5034	97.8
104	502.0902	498.6235	502.0964	497.0737	500.9809	389.5954	388.7423	99.1
105	502.6228	498.1143	503.2152	503.5704	502.415	393.9272	386.7344	99.1
106	504.2874	498.4637	503.9114	504.3951	506.8504	394.1585	393.2399	98.7
107	504.4116	497.4023	504.2623	504.5381	506.5802	393.3978	389.3941	98.4
108	504.8842	498.03	504.9209	504.3011	508.4681	396.1789	390.0281	98.8
109	504.843	499.3506	505.124	510.0133	504.9542	370.7574	354.9762	99.2
110	504.895	500.5424	505.1409	504.6652	504.9838	370.7138	356.4099	98.8
111	504.8929	498.1677	505.1316	509.6323	501.6224	371.5646	351.6664	98.1
112	504.8773	495.9004	505.3491	491.911	497.5977	365.2516	344.1639	98.9
113	505.0293	500.4163	505.3064	491.911	503.423	370.3565	353.1495	97.3
114	504.1639	499.4268	503.8313	490.1173	502.7978	392.3106	389.5307	98.3
115	502.0114	500.0707	501.6872	505.5554	497.9851	388.0145	381.8386	97
116	502.2706	500.1225	501.8978	501.2982	499.6812	390.3676	385.5257	97.1
117	502.1874	501.1538	501.7761	501.4051	501.1039	392.9197	386.8679	97.3
118	502.1845	501.3628	501.387	501.1194	495.5754	368.7508	347.9649	97.8
119	501.1336	501.0118	500.7332	497.3897	498.594	303.4731	429.6841	97.7
120	501.3204	499.2958	500.8807	498.2954	495.2651	357.4087	347.6388	96.3
121	502.6081	498.4733	501.978	499.4186	500.3158	383.3651	388.7728	96.4
122	501.8821	501.0809	501.0868	493.5826	495.6262	388.02	383.1082	98.7
123	501.2304	500.1966	500.3473	496.9731	496.1998	394.6263	372.6793	100.5
124	501.7927	500.989	500.9894	494.5561	492.645	356.2756	359.3945	99.3
125	501.4943	501.0866	501.0843	497.4174	494.7057	357.4874	358.678	99.3
126	502.5255	501.8352	502.1692	496.9023	496.7321	372.7509	374.8552	98.5
127	503.3384	502.0054	503.3042	500.6611	496.9068	377.5728	386.0985	99.3
128	503.433	502.8054	503.4333	501.5612	500.0598	382.2839	394.5143	98.9
129	503.4385	500.23	503.4251	501.0298	495.1926	373.227	381.2535	98.1
130	503.346	497.952	503.7805	498.5821	492.8301	375.532	385.5715	96.7
131	501.2304	500.1966	500.3473	501.8663	497.3712	375.1855	385.332	99
132	501.8984	501.09	501.0876	498.306	498.0409	375.2706	386.4317	96.7
133	501.4895	501.0754	501.0805	498.306	501.7428	382.8067	395.4585	99.5
134	503.3446	502.143	502.8986	505.1817	500.0429	378.9887	390.1031	98.6
135	504.3419	504.3637	504.1305	503.789	503.2539	381.0265	392.8502	99.4
136	504.7179	503.7598	504.517	505.5937	501.7825	378.8226	390.0904	99.2
137	504.719	505.099	504.5204	505.8072	503.3211	384.5371	396.1056	99.1
138	504.6861	500.8285	504.5126	505.5942	499.4131	379.2577	391.1685	98.2
139	504.9168	501.0664	504.9248	503.0336	500.9533	384.3242	394.2049	98.4
140	505.5374	500.4256	505.5259	503.6759	499.2619	379.0862	390.7381	98.9
141	506.104	498.4468	505.7657	506.0368	500.3381	378.9535	392.4636	99.2
142	505.5227	501.8168	504.919	507.9444	505.3188	393.3957	393.2076	99.4
143	505.9366	500.2983	505.3601	507.9444	504.1609	388.0937	394.6213	98.8
144	506.7279	501.7164	505.9304	508.3843	506.2272	387.1801	399.5969	99.5
145	506.9292	504.2667	506.0789	510.9455	507.0391	392.0127	401.3367	98.9
146	507.1217	505.0198	506.3354	510.3856	508.3938	391.5799	400.1718	98.5
147	507.1459	505.3986	506.3353	510.2229	508.2417	390.3766	399.9363	99.3

148	505.9918	505.693	505.5817	512.4689	505.8899	385.5208	397.2626	98.6
149	506.1847	503.2077	505.7673	512.4689	505.741	387.6029	397.8721	97.9
150	506.3656	503.0912	506.0732	512.4689	505.9486	386.0443	397.5536	98
151	502.9079	499.9775	502.1009	495.012	494.7747	408.0518	390.4165	97.5
152	503.2705	501.2011	502.4974	500.477	497.0466	410.8845	393.8628	98.7
153	504.4121	500.0483	502.3034	500.477	494.8124	400.8966	382.9247	98
154	502.6996	499.4592	501.4813	500.1677	492.1119	383.4283	380.6807	99.1
155	503.0249	501.6064	502.2181	499.2399	492.819	384.1714	376.4204	98.7
156	502.902	501.6924	502.078	497.95	497.0659	385.2498	374.0092	99.5
157	502.4847	501.9064	501.6915	497.95	492.338	378.0471	365.7768	99.4
158	502.7166	501.2232	502.1726	497.95	492.8091	381.1262	370.343	99.7
159	503.0657	501.2217	502.6497	498.1568	492.2743	381.2619	369.4407	98.8
160	502.9935	502.9914	502.5969	498.7772	495.936	385.4519	377.0774	98.7
161	503.1031	502.085	502.6931	498.7772	496.0551	389.8912	383.4563	99.5
162	503.105	501.9277	502.6975	497.5872	493.4108	384.3035	374.0972	98.9
163	503.1097	503.283	502.7013	499.5526	494.9092	384.4799	373.8563	100.1
164	503.2629	501.7448	502.8578	498.6509	493.3136	379.493	373.3225	99.5
165	503.3173	500.7717	502.9011	498.6509	493.9404	382.6775	375.7366	98.5
166	497.1513	495.1741	497.1573	483.0382	482.5445	378.2206	353.6454	97
167	498.8512	500.9028	497.6515	490.4391	486.0569	395.5047	354.2006	98.3
168	498.7497	499.1666	497.942	489.948	487.134	410.2314	364.2524	100.3
169	498.4546	499.3734	497.6537	490.1663	488.8805	412.7542	369.5608	97.3
170	498.4414	498.8365	497.599	490.821	493.8351	420.8058	377.5682	99.2
171	497.3569	497.573	496.5655	490.821	491.5597	421.7764	379.142	99.2
172	499.6835	500.5395	498.8749	491.4074	488.1749	396.4307	374.3644	98.6
173	500.324	501.0361	499.5466	493.1014	493.6691	410.9317	389.6244	96.9
174	500.838	498.9948	500.0648	493.439	491.2986	402.146	381.5294	98.5
175	502.1376	500.2421	500.4814	495.0366	496.0736	411.5217	390.8843	98.1
176	502.7593	498.9036	501.1864	498.38	496.4953	412.037	395.0848	97.7
177	505.4489	502.9012	505.0707	509.654	507.3296	397.0589	384.6482	97.7
178	505.5051	502.3776	505.1182	509.33	506.4305	385.5967	392.7289	97.2
179	506.374	502.3812	505.9724	509.5473	509.589	396.1299	395.2267	97.9
180	506.838	503.0353	506.0726	513.1155	511.1609	397.3233	396.5178	98.4
181	506.7336	503.5605	506.1315	512.7642	511.1428	396.7048	395.7083	98.4
182	506.7344	502.0729	506.1328	513.8435	510.8925	397.8272	397.6655	97.9
183	507.1745	503.0613	506.6146	512.267	510.5894	394.5193	398.429	97.8
184	507.0403	504.2315	506.6754	510.8063	505.4003	366.8198	365.473	97.1
185	508.1151	502.5441	507.6866	511.913	511.3174	396.7649	403.8415	97.5
186	508.0212	504.473	508.8333	515.5511	513.8039	402.7513	400.804	98.6
187	506.3181	504.0169	506.128	512.4689	505.4625	381.6828	395.6228	98
188	506.3194	502.2248	506.1007	513.1098	505.8712	386.1103	396.2743	97.4
189	506.5269	503.2015	506.3035	513.9933	507.7616	387.6977	399.6166	98
190	506.1015	503.5717	505.9243	510.8752	508.5809	393.9272	393.6119	97.7
191	506.3334	502.3821	506.1313	510.4291	508.0243	391.6021	393.8896	98.4
192	506.3184	501.2134	506.1352	511.0553	507.1777	390.8924	392.0427	97.8
193	506.5332	502.13	506.3332	512.5125	508.3708	392.1077	393.1371	98.3
194	506.5127	501.8045	506.3317	510.7675	508.1892	391.4393	393.863	97.5
195	506.5147	500.7295	506.332	510.5911	506.9571	388.8192	391.5114	98.2
196	506.1293	501.6361	505.695	510.0619	506.4193	388.0182	388.9363	99
197	501.4943	501.0866	501.0843	498.306	499.9811	379.7826	391.654	98.5
198	504.5668	501.0723	505.2932	499.3358	498.8916	375.2361	385.3018	98.4
199	505.1259	502.509	505.5095	504.2966	501.4681	378.4048	387.9174	100

