CONFERENCE
OMAINTEC
2018
EXHIBITION

INTERNATIONAL OPERATIONS & MAINTENANCE CONFERENCE
IN THE ARAB COUNTRIES

UNDER THE THEME
"MANAGING MAINTENANCE WITHIN INDUSTRY 4.0"
CONICIDE WITH **THE 16TH ARAB MAINTENANCE EXHIBITION**

Smart maintenance by using data analytics during industry 4.0

By

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What will be discussed

- ❖ Industry 4.0 concept.
- ❖ what is data analytics.
- ❖ Use of data analytics for machine   prognosis .
- ❖ Question and answer.

Industry 4.0

Industrial revolutions have always been driven by innovations in technology.

Four Phases of Industrialization

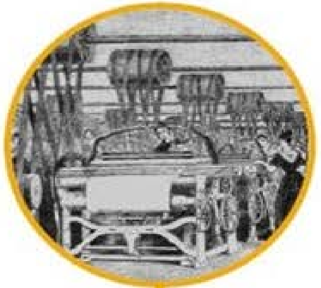
Industry 1.0

1

End of 18th century

Use of **water and steam power** to run mechanical production facilities

Industry 2.0



2

Beginning of 20th century

Use of **electrical power** to enable work-sharing mass production

Industry 3.0

3

Early 1970s

Use of **electronics and IT** to automate production

Industry 4.0

4

Today

Use of **cyber-physical systems** to monitor, analyze, and automate business

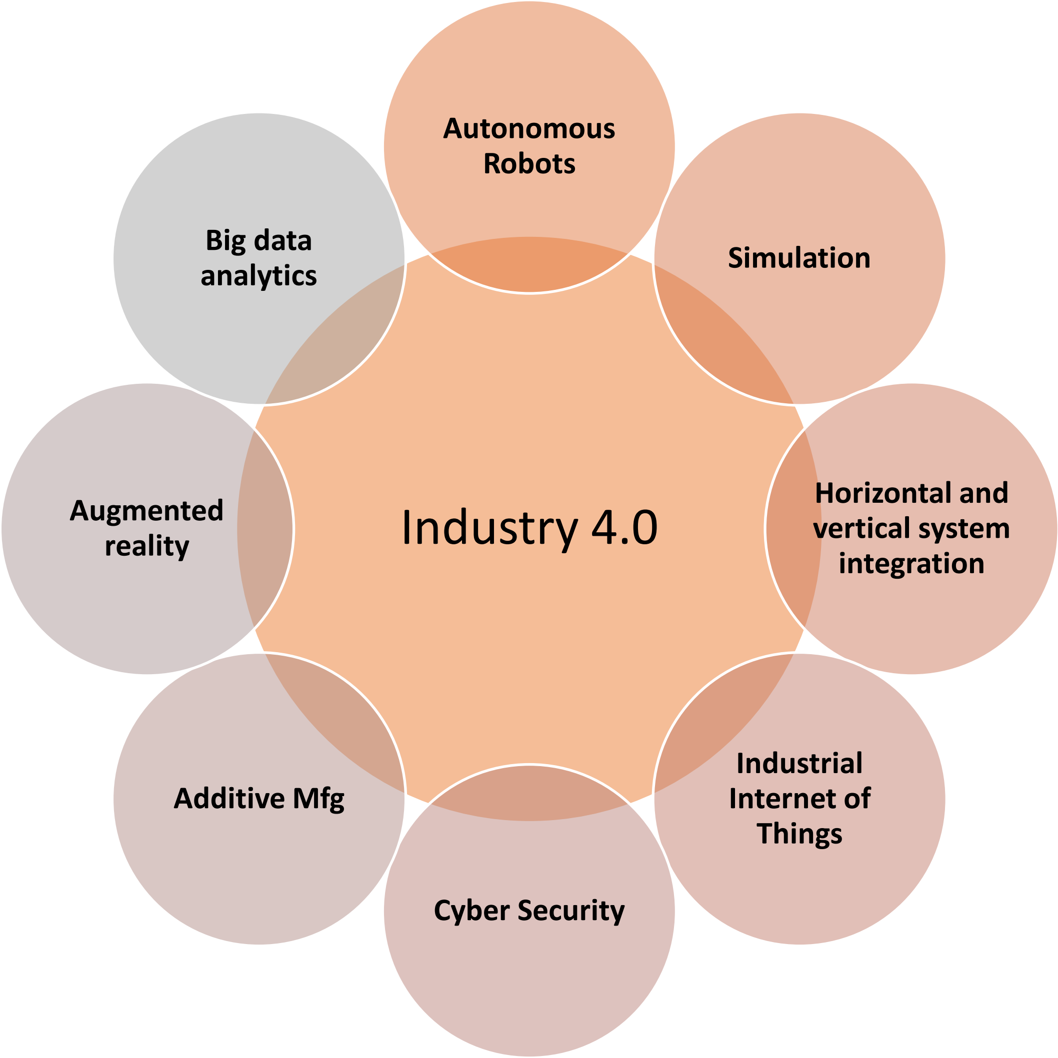
Spinning wheel
Water wheel
Steam engine

Conveyor belt
Assembly line

Electronics
IT

Integration of digital and physical system, Internet of things ,Big data,3Dprinting, Robotics

Building blocks of Industry 4.0



Industry 4.0

Internet of Things and Big Data

What is the Internet of Things

Devices with electronics and sensors connected to the public telecom network and the internet.

Big Data

Large data sets that may be analyzed computationally to reveal patterns, trends, and associations, especially relating to human behavior and interactions.