200	504.8184	504.2411	504.8032	504.2966	500.9057	379.4588	390.4676	100.1
201	504.3647	504.2131	504.1653	504.1697	502.9952	380.7409	393.1959	99.1
202	504.643	503.1615	504.4499	504.2401	500.4968	375.7063	385.8711	98.6
203	504.719	504.6451	504.5179	505.5937	503.047	384.4824	396.053	98.9
204	504.7047	503.3869	504.5176	506.4477	501.9053	382.9339	394.734	98.6
205	504.9245	500.7901	504.9174	503.0336	500.4542	381.4082	392.3776	98.85
206	504.1955	499.6973	503.3991	490.1173	503.8668	394.0501	391.0552	97.9
207	502.3169	500.5195	501.8763	505.5554	499.3615	389.9766	384.5152	96.9
208	502.1502	499.934	501.6874	505.5554	498.1789	389.0708	383.4613	96.7
209	501.1856	497.3541	501.8278	498.2942	493.1992	365.1199	361.1772	95.8
210	501.1671	497.3992	501.6897	502.7919	495.2326	376.8706	382.3588	96.1
211	504.6121	502.6739	502.6013	500.7379	510.2583	394.7932	402.813	99.9
212	484.042	479.8755	483.4293	506.0841	466.2401	321.2723	361.0162	98.5
213	492.2295	489.9459	492.2545	478.6041	480.1127	352.9493	343.6034	98.2
214	490.0722	487.5803	493.4573	472.0554	471.7157	353.5109	334.4291	95
215	491.3489	488.4943	493.8219	472.8471	474.258	363.1308	339.2646	95.8
216	493.004	491.5883	494.1994	476.6325	478.1842	368.0919	344.553	97.3
217	497.7516	492.0024	496.123	480.8634	482.4866	365.5144	356.0071	96.8
218	497.5007	495.924	496.7035	481.9811	484.2041	368.5041	357.4263	97.7
219	501.8421	498.4152	501.6983	499.9908	495.9188	345.9	374.6184	98.6
220	501.5493	497.1006	502.2199	497.3015	499.9334	371.1811	352.1228	96.6
221	502.4798	497.0876	501.6286	501.5026	500.0317	372.1892	353.0418	98.3
222	501.2858	496.8798	500.8711	499.0231	493.0268	362.5615	343.6539	96.7
223	502.2268	497.1436	501.7652	500.1911	502.6204	373.1925	355.1538	97.2
224	500.9755	500.1929	501.0568	495.8173	498.3804	388.2586	388.5062	99.4
225	502.89	498.9539	503.3076	503.511	503.9506	397.7373	395.5984	99.7
226	502.6994	497.6365	503.2022	503.5089	503.2064	390.336	385.6662	98.5
227	502.5708	499.8107	502.9859	503.1825	503.3445	394.922	393.9362	99.1
228	502.0232	496.7437	502.8901	502.2232	501.7644	390.4648	389.3935	96.9
229	503.531	499.6288	503.7072	502.2232	507.9387	396.2684	388.2637	99
230	498.4202	494.1378	502.5997	492.1602	491.0351	382.8034	369.9998	96.4
231	499.8162	494.2611	504.123	495.5688	494.6273	386.5154	376.0953	97.9
232	501.3874	494.4199	504.5004	496.4705	499.1579	389.5248	381.7337	97.2
233	500.4784	495.1172	504.7206	498.1946	495.3429	387.5946	377.1673	97.1
234	502.3867	498.6699	502.2611	495.2514	507.0636	403.5962	388.5795	99.3
235	500.5742	499.0865	500.5736	502.6588	503.5303	403.5538	389.4776	99.4
236	500.481	499.7622	500.4799	501.1765	503.9884	403.1333	389.2816	99.4
237	500.085	501.5663	500.0749	502.9421	504.7807	406.9633	390.6992	100
238	499.1213	499.3035	499.1299	500.1593	499.7065	401.3484	384.0722	98.8
239	499.4659	495.9931	500.8932	499.7933	502.4867	399.1975	388.3788	100.4
240	498.8501	493.445	500.5006	497.507	495.9552	387.1522	376.3822	97.8
241	500.1348	493.64	499.734	492.2949	494.8788	385.8389	376.9384	99.3
242	499.5976	492.8454	503.2941	497.5	493.5939	387.6558	379.2302	99.1
243	501.7251	496.482	503.3022	497.5	503.032	395.7154	389.2441	100
244	501.9454	496.0548	503.4361	500.3643	502.3996	393.0255	385.8555	99.6
245	501.9882	495.0121	503.8388	499.0754	500.4772	389.9385	381.8861	99
246	502.0424	494.6262	504.2293	499.3809	500.0116	387.2074	380.5795	98.9
247	489.9119	487.0482	490.33	498.6687	482.7666	373.8803	367.8461	98.3
248	491.6282	490.8963	492.8011	498.6687	488.5012	382.8652	383.6642	98.9
249	491.6015	492.0933	492.8125	479.584	487.1973	378.3243	377.5491	98
250	493.1102	493.5667	494.3254	480.4528	489.0098	378.2305	380.2676	98.2
251	494.4324	493.8721	495.635	484.1133	493.448	385.3383	376.3707	98.3

252	499.5215	500.0813	499.5269	493.3607	495.4161	395.8113	382.6332	98.2
253	498.4549	499.133	498.4593	496.049	496.059	400.0426	377.4374	99.9
254	498.1923	498.2574	498.1916	496.049	494.6687	397.6845	376.3153	98.8
255	498.2562	497.6964	498.2581	495.4527	493.9386	392.6853	376.8911	99.1
256	498.5831	497.9846	498.5888	493.6637	494.8936	393.1377	375.9859	99.4
257	498.2417	498.536	498.2554	495.0235	495.2817	395.4054	376.4796	99.3
258	498.257	499.5266	498.2587	495.0811	496.4098	395.8506	375.6511	99.2
259	498.2601	498.7264	498.26	495.1878	495.5625	393.2272	378.1078	99.1
260	498.4254	498.76	498.4166	494.9891	496.0344	396.8014	375.5886	99.3
261	498.6624	498.9276	499.1028	496.4296	495.5786	394.6454	374.7143	96.9
262	499.8166	495.452	499.0092	494.3046	492.9036	386.4134	378.9446	96.9
263	499.7982	495.5922	499.0466	493.6207	492.1387	387.6813	378.5068	97.5
264	499.8677	495.8106	499.0787	493.9989	490.0111	385.3788	372.5913	96.4
265	500.2952	493.9696	499.4778	495.4786	490.7161	385.9059	375.819	96.7
266	500.2475	494.6551	499.0531	495.8953	490.4667	382.6991	370.8331	96.8
267	500.2894	495.0294	499.45	496.0264	491.9581	387.1858	377.1774	97
268	500.684	496.023	499.8466	495.8351	494.463	389.5933	380.5038	100
269	501.0897	494.9262	500.2791	495.9105	493.8764	389.761	382.354	97.4
270	501.0797	495.8731	500.2661	497.5947	494.3034	389.4726	382.8566	97.5
271	500.634	496.6177	499.7862	498.0164	496.548	394.265	384.3426	100.6
272	496.9817	495.3325	496.1643	501.6558	493.2542	390.8739	376.5126	99.5
273	495.3224	493.4205	494.5234	492.2594	487.7395	391.7007	360.4247	96.9
274	496.3616	496.4675	495.5297	492.3245	489.9837	392.0692	366.0839	96.7
275	502.0889	497.2905	501.6947	497.5415	498.1895	400.094	389.8036	98.6
276	500.9677	498.6614	500.5463	498.028	498.2438	396.7951	389.7809	100.5
277	497.7463	497.762	497.3455	497.9875	496.5921	397.1881	380.5739	98.4
278	497.8432	498.3235	497.2621	498.8359	497.5524	398.8568	384.2981	98.5
279	499.5627	497.4271	498.7524	496.1068	493.8735	388.304	381.7545	97
280	499.6783	497.7521	498.8695	496.1356	493.4809	388.5309	381.5575	97
281	499.6666	497.5325	498.865	495.9219	492.6325	387.1943	376.521	96.7
282	499.67	497.2638	498.8636	495.0212	492.0935	382.9597	370.7742	96.8
283	499.8878	497.1914	499.0688	488.964	493.2877	387.3268	378.5309	97.3
284	499.8582	495.579	499.0667	494.4392	493.2969	386.1448	375.326	97.4
285	499.8777	497.5876	499.0664	494.5325	494.5427	388.5773	381.2163	97.4
286	499.8678	496.5173	499.0652	494.5325	492.8021	386.9478	377.4505	97.4
287	499.734	496.4758	498.924	494.5325	493.4813	387.8555	380.6652	97
288	476.2509	477.9777	477.3319	508.9719	502.9587	380.5589	365.9558	98.2
289	479.3583	481.2956	479.2675	506.5851	509.5429	379.6723	365.8839	99.6
290	478.3374	479.0443	479.093	513.4007	508.965	381.9984	367.5491	95
291	472.6265	477.6169	479.8251	511.249	501.1573	377.0737	346.0851	94.6
292	475.864	478.481	481.7619	511.249	503.7476	382.5301	351.5989	97.6
293	478.0618	479.1569	483.1509	511.7864	511.1196	384.3155	368.8954	97.9
294	478.9781	479.2234	482.4934	513.3985	511.0649	383.4691	369.6127	97.4
295	478.0164	477.3657	480.7633	514.5992	508.4199	383.0683	369.8198	97.1
296	481.1108	479.2292	481.7864	514.5992	512.6324	385.075	372.1156	96.4
297	479.4338	480.1568	482.1695	518.503	510.4795	387.9458	371.0405	90.4
298	476.2145	474.7785	475.8749	506.656	503.5595	378.2978	364.4644	98
299	476.4647	475.1257	476.1073	506.6311	502.7169	376.6664	363.0899	98.5
300	477.2168	475.4939	476.8468	507.0094	503.9128	378.6966	365.2965	98.8
301	477.9929	477.4172	476.524	508.3689	505.1252	379.5887	366.7282	99.6
302	480.8306	476.3957	479.5281	504.987	508.9709	390.6284	376.3945	98.8
303	481.8055	479.155	481.7769	506.8631	508.6578	379.8805	364.205	101.5

304	481.2948	477.443	480.7799	511.59	506.5893	377.7691	363.2069	101.1
305	481.0456	475.78	480.2754	508.8856	507.636	380.9898	367.0496	100.2
306	480.9706	477.0519	477.3127	508.5642	505.4043	379.0446	364.1309	100.1
307	480.8692	475.8802	477.3298	509.3427	506.883	383.4524	370.4394	99.2
308	476.4956	478.8715	477.3068	508.9719	503.5385	381.8971	369.0556	96.3
309	466.58	464.9595	465.469	491.3562	487.6325	354.6834	340.1509	96.1
310	466.8157	465.2022	465.711	492.2381	487.8925	356.0523	341.4922	96.7
311	468.8484	467.2332	467.7519	492.4503	492.062	361.5976	346.5115	97.5
312	471.3841	469.7829	470.2968	497.9099	495.0567	363.8042	348.9725	98.5
313	473.3538	470.3005	472.2568	499.7083	498.059	366.4204	352.1442	99.2
314	473.555	470.5993	472.4421	498.9594	497.6127	365.6216	350.821	99.3
315	472.6533	470.6236	471.5612	499.4614	495.1143	365.93	353.0558	98.7
316	472.9668	470.7101	471.8385	500.5263	496.1565	368.621	353.8518	98.6
317	473.0832	471.8775	471.9958	500.7703	497.0229	370.1684	355.1291	98.9
318	469.8151	471.0133	468.6976	501.5512	491.941	363.8634	351.66	96.8
319	466.5442	464.7353	465.4406	491.0859	487.12	353.2211	338.9159	96.2
320	466.7929	465.1688	465.68	491.0859	487.6294	354.3774	340.6908	96.3
321	507.4462	504.9359	508.2601	516.5048	511.6263	373.5217	375.5861	99.1
322	455.8823	449.7375	459.3175	516.5048	367.2967	301.8833	283.107	89.6
323	492.4179	492.3102	492.553	516.5048	485.0028	408.491	350.5107	97.3
324	492.7467	493.8664	492.803	480.5594	477.9687	363.2345	347.3981	95.8
325	493.7609	494.2627	493.7652	480.7027	482.2873	371.3632	351.8139	96.9
326	496.4415	494.8829	496.4411	483.0382	481.17	379.6402	349.1742	95.7
327	503.4909	499.8744	503.5115	501.0298	495.5435	374.755	385.2823	98.8
328	503.9712	503.2855	503.9212	501.8663	498.5772	376.5736	386.9943	98.9
329	501.1376	500.3546	500.3618	500.9763	497.5638	375.9033	387.5261	97.8
330	505.5125	500.2204	505.5281	505.6031	499.4136	378.9665	390.9096	97.9
331	505.8974	500.2893	505.1396	507.3378	502.7218	384.5274	393.9107	99.5
332	505.5532	501.3381	504.9175	507.4895	503.3039	389.0153	393.0354	99.4
333	506.6761	503.0798	505.9518	508.3843	509.9924	397.965	397.2819	99.2
334	500.2692	498.2934	499.0615	489.9486	488.8936	377.4272	364.1615	97.6
335	500.3269	497.9881	499.0677	489.7134	488.9338	377.6797	363.5949	98.5
336	498.602	500.2292	497.383	494.6811	489.9612	408.4161	317.2697	98
337	498.2063	497.3909	496.9864	488.8704	484.6758	414.3985	280.1446	98.8
338	497.8467	497.0465	496.6411	485.6109	481.0852	406.1841	274.2178	98.8
339	497.8588	497.0525	496.647	487.1543	488.9468	421.3867	293.6043	99.3
340	497.6977	496.8921	496.5185	490.2901	484.8793	393.153	299.1299	97.1
341	499.4754	499.067	498.6615	486.9554	487.1151	298.9943	415.0289	98.8
342	499.4702	499.0686	498.6629	492.1839	486.8525	298.1509	414.4425	98.7
343	499.9902	499.5815	499.2076	492.1839	485.8495	316.0045	375.9835	98.2
344	494.9558	494.9018	495.336	481.2866	479.2016	377.3618	350.5029	98.1
345	498.9392	499.7581	497.6645	484.8884	484.5353	379.8018	354.4765	96.3
346	498.5572	498.0758	497.6824	490.3163	487.3071	407.8859	365.6462	96.6
347	498.4576	499.3638	497.6568	489.948	488.5178	412.0039	368.3644	98.1
348	498.7404	499.4781	497.9125	490.821	490.0145	415.5573	373.2493	97.6
349	497.6481	499.9873	496.8407	490.821	493.897	421.2771	382.8651	98.8
350	497.7624	497.9282	496.949	490.821	487.8077	412.4754	373.8518	98.4
351	500.1426	497.9796	499.2727	493.1663	488.701	398.3882	376.7697	99.5
352	501.0588	500.3928	500.2354	492.9065	494.7708	411.5263	391.3691	101
353	501.6998	496.9912	500.4356	495.0366	492.5314	405.9002	385.5297	98.6
354	502.5304	500.4113	500.8875	498.38	498.5224	412.8105	394.4573	98
355	502.5358	499.1928	501.5578	494.418	494.3298	405.7587	385.0677	98.1