The size of the data is not important • Ability to analyze the data, make informed decisions and take action .

The Industrial Internet of Things

IoT + Big Data = Industrial Internet

Internet of Things and Big Data

Explosion of low-cost sensor technologies has made every manufacturing process and component a potential data source.

❖Ford: Placed sensors on virtually every piece of production equipment at its River Rouge facility.

❖ GM: Uses sensors to monitor humidity conditions during vehicle painting; if unfavourable, the work piece is moved elsewhere in plant or ventilation systems adjusted.

❖ Raytheon: Keeps track of how many times a screw has been turned in its factories.

❖Merck: Improves vaccines by conducting up to 15 billion calculations to determine what environmental and process factors influence quality of final product

IoT-enabled remote diagnostics Navistar

To help fleet and vehicle owners move from a reactive approach to a more predictive model, Navistar needed to analyze a wider range of data in real time.

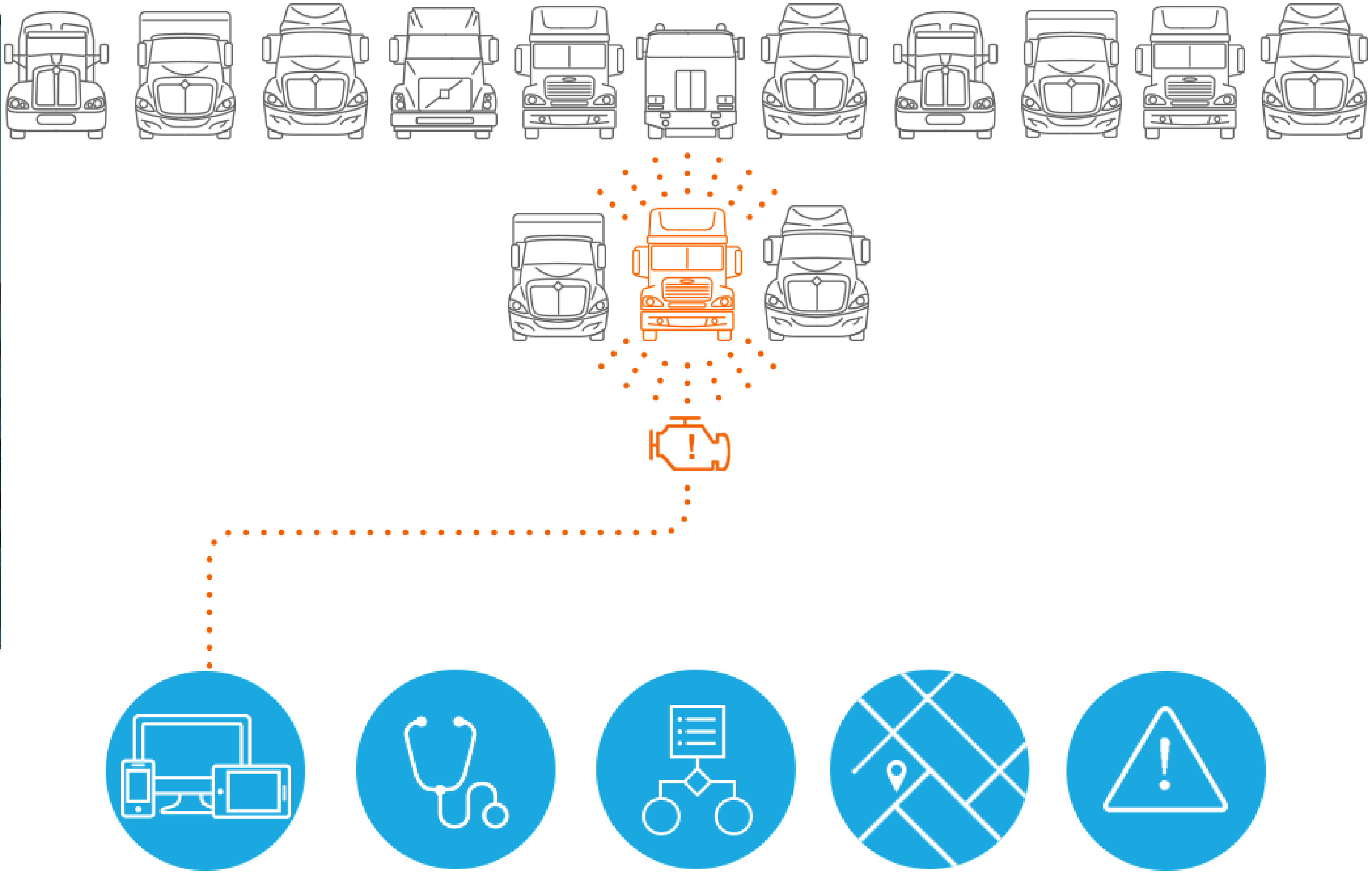
Navistar built an IoT-enabled remote diagnostics platform, called OnCommand.

The platform brings in over 70 telematics and sensor data feeds from more than 300,000 connected vehicles—including engine performance, truck speed, acceleration, coolant temperature, and brake wear.

This data is then correlated with other Navistar and third party data sources, including meteorological, geolocation, vehicle usage, traffic, historical warranty, and parts inventory information.

Navistar has helped fleet and vehicle owners reduce maintenance costs by up to 40 percent.


Text
4.0

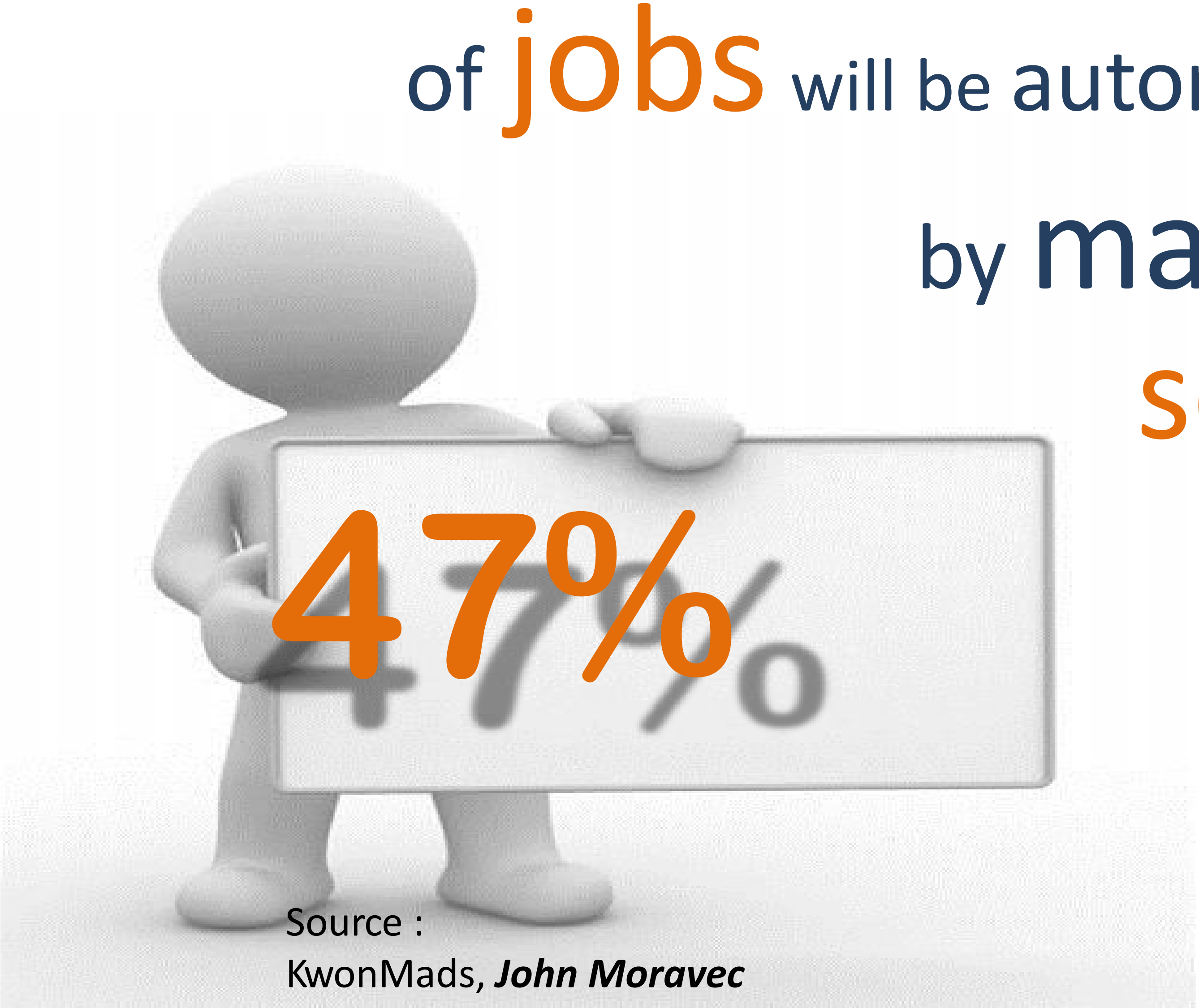

LIVE ACCESS
HEALTH REPORT
ACTION PLAN
MAPPING
ALERTS

Internet of Things and Big Data

IoT and bog Data will generate 4 primary forms of value in terms of manufacturing processes:

- ❖**Operating Efficiency;**
- ❖**Predictive Maintenance;**
- ❖**Supply Chain Management;**
- ❖**Inventory Optimization.**

In 20 years



47%

of **jobs** will be automated

by **machines** or

software

Source :
KwonMads, ***John Moravec***

BIG DATA

Is a new paradigm that represents the search for solutions to store and analyze structured and unstructured data together for an affordable and scalable data mode.