356	502.5279	501.9507	501.7982	494.418	492.3509	393.7575	377.2725	98.4
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raining data

Day	COT1	COT2	COT3	EIT1	EIT2	Recycle Flow rate	Feed flow rate	Actual RON(OUTPUT)
1	448.7189	448.7206	448.7254	490.4338	476.0344	369.0339	342.0698	96
2	451.2232	451.2478	451.2651	490.4338	470.9588	350.4498	341.3116	93.6
3	454.4965	453.5165	454.4539	490.4338	473.4031	355.0179	333.6188	94.1
4	455.2512	454.0961	455.225	490.4338	474.8091	357.9598	335.8018	94.8
5	456.302	454.5969	456.292	490.4338	475.3227	356.9874	335.4065	94.6
6	453.5358	453.5446	453.552	490.4338	473.1251	358.7642	337.1928	95
7	453.0222	454.7725	454.1321	490.4338	474.2717	359.4681	338.0001	95
8	454.9005	456.7864	456.0108	490.4338	470.039	326.0937	319.9277	94.5
9	457.7591	458.5605	457.7842	490.4338	474.8475	335.0023	324.655	95.9
10	459.6543	457.9656	457.19	490.4338	477.4945	338.0635	329.5074	96.5
11	460.2991	458.6177	457.8357	490.4338	478.5722	338.9104	330.736	96.8
12	458.6955	457.011	456.2316	490.4338	477.4897	338.6995	331.2563	96.8
13	457.74	456.9877	455.2812	490.4338	475.3105	331.3694	326.3171	95.5
14	458.631	458.0017	456.1762	490.4338	476.5226	334.0982	327.413	97
15	460.2174	459.479	459.1072	490.4338	478.7735	339.0269	329.0836	97.8
16	461.6255	460.8833	460.5125	490.4338	479.3356	334.78	327.8861	96.8
17	460.9308	460.1842	459.8112	490.4338	479.1016	332.7617	329.0067	95.8
18	463.4739	462.3618	462.3643	490.4338	480.3702	339.4099	329.5389	95.6
19	464.5691	463.4651	463.4647	490.4338	481.9798	340.6708	332.4181	96.3
20	464.7083	463.632	463.6359	490.4338	483.8131	347.9344	336.255	95.9
21	465.2298	464.1037	464.1042	490.4338	484.7393	348.7102	336.2628	96.1
22	465.5244	464.4013	464.4044	490.4338	485.3837	350.9022	338.4239	96.2
23	465.744	464.6428	464.6316	490.4338	485.6338	351.3823	337.7434	95.6
24	469.345	471.0177	468.2276	501.5512	490.9619	363.0381	350.5636	97
25	467.4317	471.1519	466.3215	501.5512	488.2435	361.2217	349.0813	95.6
26	470.2728	471.8019	471.0126	497.9718	493.0445	367.4687	356.49	97.8
27	473.2617	473.9971	472.5094	498.5856	497.8875	377.2898	365.2106	99
28	475.0026	470.7513	473.7997	504.0332	500.5685	376.7084	363.6515	98.9
29	475.5831	473.1471	474.3766	504.0332	502.4749	375.823	363.723	100.1
30	476.1709	473.0562	475.0114	504.0332	501.8668	378.6932	363.9861	99.3
31	475.8138	473.7819	474.6169	504.0332	501.7294	375.5594	363.6354	99.3
32	476.3246	473.3911	475.1636	504.0332	502.1762	378.663	363.5848	99
33	475.7391	475.3648	474.5727	505.3334	502.4616	375.9565	363.4486	99.1
34	475.6591	476.0349	474.5261	505.3334	504.279	380.0165	367.1708	99.4
35	478.4002	479.3024	481.0445	518.503	508.3426	387.806	370.7941	93.4
36	479.7757	480.4444	481.0233	515.6767	508.7667	392.6664	374.915	93.3
37	478.0889	479.4305	481.3592	515.7158	507.1121	386.4142	370.1202	90.4
38	483.8246	483.935	483.836	515.7158	464.6269	340.1173	321.3438	91.1
39	492.6407	493.0682	492.6535	479.4195	482.6542	352.1645	337.207	95.8
40	492.9297	491.7177	492.9066	479.4195	480.2141	350.0397	335.6594	95.1
41	493.0733	492.9951	493.0854	479.5508	479.5245	351.5548	348.3509	94.4
42	494.577	494.1821	494.5671	479.9448	483.9976	369.8282	366.9612	93.3
43	496.1382	493.9783	496.14	485.5623	486.4663	375.8306	375.141	94.6



44	496.9627	497.3838	496.9572	488.6724	493.8085	393.3676	389.3127	98.2
45	497.6586	499.0759	497.6551	497.0778	497.2523	401.3942	393.0142	100
46	497.2633	496.8771	497.2507	497.3558	495.2365	398.6716	386.4034	97.9
47	502.0505	496.7653	501.6447	497.3794	496.8552	398.1718	391.6292	98
48	500.428	494.5648	499.6618	492.7601	494.5815	395.3385	380.2903	95.4
49	502.5871	494.9704	501.6886	496.2756	495.8743	391.865	379.7586	97
50	500.6631	494.9278	501.4819	495.1594	490.7561	383.1258	370.9499	96.6
51	500.4889	497.3682	500.4954	495.1594	491.7733	383.512	373.3155	96.8
52	500.6245	498.3147	500.6212	493.2414	492.9252	384.1442	373.2157	97
53	501.0183	497.0275	501.0287	493.4436	491.8736	381.8685	371.0802	97.1
54	501.0074	498.388	501.0035	493.7101	494.6278	391.9367	378.2109	98
55	500.3769	498.3207	500.3589	494.2222	494.0381	393.5009	379.4425	98.9
56	499.4811	500.5031	499.468	493.3607	495.6005	395.682	381.8279	98.7
57	499.1208	499.2283	499.1287	493.2575	493.4317	394.4018	379.9356	98
58	499.6752	499.7217	499.6717	492.9478	495.8007	397.2952	383.7259	98.9
59	498.4536	498.3928	498.4554	497.3732	494.3778	396.4266	380.5326	99
60	501.9865	498.0524	501.9948	496.1331	497.3727	395.2166	382.8991	98.5
61	500.465	499.2156	500.4651	500.6905	502.5132	404.4487	382.2721	101
62	501.2322	496.7435	501.2316	500.7931	498.5096	401.0413	379.4374	99.2
63	501.4967	497.9984	501.4921	499.0185	499.1833	394.1862	382.125	99.2
64	502.0203	498.5359	501.9899	497.2893	500.0732	397.2633	380.4639	99.3
65	501.3763	498.7031	501.4093	497.1775	501.6895	397.8989	378.2568	98.8
66	501.0794	498.1875	501.9065	496.8421	498.1795	403.0203	373.407	98.4
67	500.8952	496.8593	501.6781	496.8421	492.5418	389.7978	358.6582	97.8
68	500.2783	498.5865	501.0849	496.8421	493.5405	400.4865	372.9729	97.7
69	497.8906	496.5526	498.8159	496.8421	491.3103	396.7296	374.0536	98.3
70	502.8757	498.487	503.3272	498.6687	499.8491	399.0936	385.6275	98.8
71	494.4135	494.909	495.6067	487.2755	494.7498	386.1736	382.6603	99.2
72	494.0855	494.8317	495.2417	488.009	494.0133	385.118	386.8132	99.5
73	494.3119	494.2125	495.5192	486.1305	492.6193	383.907	380.3098	98.8
74	494.4155	493.1736	495.632	487.696	490.3993	378.9033	374.1591	98.5
75	496.7148	495.3177	497.9509	485.8312	491.6032	380.6095	370.4767	98.5
76	499.7774	495.3271	500.9755	492.4719	499.1619	384.6705	374.9219	99.3
77	499.6141	495.7387	500.6388	493.8416	497.0802	385.494	381.1629	98.3
78	499.8758	495.9915	500.6596	495.0081	497.8883	386.8137	385.2871	98.8
79	499.8824	494.5694	500.4877	494.4703	495.896	384.3463	386.496	98.6
80	492.9563	488.4325	493.9514	497.2608	479.2044	384.0009	380.0837	98.1
81	500.4883	494.7786	502.3338	495.4087	503.0638	394.0413	388.8921	99.9
82	500.8024	497.6303	503.1448	501.5853	503.2557	387.2114	375.3043	99.4
83	499.7758	496.2842	501.3608	499.9763	502.9541	397.7732	389.0719	99.7
84	501.6471	495.1719	503.8924	499.1517	498.5055	388.2069	378.8916	98.8
85	500.9151	493.539	501.3042	500.9102	503.7784	405.8893	380.4676	99.8
86	500.0166	495.9355	500.4432	504.0236	503.3673	410.13	378.5031	99.7
87	500.2171	496.268	500.2234	502.0506	497.5286	363.1214	345.1004	99.7
88	498.8602	496.263	498.8624	495.4736	493.9415	303.0819	417.3486	99.1
89	498.8627	497.0167	498.8683	493.4997	492.0811	299.4212	412.8496	99.1
90	499.3661	495.4681	499.2319	493.4997	494.3183	317.1903	404.9879	98.7
91	500.7036	494.2835	502.8931	494.5219	496.4741	397.037	371.6747	97.6
92	500.0018	493.9262	502.4982	496.7765	493.7208	393.388	367.4049	97
93	499.215	491.7666	499.9096	494.3403	496.1495	393.5227	380.3705	98.2
94	499.8657	493.0137	500.2958	494.3403	496.1256	390.6193	380.7337	97
95	499.4933	500.8037	499.4974	502.9421	502.5444	404.6809	387.7576	99.4

96	500.512	496.955	502.4962	495.4087	505.4042	395.5128551	393.0238	99.9
97	501.621	495.4812	503.8968	501.5853	504.5469	396.6045717	382.5691	100
98	499.304	495.7953	500.7259	499.2444	501.407	397.6133496	386.3149	99.5
99	500.022	493.403	501.7666	492.2949	496.9838	385.1865164	377.8094	98.8
100	499.862	492.8448	501.1617	493.5962	493.4918	389.1684709	380.7987	98.2
101	500.79	494.2319	503.2931	497.5	497.1195	391.0592606	381.6708	98.8
102	501.855	495.7404	503.5286	497.5	502.2966	393.435874	384.8441	99.5
103	501.522	496.1581	503.0636	500.3643	500.8393	392.0021686	386.0586	99.6
104	501.426	494.6115	503.9011	499.0754	498.0375	388.040614	379.9391	99.2
105	501.559	493.9939	504.1526	499.3809	498.2653	386.5008545	380.9268	98.5
106	501.386	492.6306	502.7687	499.3809	500.6186	389.8552257	382.1943	99.2
107	501.449	493.4589	501.799	499.3809	504.7158	401.7940064	383.2889	100.8
108	501.349	498.9238	501.7315	500.9102	508.7626	415.5405712	388.7473	101.1
109	500.371	494.1235	500.5861	504.0236	500.2944	395.4137126	367.5015	99.9
110	499.524	497.7599	499.4971	496.1316	498.4516	322.9933159	402.9182	99.6
111	498.857	495.6029	498.8643	493.4997	491.7463	299.1148016	412.5513	98.6
112	498.459	490.5326	501.4384	493.4997	487.0721	374.6357214	351.5246	97.5
113	499.751	493.8569	502.9085	497.5886	493.4669	392.5658406	365.0992	96.5
114	500.84	494.4703	502.6102	497.5886	496.2695	396.1288438	368.0779	97.7
115	501.929	495.0341	501.7643	494.3403	501.081	400.0611122	381.7466	98.2
116	501.094	493.8047	500.6037	494.3403	500.7551	395.9577381	383.9812	99.6
117	498.69	494.5373	503.5233	492.1602	491.8437	383.4535407	372.5053	97.3
118	501.351	494.4697	504.1131	495.5688	499.2008	389.7958745	380.6739	97.2
119	501.899	495.342	504.7082	499.1756	500.8239	390.6837958	383.9521	97.5
120	500.352	495.1577	504.7186	495.2514	495.1116	387.9027545	377.726	97.1
121	501.688	498.6235	501.6924	497.1033	504.8118	400.5743394	386.1877	99
122	500.478	499.3011	500.4797	502.2882	503.5855	403.3278368	389.1305	99.2
123	500.474	500.2676	500.4785	501.1765	503.9728	403.1167008	388.5531	99.4
124	499.262	500.1495	499.2657	502.2464	501.5162	403.5705671	386.3108	99.4
125	500.144	495.6406	500.1412	498.8735	495.7341	391.4382402	380.9555	97.4
126	499.863	494.2312	499.9237	495.0163	494.8908	390.3880807	380.0738	96.9
127	499.264	494.5644	499.2684	495.0191	493.3796	389.0101111	377.1721	96.9
128	499.263	497.6408	499.265	494.6222	495.1524	390.9873287	379.9762	97.5
129	501.739	501.5315	501.2872	494.1214	490.7098	423.9905814	292.9694	99.1
130	501.567	500.1921	501.1928	491.8866	494.1465	302.0975486	424.0202	98.9
131	502.369	500.8758	501.9657	497.3015	498.6742	369.9276665	349.5401	99.6
132	501.44	495.6113	502.3077	498.3518	500.884	373.1335283	353.5573	96.7
133	501.795	497.6094	500.9807	501.5026	499.2419	367.555713	355.7516	97.8
134	501.947	496.3238	501.4285	499.0231	498.9779	368.2419757	350.5189	96.8
135	502.279	497.0196	501.8891	503.6951	499.12	386.1523571	379.3027	96.6
136	503.232	499.2294	502.805	502.4125	498.1862	392.4378418	390.172	97.9
137	333.085	332.1151	335.35	498.5646	500.3662	395.3350409	393.0112	96.3
138	501.642	497.3854	502.4319	503.5901	500.2633	396.6500498	388.4311	97.8
139	502.593	498.6468	502.9993	503.511	502.5897	395.0465745	392.7933	98.7
140	503.143	497.6209	503.5586	503.5023	504.8652	392.2178303	390.5151	99.9
141	502.284	497.4161	502.8963	502.2232	500.3688	388.1330368	386.8159	98.6
142	503.371	500.4325	503.2814	502.2232	508.3145	397.4642835	393.0655	99.6
143	503.147	499.887	503.707	502.7477	505.926	394.059597	393.9594	98.4
144	503.087	499.2274	503.914	504.321	504.5017	394.7453018	395.6502	97.9
145	504.352	498.2225	503.9126	504.6171	506.7123	393.9807149	391.9021	98.5
146	504.761	496.5464	504.788	504.3011	506.6844	393.9664905	391.2801	98.7
147	504.95	497.9695	504.9277	505.7292	510.7025	399.0189102	388.6483	98.6

148	504.865	500.9717	505.121	508.6763	506.5955	372.5163574	357.296	99.2
149	504.941	499.8359	505.1367	504.6652	505.3839	371.819226	356.9589	98.9
150	504.963	497.5212	505.1419	509.6323	501.2374	370.1711013	351.9935	98
151	505.399	498.0239	505.324	491.911	501.599	370.2485099	349.3315	99.1
152	489.934	489.2294	491.0301	491.4626	435.597	343.6003302	334.3745	93.4
153	503.877	499.8792	503.1576	493.9768	503.1809	392.8426534	389.3151	98
154	501.634	499.4389	501.695	505.5554	496.1476	387.6564789	380.1619	97.4
155	502.09	500.6185	501.6947	504.4911	498.7338	389.2393956	383.2709	96.7
156	502.148	499.7004	501.8853	501.3249	498.8543	389.8118645	384.7251	96.8
157	502.08	501.1429	501.6942	501.4051	501.7572	393.9699596	387.5237	97.4
158	502.092	501.2073	501.692	501.1194	499.4083	391.2124594	384.8876	97.3
159	500.522	499.53	500.4114	500.187	489.7625	365.0106989	354.2679	97.6
160	501.541	501.0298	501.1234	497.3897	499.6373	304.4040609	431.6379	97.8
161	500.916	499.7505	500.5268	497.6162	496.9399	301.2371772	426.1191	98.1
162	501.312	499.3354	500.8908	498.2958	494.2504	356.3861744	345.0718	96.6
163	501.935	498.197	501.9549	502.2784	497.7051	380.4327438	386.257	96.3
164	503.405	504.495	501.9703	500.7379	508.8873	390.9321288	404.2452	100.3
165	492.45	489.1035	492.8022	478.6041	480.3828	360.371772	350.8487	97.2
166	490.505	487.926	493.7936	472.0554	472.3447	358.4157916	336.7204	95.5
167	491.378	488.2141	493.8107	475.2222	473.6661	362.2789035	338.1946	96
168	495.723	495.1109	495.6925	480.8634	485.0326	371.8621501	360.1511	98.3
169	493.961	489.9055	495.5589	480.8634	475.5312	365.0510036	349.5454	97
170	497.318	495.3701	496.5181	485.3341	482.608	365.4903402	353.7504	97.3
171	497.253	495.2915	496.0383	485.4288	484.8748	367.1389389	353.472	97.5
172	496.846	494.9955	495.6342	485.4394	484.7732	367.9479217	353.4839	96.5
173	497.552	496.2803	496.3422	484.6192	483.2129	365.4730765	352.766	96.7
174	498.309	496.0321	497.1214	486.0444	482.6822	364.3347271	350.7343	96.7
175	498.877	497.9132	497.6597	486.2114	484.8359	366.8863216	355.1959	97.4
176	498.897	499.4673	497.6522	487.9318	488.5837	371.1933985	359.0371	98.1
177	496.843	496.3887	496.0334	485.3341	486.5441	372.0871502	358.8933	97.5
178	496.932	495.1956	495.7369	485.7128	484.8782	367.3588518	352.39	97.5
179	497.25	495.4827	496.0417	484.6192	480.8658	362.5035509	348.7098	96.3
180	498.067	496.2866	496.8452	486.0444	483.0091	365.3147154	352.4495	97.2
181	498.608	495.8294	497.3989	486.0862	482.5247	364.6201285	350.5975	96.7
182	498.703	500.5355	497.499	493.0931	490.4706	380.4944959	368.7247	98.4
183	499.242	498.5634	498.0518	489.8252	487.9315	377.1964581	362.646	97.4
184	499.265	497.6865	498.0596	489.8252	487.3094	377.8994395	365.1957	96.8
185	499.581	497.5842	498.3775	488.8148	487.121	375.246675	361.9569	97.1
186	500.056	498.4282	498.8699	489.0983	488.8145	380.8981569	365.1447	96.9
187	500.273	497.3976	499.0634	489.9486	488.3352	380.0867245	364.7628	97.3
188	500.267	497.3136	499.0723	489.7134	487.8775	374.7119241	361.2963	97.3
189	499.805	500.3355	498.5942	494.6811	492.6557	386.6289153	376.4351	98.8
190	498.476	497.6579	497.2512	493.2284	484.0559	412.0224034	276.5861	98.7
191	497.87	497.0492	496.6497	488.0555	482.5097	409.9488082	275.6961	98.3
192	498.264	497.4543	497.2525	485.8065	479.9088	341.716478	327.3435	97
193	497.861	497.0514	496.8492	486.0937	482.6304	282.7125831	400.6718	98.3
194	498.295	498.2628	497.3287	486.9554	483.9347	398.7081052	291.9302	96.6
195	499.711	499.4878	498.9026	486.9554	490.1856	415.4398818	302.0418	99.2
196	499.472	499.068	498.6624	492.1839	487.0287	297.379521	413.4492	98.5
197	501.881	501.0851	501.0904	492.1839	495.7905	387.0564202	380.4136	99.2
198	502.205	500.8259	501.3937	497.7788	496.0749	387.2247758	382.4858	98.6
199	501.489	500.6797	500.6835	494.5561	490.8611	353.6667923	357.0545	98.5