PREDICTIVE ANALYTICS

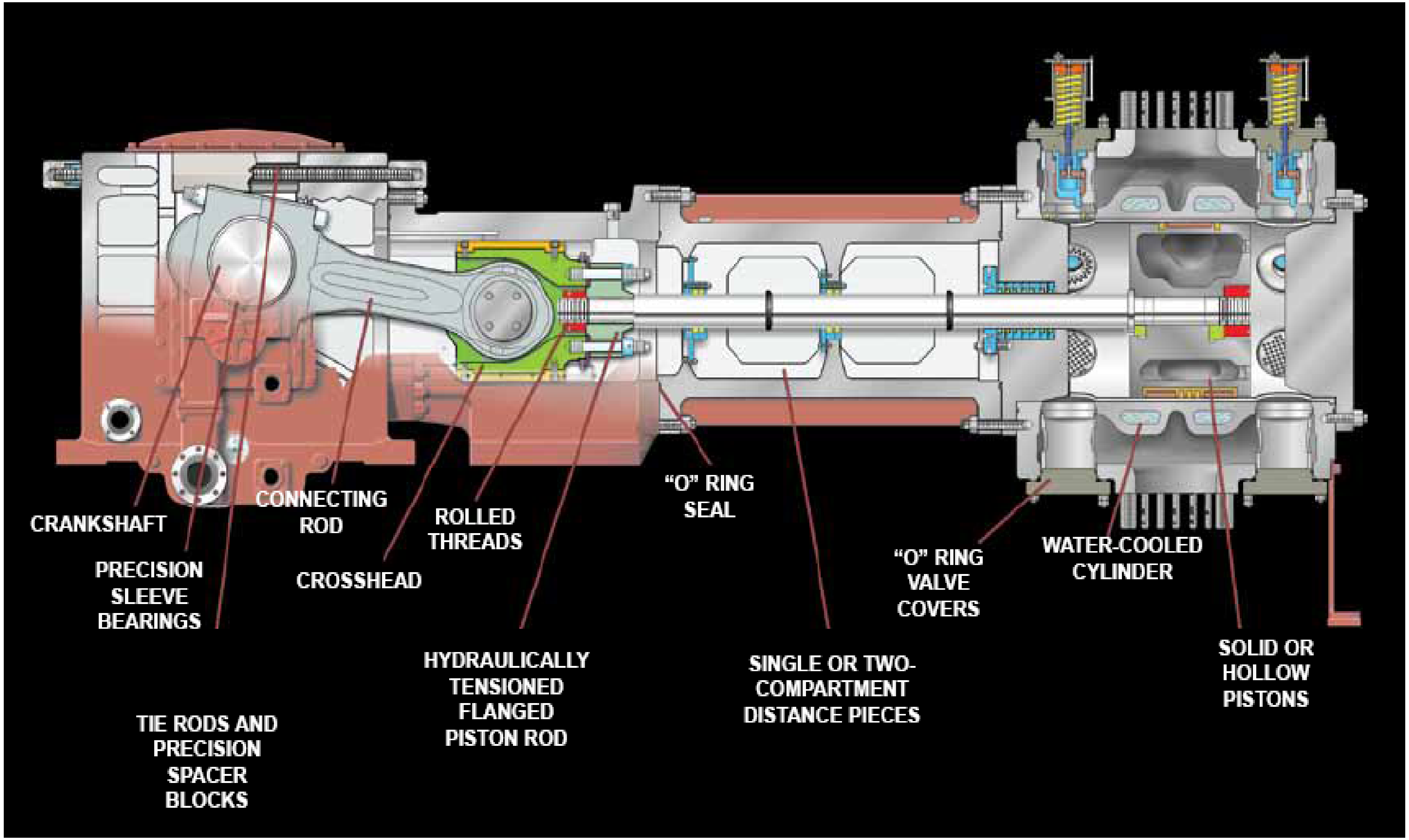
A variety of statistical techniques from modeling, machine learning, and data mining that analyze current and historical facts to make predictions about future, or otherwise unknown, events.

PROGNOSTICS

Algorithms to detect interesting patterns in data. Statement about the way things will happen in the future

Case study


4.0


CRANKSHAFT
PRECISION SLEEVE BEARINGS
TIE RODS AND PRECISION SPACER BLOCKS
CONNECTING ROD
CROSSHEAD
ROLLED THREADS
HYDRAULICALLY TENSIONED FLANGED PISTON ROD
"O" RING SEAL
SINGLE OR TWO-COMPARTMENT DISTANCE PIECES
"O" RING VALVE COVERS
WATER-COOLED CYLINDER
SOLID OR HOLLOW PISTONS