200	501.589	501.0845	501.0848	497.4174	494.958	357.8099764	359.6968	99.2
201	501.699	501.2812	501.2746	496.9023	495.0631	359.7809158	357.7345	98.8
202	503.286	502.8483	502.9032	497.8638	498.7534	381.3357984	390.0731	99.3
203	503.013	502.3224	502.747	500.7482	497.1696	377.6071566	384.3754	99
204	503.144	501.846	503.1444	500.6611	496.1924	376.3624254	384.9322	98.7
205	503.295	502.8513	503.3053	500.8861	497.9598	379.3044225	389.8923	98.7
206	503.291	502.6768	503.3382	501.4283	499.0188	379.4479973	389.4219	98.5
207	503.511	499.3081	503.5089	500.4179	494.505	372.5309601	382.2004	98.2
208	501.793	500.989	500.9894	498.306	497.6574	374.4232482	385.7591	99
209	501.699	501.2812	501.2746	500.0249	500.1513	378.7588163	387.8688	99.6
210	505.181	502.0711	505.5131	500.576	501.6767	378.8058289	388.6927	99.2
211	502.029	497.4674	502.4364	504.2966	488.826	369.5714552	375.0459	98.6
212	504.513	505.1507	504.3121	504.2966	504.3291	385.4380023	396.6732	99.6
213	505.098	501.5958	505.122	503.0336	501.3423	384.910832	396.5512	98.6
214	506.135	499.8824	506.061	505.6031	500.6713	379.1986244	391.8124	99.1
215	505.525	501.6436	504.9233	507.9444	505.273	395.2171105	394.9813	99.4
216	505.532	502.0884	504.9237	507.9444	506.584	395.8030984	395.9511	99.1
217	506.688	501.7716	505.933	508.3843	506.3024	389.7122653	400.2982	99.2
218	506.931	505.3062	506.1273	510.4398	508.4059	394.5789621	402.8879	98.2
219	507.139	504.2626	506.3307	510.2229	506.9547	388.4456861	398.1128	99.4
220	506.503	505.4795	505.8929	512.4689	506.9344	387.3617429	399.0741	98.6
221	506.028	502.2976	505.6242	512.4689	503.895	383.315841	394.4475	97.9
222	506.307	502.9522	505.9254	512.4689	506.1372	386.8358757	397.7153	97.7
223	506.33	504.6404	506.1329	512.4689	506.3078	384.9317109	396.5887	98.3
224	506.525	503.4715	506.2902	515.0326	508.8681	393.4691369	400.8904	98
225	506.131	503.4783	505.9288	510.8752	508.9541	394.1849654	394.6974	98.2
226	506.28	502.6636	506.074	510.7637	508.0301	392.135769	394.4788	98.1
227	506.325	501.8602	506.1266	511.0553	507.279	388.8264474	394.6087	97.9
228	506.506	501.3779	506.2869	511.0553	507.9541	391.8892601	392.6181	98.2
229	506.528	502.08	506.3285	512.0762	508.5497	392.8684217	393.0285	98
230	506.539	500.7858	506.3348	510.7675	507.2416	389.2764767	391.6136	98.3
231	505.594	502.6154	505.1734	509.654	507.6115	391.110276	392.1029	98.5
232	505.808	501.5853	505.4051	508.3578	506.7777	384.3920912	394.0641	97.6
233	506.551	503.3682	506.1318	513.1155	510.7783	397.1738085	395.8054	98.1
234	506.734	502.5645	506.132	513.0277	510.0202	395.8802096	394.7523	98.1
235	506.733	503.1035	506.1317	513.034	511.0379	395.6982539	395.9398	98.1
236	506.746	502.25	506.1309	513.8435	510.5328	397.0645099	396.3438	98
237	507.068	504.1502	506.6438	512.267	509.0465	385.038793	390.1088	98.7
238	507.46	502.7771	507.0389	510.8063	506.949	373.9356018	377.6078	97
239	508.175	504.5651	508.9623	515.2332	514.4945	402.0225998	401.3679	98.8
240	507.337	504.3463	508.1474	516.5048	510.8473	356.576569	364.9142	98.9
241	493.449	493.4523	493.4463	516.5048	493.7592	428.0108204	385.7107	100.3
242	492.324	492.8311	492.7459	507.5184	478.1114	377.2053949	350.9208	97.7
243	492.969	493.7342	493.2054	480.5952	482.9969	371.4979794	351.0935	97.2
244	494.047	495.2845	494.016	480.7027	479.5093	368.7756814	350.0724	96.8
245	497.911	496.1874	497.6481	483.0382	480.6377	376.647777	354.3703	95.6
246	498.874	500.7691	497.6597	490.4391	487.1161	396.1726277	355.0834	98.6
247	498.552	499.7549	497.7455	489.948	490.0547	414.0497739	370.1989	97.9
248	499.133	498.2433	498.3617	490.821	492.6801	422.3837801	382.6464	97.9
249	497.671	500.0067	496.8526	490.821	493.0988	422.2228763	381.5514	100
250	498.718	501.6209	497.9448	490.821	487.213	397.2864983	371.0082	97.8
251	499.957	498.1079	499.2667	493.1663	487.2779	394.4904884	374.9143	98.4

252	500.108	498.9769	499.2705	493.1663	490.5644	407.0351763	384.3003	97.8
253	501.032	500.5105	500.2171	492.9065	494.4468	410.2305579	388.7395	99.4
254	501.028	498.7139	500.2226	495.0366	491.4507	401.3494221	380.3414	97.8
255	502.343	499.8125	500.7645	495.8724	496.6475	410.837101	388.6301	98.3
256	502.675	500.1877	501.2775	497.3895	497.2794	413.1701229	395.966	98.1
257	502.493	500.3804	501.6919	494.418	493.9948	402.6782406	385.2577	97.7
258	502.766	499.8148	502.0006	494.5665	494.7832	406.3863708	388.3166	98.4
259	503.302	500.2454	502.4969	496.3783	496.4073	409.5512381	392.3611	98.9
260	503.813	500.6708	502.3548	500.477	495.723	406.7848196	387.1317	99.5
261	503.118	502.1117	501.8912	500.477	495.4751	389.7838461	383.0834	99.9
262	502.458	501.9296	501.6489	499.2399	494.948	388.2195396	382.7596	98.6
263	503.368	502.5809	502.5612	499.1386	494.2561	383.5360916	372.8729	99
264	503.304	500.8989	502.4996	498.8415	493.0076	385.0261763	371.8952	98.9
265	502.474	501.2371	501.6616	497.95	490.9154	378.3489359	366.1146	98.4
266	502.404	501.2899	501.8736	497.95	490.982	377.2927011	367.081	99
267	502.441	501.0978	501.7952	497.95	490.9267	377.2987184	365.9135	99
268	502.872	500.8895	502.4369	497.95	491.2316	381.7294481	367.9213	98.4
269	503.105	503.025	502.7024	498.7772	494.3444	381.8581417	372.9295	99.7
270	503.04	501.3169	502.64	498.7772	494.9429	383.6810252	377.8457	99
271	503.056	501.4626	502.6498	497.5872	492.2162	385.2092757	373.4654	98.6
272	503.096	501.7509	502.6996	499.5526	492.1636	381.0843303	368.5962	98.7
273	503.098	501.4638	502.7033	499.3272	493.4843	380.2151272	373.1439	98.5
274	503.309	500.704	502.9017	498.6509	494.9012	383.586778	376.48	98.9
275	450.224	450.244	450.2355	490.4338	473.5606	358.7141236	342.0053	93.9
276	456.114	454.9561	456.08	490.4338	474.9491	357.1027945	335.5828	94.9
277	455.553	452.6415	455.5904	490.4338	473.6998	358.704007	336.3736	95.6
278	452.923	454.1669	454.017	490.4338	474.2365	359.3731237	338.5234	94.9
279	455.804	457.7014	456.9219	490.4338	474.0297	334.9043692	324.6403	95.5
280	460.168	458.4857	457.7058	490.4338	478.0636	338.6819724	329.8796	97.3
281	473.032	472.0875	471.9272	500.51	497.1837	369.9532246	354.7113	98.8
282	472.664	472.1296	471.5523	501.5512	496.2751	369.1651814	354.1773	98.7
283	468.639	471.017	467.5448	501.5512	489.941	362.0789132	349.5024	97
284	469.178	471.3236	468.1174	501.5512	490.6717	365.0534006	352.3381	96.7
285	471.058	471.468	471.8324	498.1253	493.7188	368.8979471	357.2155	97.7
286	473.705	472.8809	472.9594	498.5856	498.9851	378.5950703	366.6885	98.6
287	475.809	473.5998	474.6464	504.0332	501.3095	374.4019947	362.7238	98.9
288	477.053	473.1948	475.8679	504.3583	502.5986	378.389573	364.0166	99
289	475.719	475.6435	474.5292	505.3334	502.9783	379.1401993	365.0466	99.5
290	475.159	473.7094	474.4568	505.3334	503.1506	379.2278496	366.967	98.6
291	477.597	475.5117	476.1896	508.3689	504.3049	379.1161123	365.7902	98.7
292	479.129	478.8336	481.0658	518.503	509.6247	391.8266851	374.2665	95.1
293	491.143	489.1276	491.1738	506.2504	475.1164	338.7990322	327.1783	94.9
294	492.691	492.58	492.6841	477.854	483.9581	354.8558248	339.7802	96.7
295	492.805	493.9233	492.8096	479.4195	481.2111	353.9504863	338.5823	94.9
296	494.885	494.2469	494.8954	481.3491	484.4356	371.9996744	370.1418	93.9
297	496.396	494.2663	496.3723	486.3398	487.6184	377.7507526	377.2764	95.4
298	497.469	499.9134	497.4721	488.6724	496.2213	397.8657941	388.7129	98.9
299	497.367	497.4674	497.3741	497.0778	496.2952	399.1288531	392.7113	98.9
300	501.344	496.4069	500.9451	497.3794	494.5382	396.3793051	389.7499	98.2
301	501.677	497.8605	501.2422	498.028	497.3354	399.5107826	393.7305	100
302	499.869	497.1471	499.0673	494.5325	493.9566	388.265239	379.9871	97.4
303	499.869	496.7244	499.0606	494.5325	493.4929	388.5725466	380.171	97.9

304	499.67	496.3957	498.8713	494.5325	492.8846	386.8877902	378.5314	96.8
305	499.882	495.8229	499.0613	493.6207	492.3419	387.8750882	379.5392	97.2
306	500.001	494.9033	499.1041	493.7152	490.4495	385.6617757	372.8494	96.9
307	500.16	494.9387	499.3407	495.4786	490.7389	386.2026767	374.2958	96.6
308	502.503	495.3419	501.6908	495.9966	495.3746	387.7695237	376.9566	97.7
309	500.306	496.3211	500.4209	495.1594	490.8597	382.5365425	370.9411	96.9
310	500.492	497.8325	500.4809	494.6799	491.888	383.2957463	372.3743	96.6
311	500.668	497.5569	500.6721	493.292	491.827	383.0357362	371.9954	96.3
312	501.292	497.672	501.2859	493.4436	493.0244	382.9513535	372.7383	97.5
313	500.744	497.9659	500.7434	494.5094	493.912	393.8937146	378.9764	98.3
314	499.465	499.853	499.4718	493.3607	495.0625	396.284753	381.6349	98.6
315	499.216	499.5911	499.2123	492.9478	494.2103	395.5527666	381.8444	98
316	499.408	500.4636	499.3892	494.0541	497.9254	400.6181936	381.0031	100.7
317	498.153	498.2817	498.1556	496.049	495.1029	398.977232	377.3331	98.9
318	498.255	498.5062	498.2582	496.049	494.8794	395.8875858	375.5461	99.1
319	498.26	497.64	498.2623	493.6637	493.3841	391.3713112	376.3657	99.1
320	504.352	498.2225	503.9126	504.6171	506.7123	393.9807149	391.9021	98.5
321	504.761	496.5464	504.788	504.3011	506.6844	393.9664905	391.2801	98.7
322	503.312	501.9017	503.3033	500.6611	496.4193	376.9950765	385.2416	99.1
323	503.506	500.1649	503.5077	501.0298	495.7704	374.3115248	383.3148	98.3
324	502.526	501.8352	502.1692	505.1817	499.6631	377.6519203	386.3677	98.9
325	504.582	500.6863	505.4606	499.3358	498.5703	375.5030499	384.8147	99.3
326	502.881	499.8301	502.1936	504.2966	493.5759	372.3164069	379.9907	99.2
327	497.762	497.9282	496.949	490.821	487.8077	412.4753776	373.8518	98.4
328	500.143	497.9796	499.2727	493.1663	488.701	398.3881981	376.7697	99.5
329	501.059	500.3928	500.2354	492.9065	494.7708	411.526272	391.3691	101
330	501.7	496.9912	500.4356	495.0366	492.5314	405.9002326	385.5297	98.6
331	502.536	499.1928	501.5578	494.418	494.3298	405.7586725	385.0677	98.1
332	498.605	499.7255	497.4018	492.2762	488.8754	379.4749855	364.3612	97.9
333	500.223	497.7863	498.9909	489.9486	488.7368	380.4210777	365.184	97.3
334	499.954	499.5065	498.7208	490.9553	491.4756	384.7421965	373.1203	98
335	497.854	497.0454	496.6474	485.6109	484.7541	414.626726	284.3359	99
336	497.452	496.6478	496.2424	491.7847	487.1004	417.8131155	283.52	98.9
337	498.268	497.4562	497.1795	485.8065	480.1274	341.8235467	326.8628	97.1
338	497.903	497.0819	496.8801	485.8065	482.1347	295.385305	384.3016	98.2
339	502.016	496.8411	501.632	499.0231	500.1899	368.8143635	351.22	97.1
340	502.702	497.5568	502.2524	503.6951	496.8383	392.5304188	390.9063	97.4
341	501.505	497.6464	501.994	498.5646	500.296	394.6991245	392.1151	98.5
342	502.104	499.0526	502.0988	495.8173	499.2166	388.5847715	389.1625	98.9
343	502.077	498.4914	502.0976	503.5901	503.0649	401.0507137	394.0709	99.3
344	502.523	497.0832	502.8866	503.511	501.7334	392.0251827	390.9055	98.2
345	502.975	500.201	502.4984	500.477	493.4994	404.1067727	386.4682	100.2
346	504.277	501.0502	502.4432	500.477	493.2222	385.7708464	374.5992	99.5
347	502.396	502.0648	501.2866	499.2399	494.791	388.2432096	382.1251	99.4
348	503.441	503.837	502.6305	499.2146	495.8909	384.2721794	375.9256	97.5
349	503.292	501.0071	502.4921	499.1386	493.325	383.2755846	372.4283	98.7
350	503.307	500.8033	502.4989	497.95	493.4662	386.4180363	371.1764	99.9
351	502.483	501.3697	501.6946	497.95	494.067	381.9054291	371.1425	99.3
352	502.822	500.9304	502.2538	497.95	491.7948	382.1024259	369.928	98.6
353	503.106	503.1712	502.7023	498.7772	494.59	382.8435934	372.4614	99.6
354	502.901	502.6621	502.4864	498.7772	495.6723	383.0996529	375.848	98.7
355	502.941	501.5585	502.5466	498.4797	493.915	386.6179596	380.6604	98.4

356	503.107	501.5654	502.7078	498.0785	493.9191	383.7218342	373.1711	98.6
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**Appendix 4: Actual and predicted RON in 30 days moving average**

Testing data

Predicted ron	After bias updating	Actual RON
91.7	NaN	93.4
91.8	NaN	94.6
91.8	NaN	94.5
91.9	NaN	94.9
91.7	NaN	94.5
92.1	NaN	94.8
92.3	NaN	95.1
92.2	NaN	96.7
92.1	NaN	96.8
92.1	NaN	97.5
92.1	NaN	97.4
92.1	NaN	96.8
92.1	NaN	95.4
92.2	NaN	96
92.2	96.2	96.2
92.1	96.2	96.6
92.3	96.2	97.3
92.3	96.2	96.8
92.3	96.3	97
92.3	96.3	96.8
92.3	96.4	94.5
92.2	96.4	94.9
92.2	96.4	96.5
92.3	96.5	95.8
92.2	96.5	96.3
92.3	96.5	96
92.2	96.5	95.8
92.3	96.6	96
92.3	96.6	96.1
92.4	96.7	95.6
92.5	96.9	96.2
92.6	97.0	96.2
92.6	97.1	95.6
92.9	97.2	96.9
93.3	97.3	98.5
93.1	97.4	99
93.3	97.5	99.1
93.2	97.6	98.8
93.0	97.7	96.7
92.9	97.8	99
91.3	97.8	97.2
92.8	98.0	98.6
94.0	98.1	98.4
94.7	98.3	98.9
95.2	98.3	98.5
95.8	98.4	99.7



95.4	98.5	99.2
95.8	98.6	99.2
95.5	98.7	99.3
95.5	98.7	98.4
95.6	98.7	99.2
94.8	98.7	99.8
95.8	98.6	98.6
94.6	98.6	98.7
95.1	98.5	98.5
93.6	98.6	99.4
96.3	98.5	98.4
97.2	98.5	99.8
96.8	98.3	99.3
92.6	98.1	100.6
96.2	97.9	100.9
95.2	97.8	99.6
95.8	97.6	99.1
94.5	97.4	99.3
93.4	97.1	98.6
94.5	96.9	97.8
93.8	96.8	98.5
91.0	96.7	98.9
90.4	96.6	97.6
92.0	96.5	98.5
92.8	96.4	97.7
91.1	96.2	98.1
92.4	96.1	96.6
90.5	95.9	95.7
89.6	95.9	92.8
89.9	95.8	94
90.2	95.8	91.4
90.3	95.7	92.4
90.5	95.6	90.6
85.0	95.7	76.4
90.4	95.6	95.1
91.6	95.6	94.9
91.8	95.7	96.9
91.6	95.8	96.3
91.8	95.8	94.6
91.7	95.8	93.8
91.8	96.0	93.1
92.2	96.0	94
92.6	96.2	94.5
92.7	96.3	96.8
93.3	96.5	99.5
93.0	96.6	98.9
93.1	96.7	99.1
93.7	96.8	98.2
93.9	97.1	97.8
93.8	97.2	100
92.9	97.3	99.1
92.9	97.4	98.6

93.2	97.5	96.3
93.5	97.5	97
93.7	97.6	97
94.2	97.7	97.1
95.2	97.7	96
94.1	97.8	97.5
94.4	97.8	97.5
94.0	97.9	97.4
94.1	97.9	97
94.0	97.9	97.4
93.9	97.9	97.9
93.9	97.9	96.8
94.0	97.9	96.5
93.9	97.9	97.2
93.8	97.9	97.2
93.9	97.9	96.9
93.9	98.0	96.9
94.0	98.0	96.7
94.0	98.0	96.6
94.0	98.0	96.8
93.5	98.0	96.6
94.1	98.0	97.1
94.4	98.1	97.3
94.0	98.1	97
94.2	98.1	97.4
92.3	98.2	99.4
93.9	98.2	98.3
93.2	98.2	96.4
93.2	98.2	94.3
93.3	98.2	96.2
93.7	98.2	96.9
95.1	98.2	97.2
95.1	98.2	97.7
95.1	98.1	97.2
94.7	98.1	96.9
94.6	98.1	96.8
94.6	98.1	97
94.7	98.0	96.6
94.8	98.0	97.2
94.8	98.0	96.3
95.1	98.1	97.2
95.1	98.1	97.5
94.2	98.1	97.8
93.9	98.1	98.7
93.6	98.2	98.2
93.7	98.2	98.4
93.9	98.1	99
92.8	98.1	99
93.0	98.1	99.4
93.3	98.1	98.7
93.5	98.1	99.2
93.9	98.1	98.3

93.3	98.1	99.1
93.6	98.1	99.4
93.8	98.1	99.3
93.9	97.9	99.1
93.8	97.8	98.6
93.6	97.8	99.5
94.4	97.7	97.9
94.6	97.7	98.2
93.4	97.7	100.4
94.0	97.7	98.8
94.3	97.7	99.2
95.0	97.7	98.3
95.2	97.7	100.1
94.7	97.8	98.6
95.1	97.9	97.7
94.7	98.0	97.8
93.7	98.0	98.3
94.0	98.1	98.5
90.4	98.1	98.2
92.9	98.2	96.9
93.3	98.3	98
92.1	98.3	97.8
92.6	98.4	98.3
92.9	98.5	99.1
93.5	98.5	98.5
93.4	98.5	98.8
93.5	98.5	97.9
94.1	98.6	98.3
95.9	98.7	98.7
96.2	98.7	98.9
95.7	98.7	98.5
95.3	98.8	98.4
95.3	98.9	99.1
95.0	99.1	98.8
96.0	99.2	99.3
96.0	99.3	98.7
96.5	99.4	99.2
96.4	99.5	100.4
95.4	99.6	99.9
95.4	99.7	99.4
95.0	99.7	98.8
95.9	99.8	99
96.2	99.8	99.2
96.9	99.8	99.9
95.7	99.9	99.9
96.8	99.9	99.3
96.6	100.0	98.4
96.9	99.9	100.1
96.4	99.9	100.5
94.0	99.8	100.5
96.4	99.6	99.8
95.3	99.6	99.1

94.9	99.5	99
96.0	99.5	98
96.5	99.5	98.2
95.2	99.4	99.3
95.0	99.4	100
95.4	99.4	96
96.5	99.4	96
96.8	99.5	96.3
96.6	99.5	97
96.8	99.5	101
93.6	99.4	100
93.7	99.3	99.6
93.1	99.3	99.7
92.8	99.3	99.1
94.7	99.2	97.6
94.6	99.2	97.4
94.3	99.2	97.1
94.1	99.1	97.5
93.6	99.1	99
95.4	99.1	98.8
97.6	99.1	95.4
96.4	99.0	98.4
97.6	99.0	96.3
96.4	99.0	97.8
97.3	99.0	97.1
92.9	98.9	97.4
95.0	99.0	98.5
95.1	99.1	98.9
93.6	99.2	99.3
94.6	99.3	98.2
94.9	99.3	99.6
94.7	99.3	99.4
95.3	99.4	99
95.2	99.6	98.4
94.4	99.3	98.3
94.5	99.2	97.9
95.0	99.2	99
95.6	99.0	98.5
96.1	98.9	98.7
96.0	98.7	98.6
93.3	98.8	98.8
94.2	98.7	99.2
96.7	98.7	92.1
96.8	98.8	98.9
96.2	98.9	99.3
94.0	98.9	98
96.8	98.9	99.1
96.7	98.9	99.1
97.6	98.9	98.8
88.9	98.9	93.4
94.1	98.9	97.5
95.7	98.8	98

91.8	98.7	97
91.9	98.5	96.9
93.7	98.4	97.3
93.8	98.4	98.1
93.4	98.4	97.4
95.5	98.2	98.3
96.0	98.1	96.5
96.5	98.0	96
95.2	97.9	96.3
94.5	97.8	96.3
95.1	97.8	97.4
95.8	97.7	99.4
94.2	97.8	97.3
94.7	97.8	98.2
91.7	97.8	95
92.5	97.8	95.8
92.4	97.9	95.8
92.2	97.9	97.4
92.7	97.9	97.8
92.9	97.9	99.8
92.8	97.9	98.2
92.5	97.8	96.9
92.9	97.7	96.7
93.0	97.7	97.2
93.4	97.6	97.4
95.0	97.6	98.4
94.0	97.5	97.9
94.4	97.4	97.7
93.8	97.4	97.1
93.9	97.5	97.4
94.0	97.6	97.3
94.2	97.7	97.7
94.0	97.7	98
92.1	97.8	98.8
94.0	98.0	98.2
94.3	98.1	98.8
94.4	98.1	99
93.9	98.2	99
93.8	98.2	98.9
93.1	98.2	97.1
93.2	98.2	98.2
93.9	98.3	98.8
93.0	98.2	96.8
94.1	98.2	98.8
94.1	98.3	99.1
94.2	98.2	98.5
96.0	98.2	98.7
93.6	98.2	98.1
95.9	98.2	98.6
96.5	98.1	99.6
96.4	98.1	99.1
94.8	98.1	99.1