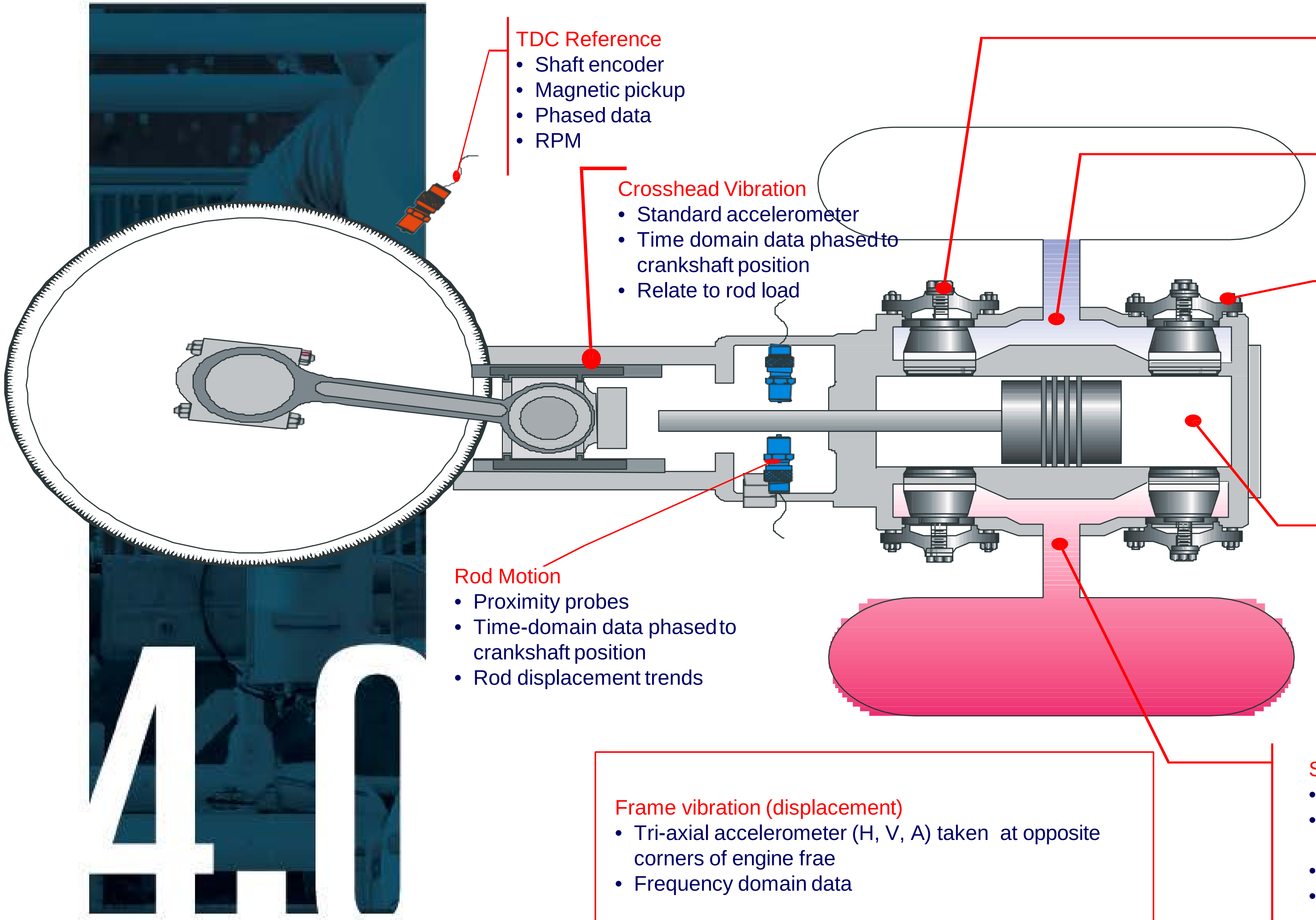
PARAMETERS

- **Safety**
- **Condition monitoring**

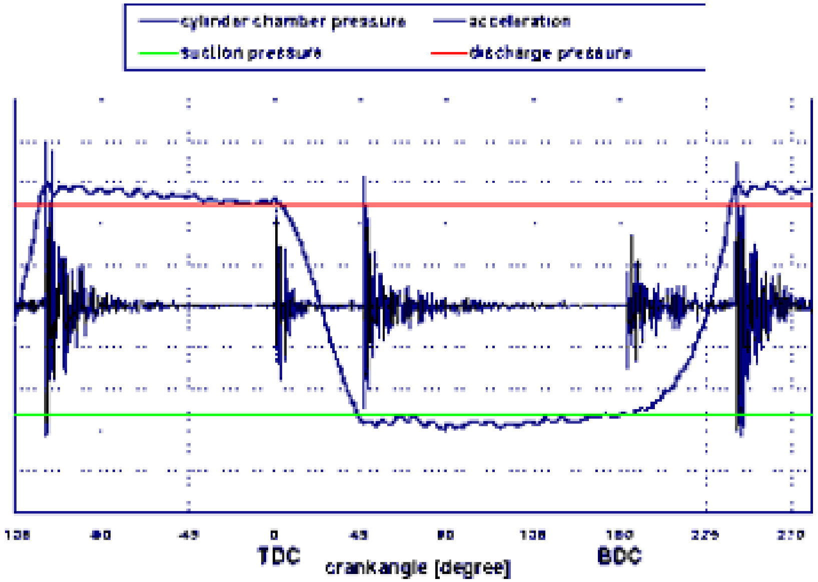
  -early failure detection
  -wear monitoring
  -integration and analysis of process data

- **Efficiency optimisation.**

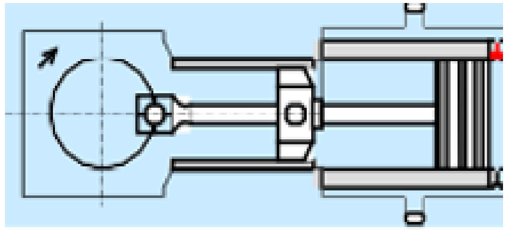
Compressor Data



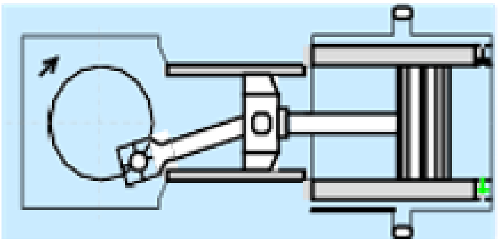
Safety Crank Angle Related Vibration Signal.



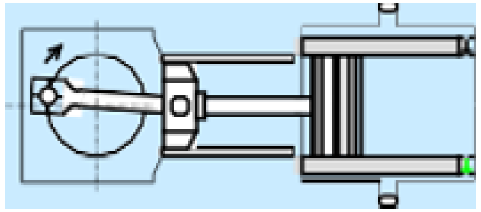
TDC (piston position): *discharge valve closes*



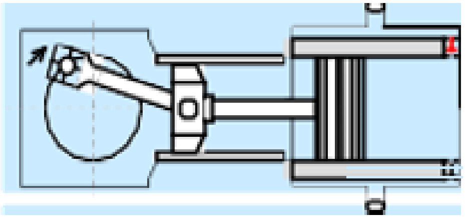
45° after TDC: *suction valve opens*



BDC: *suction valve closes*

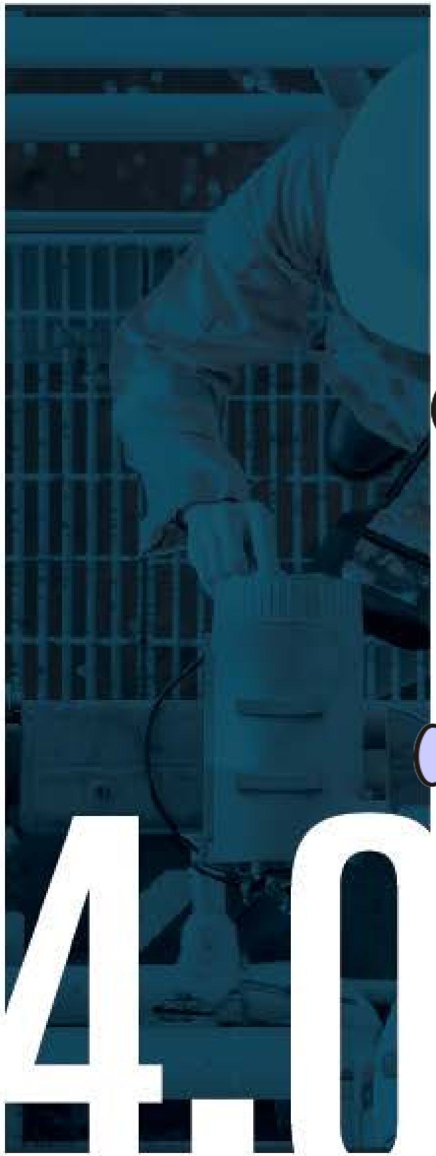


120° before TDC: *discharge valve opens*



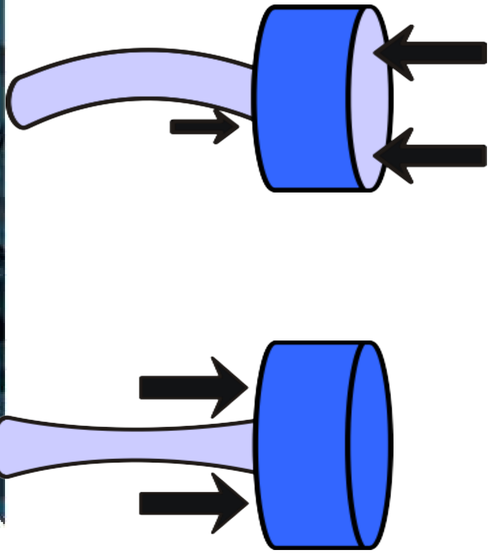
Messages from the system must be created .Modern communication systems like e-mail, short message service (SMS), .are used to transport the information to the responsible people in time, no matter where they are when the event occurs.

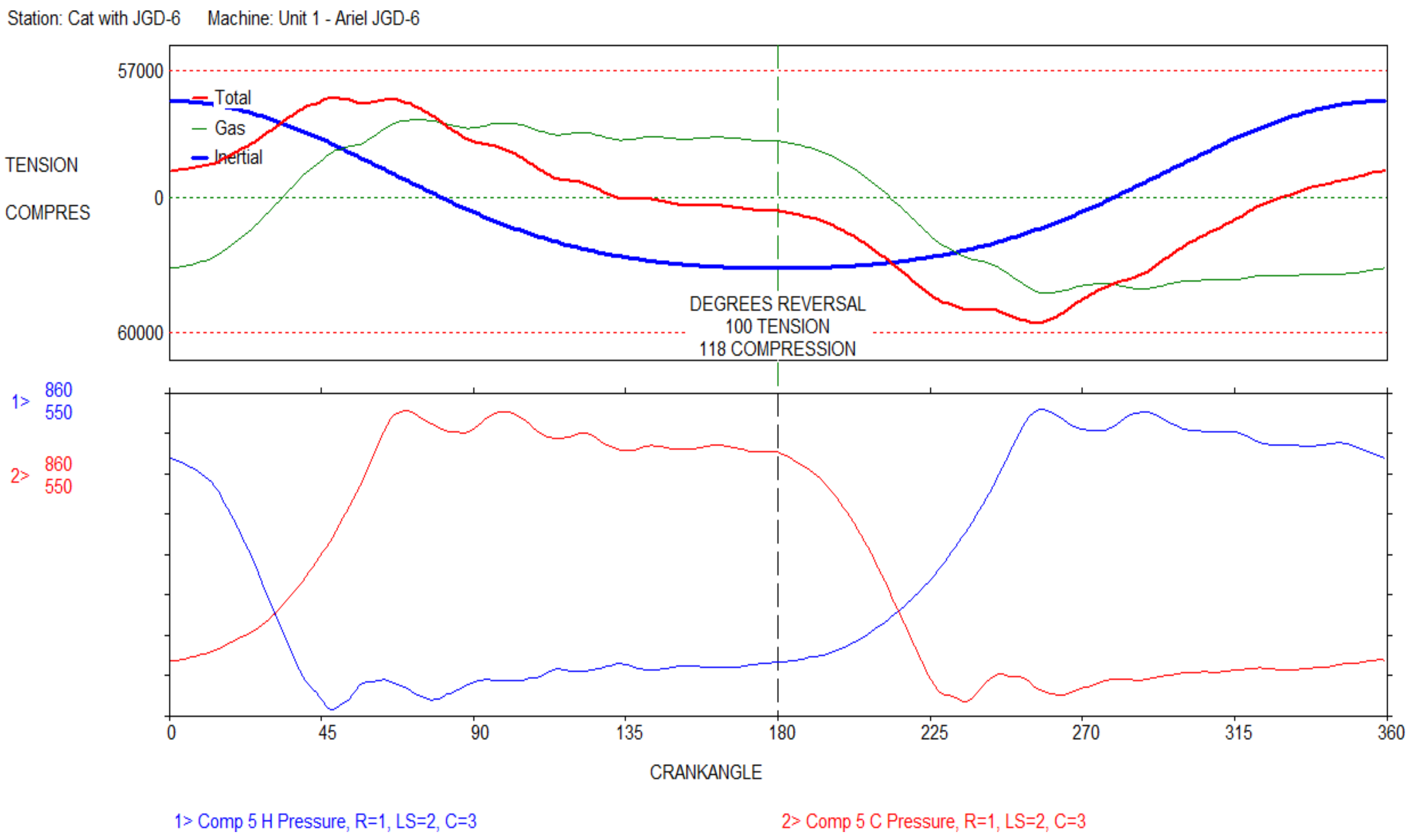
Dynamic Load - Combined



Static + Inertial = Dynamic (Total) Rod Load

Most of the time, inertial load reduces peaks of total load.