93.7	98.2	99.6
93.5	98.2	98.4
94.2	98.1	99.8
95.0	98.1	97.6
95.1	98.1	98
93.4	98.2	99
94.4	98.1	99
94.4	98.0	98.3
93.0	98.0	98.6
92.7	97.8	99.4
93.3	97.7	98.5
92.7	97.6	99.1
92.2	97.4	99.2
94.8	97.2	98.1
94.4	97.1	99.1
94.9	97.1	99
93.2	97.1	99.6
92.6	97.0	99.5
92.9	96.9	99.5
93.8	96.8	98.7
93.8	96.8	99.2
92.4	96.7	99.1
92.4	96.6	99.2
92.0	96.6	99.3
91.1	96.6	97.4
91.5	96.6	98.1
91.4	96.5	98.2
91.5	96.5	98
91.2	96.4	97.8
91.8	96.4	98.3
92.5	96.2	98.3
92.4	96.2	98.3
92.2	96.1	98.5
91.8	96.0	98.2
92.9	96.0	98.1
93.1	NaN	98.7
91.3	NaN	98.5
92.1	NaN	98
93.6	NaN	97.6
91.6	NaN	98
91.7	NaN	98.7
91.6	NaN	98.1
91.5	NaN	97.5
91.6	NaN	97.7
93.5	NaN	97
91.6	NaN	97.7
91.2	NaN	99.2
91.2	NaN	98.7
90.5	NaN	100
92.0	NaN	99.1

## Validation data

Predicted	After bias updating	Actual RON
95.2	NaN	95.1
95.6	NaN	93.5
96.4	NaN	94.6
98.0	NaN	94.9
98.0	NaN	97.1
98.0	NaN	96.3
98.1	NaN	97.1
98.2	NaN	95.6
98.1	NaN	95.8
98.1	NaN	95.9
98.2	NaN	96.1
98.3	NaN	96.9
98.5	NaN	98.7
98.7	NaN	98.7
98.8	97.8	99.2
98.7	97.8	98.9
99.2	97.9	98.9
99.4	98.6	98.7
98.1	98.5	98.8
99.1	98.4	99.1
98.9	98.4	99.2
98.0	98.3	98.3
98.2	98.3	98.7
97.9	98.3	98.6
99.0	98.2	98.7
98.7	98.2	96.9
97.0	98.2	101.8
98.4	98.2	100.3
97.8	98.2	99.4
97.5	98.2	98.4
97.3	98.2	97.9
99.1	98.2	98.7
96.1	98.2	96.0
95.9	98.2	97.1
96.2	98.2	97.4
97.0	98.2	97.4
96.7	98.3	97.6
96.9	98.3	97.0
96.6	97.7	96.1
96.1	97.7	92.1
98.1	97.7	98.2
98.3	97.7	99.0
98.2	97.7	98.4
99.0	97.7	96.9
98.9	97.7	96.7
99.3	97.8	96.9

98.5	97.8	97.4
99.5	97.9	97.0
99.6	98.0	97.5
98.9	98.1	96.9
99.2	98.2	97.7
98.9	98.3	97.0
99.7	98.4	100.2
98.6	98.5	97.6
98.5	98.5	97.7
99.0	98.5	97.7
97.2	98.5	102.4
97.4	98.6	98.1
98.2	98.5	96.9
98.6	98.5	97.2
98.6	98.5	95.4
99.9	98.5	100.3
99.1	98.4	99.2
99.3	98.4	99.3
99.3	98.3	98.8
99.5	98.2	98.8
99.2	98.9	100.4
99.4	98.2	98.1
99.6	98.8	99.6
97.7	98.9	100.3
98.2	98.9	99.0
98.9	98.3	99.1
99.8	98.4	100.3
95.7	98.5	87.8
99.4	98.5	97.9
98.4	98.6	98.2
98.7	98.6	97.2
98.0	98.6	98.0
98.5	98.7	98.3
96.5	98.7	97.2
97.2	98.7	98.2
98.5	98.7	98.2
98.7	98.7	98.4
99.3	98.7	99.3
99.2	98.8	99.1
99.2	98.8	98.6
98.6	98.9	98.0
100.3	98.9	98.8
100.4	99.0	99.0
100.4	99.0	98.6
100.1	99.0	99.0
100.3	99.1	99.6
100.0	99.1	99.0
100.2	99.1	98.6
99.8	99.2	98.6
100.4	99.4	99.9
99.4	99.4	100.0
99.0	99.4	99.5



100.2	99.4	98.8
99.5	99.4	98.2
99.7	99.5	98.8
100.2	99.5	99.5
99.1	99.5	99.6
99.7	99.5	99.2
99.7	99.5	98.5
99.8	99.5	99.2
99.8	99.4	100.8
98.8	99.3	101.1
97.5	99.2	99.9
101.4	99.2	99.6
101.2	99.1	98.6
98.4	99.1	97.5
99.1	99.2	96.5
99.5	99.0	97.7
100.3	99.1	98.2
100.2	99.0	99.6
99.6	99.0	97.3
100.5	99.0	97.2
99.9	99.0	97.5
100.1	98.9	97.1
100.1	98.8	99.0
97.7	98.8	99.2
98.1	98.7	99.4
97.1	98.7	99.4
98.5	98.6	97.4
99.6	98.5	96.9
99.3	98.6	96.9
99.6	98.5	97.5
95.4	98.5	99.1
101.4	98.4	98.9
98.9	98.4	99.6
99.1	98.4	96.7
99.2	98.3	97.8
98.9	98.3	96.8
97.7	98.8	96.6
97.3	98.8	97.9
97.3	98.7	96.3
97.2	98.1	97.8
97.8	98.1	98.7
98.7	98.0	99.9
98.4	98.0	98.6
99.3	98.6	99.6
98.9	98.5	98.4
98.0	98.0	97.9
98.6	98.0	98.5
98.9	98.1	98.7
99.0	98.1	98.6
98.6	98.0	99.2
99.5	98.1	98.9
97.1	98.1	98.0

99.1	98.1	99.1
93.9	98.2	93.4
100.6	98.2	98.0
96.3	98.2	97.4
96.8	98.2	96.7
98.1	98.2	96.8
98.3	98.1	97.4
98.1	98.1	97.3
98.5	98.1	97.6
101.5	98.1	97.8
101.5	98.1	98.1
98.6	98.1	96.6
98.2	98.1	96.3
99.8	98.0	100.3
98.1	98.0	97.2
98.6	98.0	95.5
98.5	98.2	96.0
98.3	98.1	98.3
98.2	98.2	97.0
98.0	98.2	97.3
98.1	98.2	97.5
98.1	98.3	96.5
98.1	98.3	96.7
98.1	98.3	96.7
98.2	98.0	97.4
98.5	97.8	98.1
98.2	97.8	97.5
98.1	97.9	97.5
98.0	97.8	96.3
98.0	97.8	97.2
98.1	97.9	96.7
99.2	97.9	98.4
98.5	98.0	97.4
98.4	98.0	96.8
98.4	98.0	97.1
98.6	98.1	96.9
98.5	98.1	97.3
98.5	98.2	97.3
99.3	98.2	98.8
94.0	98.2	98.7
95.0	98.2	98.3
98.2	98.3	97.0
99.8	98.3	98.3
97.6	98.4	96.6
98.1	98.4	99.2
101.1	98.4	98.5
100.2	99.0	99.2
99.2	99.0	98.6
99.2	99.0	98.5
99.5	98.9	99.2
99.4	98.9	98.8
99.8	98.8	99.3

98.9	98.8	99.0
98.9	98.7	98.7
98.8	98.8	98.7
98.8	98.8	98.5
99.2	98.8	98.2
99.9	98.7	99.0
99.5	98.6	99.6
99.9	98.6	99.2
96.6	98.5	98.6
98.3	98.4	99.6
98.4	98.3	98.6
97.9	98.2	99.1
97.0	98.1	99.4
97.2	98.0	99.1
97.6	98.0	99.2
97.1	97.9	98.2
97.1	97.8	99.4
96.6	97.8	98.6
96.4	97.7	97.9
96.6	97.6	97.7
96.6	97.6	98.3
96.5	97.5	98.0
97.0	97.4	98.2
96.9	97.4	98.1
96.9	97.3	97.9
96.9	97.3	98.2
96.8	97.3	98.0
97.0	97.3	98.3
97.1	97.3	98.5
97.8	97.3	97.6
96.7	97.4	98.1
96.7	97.4	98.1
96.9	97.4	98.1
96.7	97.5	98.0
97.0	97.5	98.7
97.6	97.6	97.0
96.8	97.6	98.8
97.6	97.7	98.9
96.2	97.7	100.3
95.8	97.7	97.7
98.2	97.8	97.2
98.2	97.8	96.8
98.2	97.8	95.6
97.5	97.8	98.6
97.6	97.8	97.9
97.8	97.9	97.9
97.8	98.0	100.0
97.7	98.1	97.8
97.7	98.1	98.4
97.7	98.2	97.8
98.4	98.2	99.4
98.0	98.3	97.8

98.1	98.4	98.3
97.4	98.5	98.1
98.7	98.6	97.7
98.5	98.6	98.4
98.0	98.6	98.9
96.7	98.5	99.5
97.7	98.5	99.9
98.2	98.4	98.6
98.9	98.4	99.0
98.7	98.4	98.9
99.0	98.4	98.4
99.1	98.4	99.0
99.1	98.5	99.0
98.9	98.4	98.4
99.2	98.4	99.7
99.1	98.4	99.0
98.9	98.5	98.6
98.5	98.5	98.7
99.0	98.5	98.5
99.3	98.5	98.9
95.5	98.6	93.9
96.5	98.6	94.9
96.1	97.9	95.6
95.9	98.3	94.9
98.0	97.7	95.5
98.0	97.6	97.3
98.8	97.6	98.8
98.5	97.6	98.7
97.3	97.6	97.0
97.3	97.6	96.7
98.7	97.6	97.7
99.3	97.5	98.6
98.9	97.6	98.9
98.9	97.6	99.0
98.3	97.6	99.5
98.5	97.7	98.6
97.6	97.8	98.7
96.1	97.9	95.1
93.3	98.0	94.9
98.2	98.0	96.7
98.2	98.1	94.9
98.3	98.1	93.9
98.6	98.2	95.4
99.6	98.2	98.9
97.9	98.3	98.9
98.1	98.3	98.2
98.2	98.3	100.0
99.5	98.3	97.4
99.3	98.3	97.9
99.3	98.4	96.8
99.2	98.4	97.2
98.9	98.4	96.9