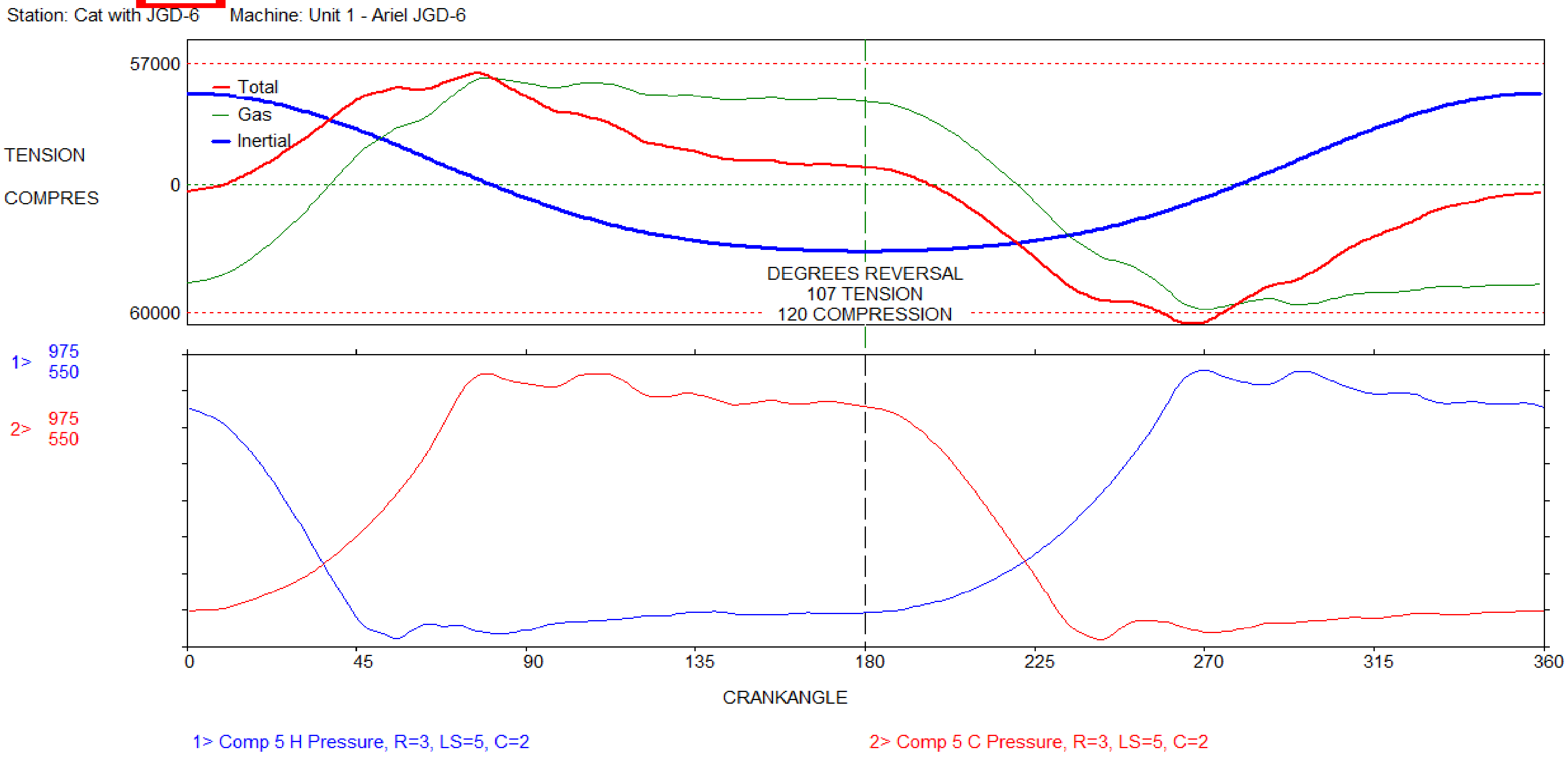




Exceeding Rod Load

Compressor Calculations

Comp Cyl	IHP	RPM	Toe Pd	Press Ps	%Vol Dis	Eff Suc	%Pow Dis	Loss Suc	Flow Bal	Clear Set	% Cal.	
1> CH5	508.29	1000.0	897.5	601.9	63.1	84.1	7.1	4.6	1.02	46.3	47.5	5-19-09 14:24:53
2> CC5	579.15	1200.0	899.0	601.7	62.8	83.7	6.0	4.3	1.02	46.6	48.2	5-19-09 14:25:12