98.8	98.5	96.6
99.8	98.7	97.7
99.2	98.7	96.9
99.5	98.7	96.6
99.5	98.7	96.3
99.7	98.6	97.5
99.3	98.6	98.3
99.5	98.6	98.6
99.4	98.6	98.0
99.7	98.6	100.7
98.7	98.6	98.9
99.0	98.6	99.1
99.4	98.5	99.1
98.6	98.5	98.5
98.9	99.0	98.7
98.9	98.9	99.1
99.0	98.9	98.3
97.4	98.9	98.9
100.2	98.8	99.3
97.1	98.8	99.2
97.0	98.8	98.4
97.8	98.7	99.5
98.3	98.7	101.0
97.8	98.6	98.6
98.5	98.5	98.1
98.7	98.5	97.9
98.6	98.5	97.3
99.3	98.5	98.0
96.6	98.5	99.0
95.4	98.5	98.9
98.2	98.5	97.1
98.5	98.5	98.2
99.0	98.6	97.1
96.7	98.5	97.4
99.0	98.6	98.5
100.0	NaN	98.9
97.4	NaN	99.3
97.9	NaN	98.2
96.6	NaN	100.2
97.9	NaN	99.5
98.2	NaN	99.4
99.1	NaN	97.5
98.8	NaN	98.7
99.1	NaN	99.9
99.5	NaN	99.3
99.0	NaN	98.6
99.2	NaN	99.6
99.3	NaN	98.7
98.6	NaN	98.4
99.3	NaN	98.6

Training data

Predicted	After bias updating	Actual RON
97.4	NaN	96
97.4	NaN	93.6
97.5	NaN	94.1
97.5	NaN	94.8
97.5	NaN	94.6
97.4	NaN	95
97.4	NaN	95
97.7	NaN	94.5
97.8	NaN	95.9
97.8	NaN	96.5
97.9	NaN	96.8
97.8	NaN	96.8
97.8	NaN	95.5
97.8	NaN	97
98.0	97.2	97.8
98.2	97.2	96.8
98.2	97.3	95.8
98.3	97.3	95.6
98.3	97.3	96.3
98.3	97.3	95.9
98.3	97.3	96.1
98.3	97.2	96.2
98.4	97.1	95.6
98.2	97.1	97
98.1	97.1	95.6
98.4	97.1	97.8
98.0	97.1	99
98.1	97.1	98.9
98.0	97.1	100.1
98.2	97.1	99.3
98.0	97.1	99.3
98.2	97.1	99
98.0	97.2	99.1
98.4	97.2	99.4
96.3	97.2	93.4
96.6	97.3	93.3
96.8	97.3	90.4
93.3	97.4	91.1
97.8	97.4	95.8
97.9	97.5	95.1
97.4	97.5	94.4
97.2	97.5	93.3
97.9	97.6	94.6
98.5	97.6	98.2
98.2	97.6	100
98.6	97.6	97.9

99.0	97.7	98
99.2	97.7	95.4
99.6	97.8	97
99.6	97.9	96.6
99.5	98.0	96.8
99.6	98.0	97
99.5	98.2	97.1
99.5	98.3	98
99.4	98.3	98.9
99.2	98.4	98.7
99.2	98.4	98
99.1	98.5	98.9
98.7	98.5	99
99.5	98.5	98.5
98.6	98.5	101
99.0	98.5	99.2
99.4	98.5	99.2
99.6	98.5	99.3
99.6	99.9	98.8
99.6	99.9	98.4
99.2	99.9	97.8
99.3	99.9	97.7
99.1	100.0	98.3
99.4	100.0	98.8
98.8	99.9	99.2
98.7	99.9	99.5
98.5	99.9	98.8
98.6	100.0	98.5
98.4	100.0	98.5
99.7	100.0	99.3
99.7	100.0	98.3
99.6	100.0	98.8
99.5	100.0	98.6
98.7	100.0	98.1
99.9	100.0	99.9
99.9	100.0	99.4
99.4	100.0	99.7
100.1	100.0	98.8
99.7	100.0	99.8
98.2	100.0	99.7
98.8	100.0	99.7
99.9	98.6	99.1
99.5	98.7	99.1
99.5	98.7	98.7
99.8	98.7	97.6
99.7	98.7	97
99.5	98.7	98.2
99.6	98.7	97
97.5	98.7	99.4
98.9	98.7	97.6
99.4	98.6	98
99.3	98.6	97.5

99.3	98.6	97.3
99.8	98.5	99
100.2	98.6	98.4
99.1	98.6	99.6
99.1	98.5	97.8
99.5	98.5	99.1
99.1	98.5	99.1
99.3	98.5	98.7
99.5	98.5	98.4
99.6	98.5	98.8
99.4	98.5	99.2
99.5	98.5	98.8
99.3	98.5	98.1
98.7	98.5	98.9
98.8	98.5	97.3
99.6	98.5	98.3
97.9	98.5	97
98.9	98.5	97.1
98.7	98.5	97.3
98.7	98.5	97.8
100.4	98.5	97.7
98.5	98.5	96.3
99.5	98.5	96.4
99.4	98.4	98.7
99.3	98.4	100.5
98.7	98.4	99.3
98.9	98.4	99.3
99.8	98.4	98.5
99.3	98.4	99.3
99.0	99.8	98.9
99.7	99.8	98.1
99.8	99.7	96.7
99.1	99.7	99
99.5	99.7	96.7
99.2	99.6	99.5
98.6	99.5	98.6
98.9	99.5	99.4
98.7	99.5	99.2
98.2	99.4	99.1
98.9	99.4	98.2
99.3	99.4	98.4
99.5	99.4	98.9
99.5	99.4	99.2
98.1	99.4	99.4
98.6	99.4	98.8
98.8	99.4	99.5
97.6	99.4	98.9
97.7	99.4	98.5
97.8	99.4	99.3
97.1	99.4	98.6
97.3	99.4	97.9
97.5	99.4	98



98.6	99.4	97.5
97.7	99.4	98.7
98.4	99.4	98
99.0	99.4	99.1
99.2	99.4	98.7
99.6	99.3	99.5
99.4	99.4	99.4
99.5	99.4	99.7
99.6	99.4	98.8
99.3	99.4	98.7
99.1	99.4	99.5
99.6	99.4	98.9
99.2	99.4	100.1
99.6	99.4	99.5
99.6	99.4	98.5
97.8	99.4	97
98.9	99.4	98.3
98.9	99.3	100.3
98.8	99.3	97.3
98.6	99.3	99.2
98.2	99.2	99.2
99.1	99.2	98.6
98.2	99.1	96.9
98.9	99.0	98.5
98.3	98.9	98.1
98.1	98.9	97.7
97.3	98.8	97.7
98.2	98.8	97.2
98.0	98.7	97.9
97.2	98.7	98.4
97.2	98.7	98.4
97.1	98.7	97.9
97.6	98.7	97.8
98.9	98.8	97.1
98.0	98.8	97.5
96.9	98.8	98.6
97.5	98.8	98
97.4	98.8	97.4
97.3	98.8	98
97.5	98.8	97.7
97.9	98.9	98.4
97.9	98.9	97.8
97.4	98.9	98.3
98.0	98.9	97.5
98.2	99.0	98.2
98.1	99.0	99
99.3	99.1	98.5
100.0	99.1	98.4
99.3	99.1	100
98.8	99.0	100.1
98.8	99.1	99.1
99.1	99.1	98.6

98.3	99.1	98.9
98.3	99.1	98.6
99.4	99.2	98.85
99.5	99.2	97.9
97.9	99.2	96.9
97.9	97.9	96.7
99.1	97.9	95.8
99.4	99.4	96.1
99.3	98.0	99.9
98.5	98.0	98.5
97.6	98.0	98.2
97.8	98.0	95
97.7	98.0	95.8
97.5	98.0	97.3
97.3	98.1	96.8
97.6	98.1	97.7
99.6	98.2	98.6
98.8	98.1	96.6
99.1	98.1	98.3
98.5	98.1	96.7
99.1	98.1	97.2
99.3	98.1	99.4
98.9	98.1	99.7
99.4	98.1	98.5
98.8	98.2	99.1
99.5	98.3	96.9
99.5	98.3	99
99.5	99.8	96.4
100.1	98.5	97.9
100.2	98.6	97.2
100.2	98.6	97.1
99.6	99.9	99.3
98.3	99.9	99.4
98.5	99.9	99.4
97.6	99.9	100
98.3	99.9	98.8
99.4	99.9	100.4
99.9	99.9	97.8
99.2	99.9	99.3
100.1	99.9	99.1
99.9	99.9	100
99.9	99.9	99.6
100.1	99.9	99
100.2	99.8	98.9
99.2	99.8	98.3
98.9	99.8	98.9
97.2	99.8	98
97.4	99.8	98.2
98.1	99.8	98.3
99.2	99.9	98.2
98.9	99.9	99.9
99.0	98.5	98.8

99.2	98.5	99.1
99.4	98.5	99.4
99.2	99.9	99.3
99.2	98.4	99.2
99.2	98.4	99.1
99.2	98.4	99.3
99.2	99.7	96.9
99.3	99.7	96.9
99.3	99.7	97.5
99.3	98.3	96.4
99.4	98.4	96.7
99.4	98.4	96.8
99.4	98.4	97
99.4	98.4	100
99.4	98.5	97.4
99.3	98.5	97.5
99.1	98.5	100.6
98.4	98.5	99.5
99.0	98.4	96.9
99.2	98.4	96.7
99.1	98.4	98.6
98.9	98.3	100.5
98.7	98.2	98.4
98.4	98.2	98.5
99.2	98.2	97
99.1	98.1	97
99.3	98.1	96.7
99.4	98.0	96.8
98.9	98.0	97.3
99.4	97.9	97.4
99.3	97.9	97.4
99.4	97.9	97.4
99.3	97.9	97
98.4	98.0	98.2
99.0	98.0	99.6
97.9	98.0	95
96.8	98.0	94.6
97.8	98.0	97.6
98.6	98.0	97.9
98.3	98.0	97.4
97.8	98.0	97.1
98.1	97.9	96.4
96.4	97.9	90.4
98.4	97.9	98
98.3	97.9	98.5
98.8	99.3	98.8
98.8	99.2	99.6
99.7	99.2	98.8
99.6	99.2	101.5
99.2	99.2	101.1
99.7	99.2	100.2
99.1	99.2	100.1

99.3	99.0	99.2
98.3	98.9	96.3
98.4	98.9	96.1
98.5	98.9	96.7
98.6	98.9	97.5
98.6	99.0	98.5
98.5	99.0	99.2
98.6	99.1	99.3
98.5	99.1	98.7
98.4	99.1	98.6
98.3	99.0	98.9
98.2	99.0	96.8
98.4	99.0	96.2
98.4	98.9	96.3
97.3	98.9	99.1
92.4	98.9	89.6
96.4	98.9	97.3
97.5	98.9	95.8
97.5	99.0	96.9
97.9	99.0	95.7
99.6	99.0	98.8
99.2	99.0	98.9
99.1	99.0	97.8
99.2	99.0	97.9
98.8	99.0	99.5
98.3	99.0	99.4
98.2	99.0	99.2
98.9	99.0	97.6
98.8	99.0	98.5
98.2	99.1	98
98.8	99.3	98.8
99.1	99.3	98.8
98.8	99.4	99.3
98.8	99.4	97.1
98.9	99.4	98.8
99.6	NaN	98.7
98.4	NaN	98.2
97.7	NaN	98.1
98.3	NaN	96.3
98.9	NaN	96.6
98.9	NaN	98.1
98.7	NaN	97.6
98.1	NaN	98.8
98.5	NaN	98.4
99.0	NaN	99.5
98.4	NaN	101
98.7	NaN	98.6
98.0	NaN	98
98.9	NaN	98.1
99.4	NaN	98.4