Early Failure Detection

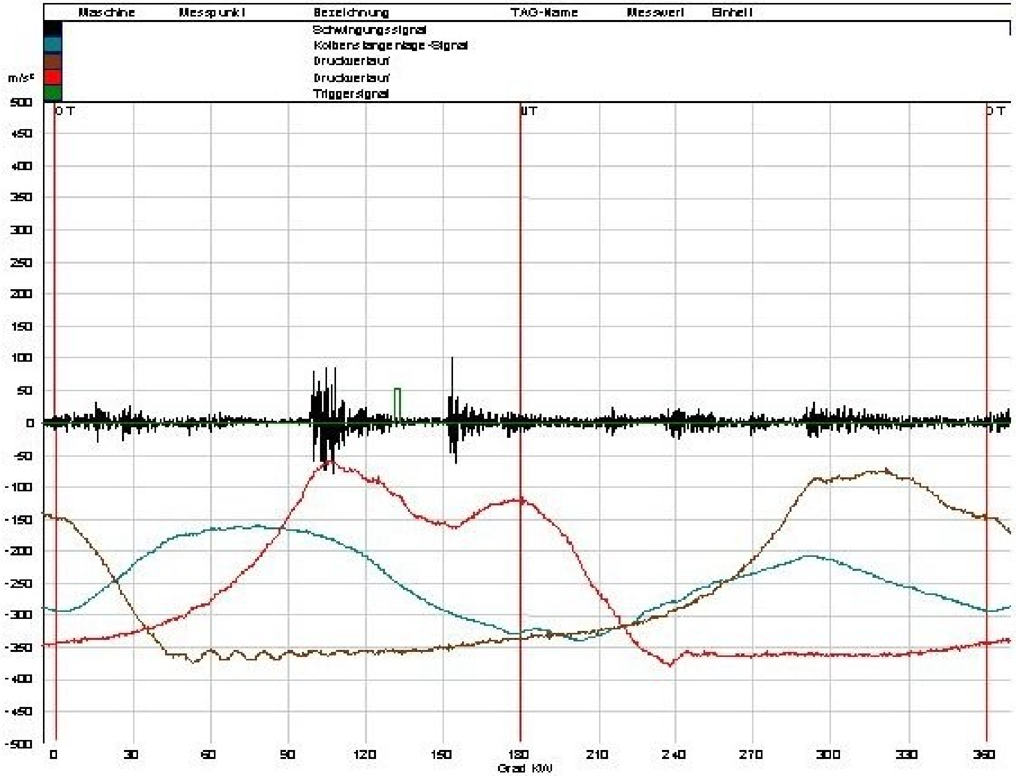
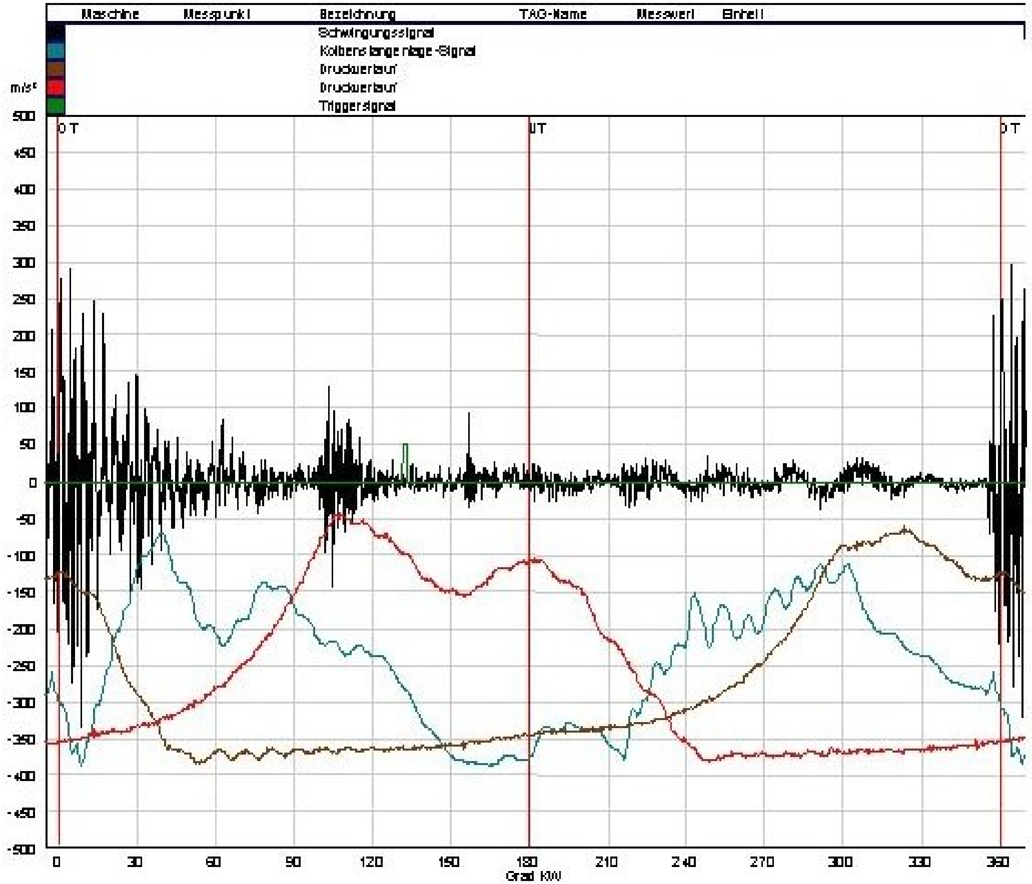


Figure shows crosshead vibration, dynamic pressure crank end, dynamic pressure head end, and rod position during one cycle of the machine. The machine is in good condition.



The vibration signal in Figure shows a drastic change near top- dead-center; the rod position signal is affected over the entire cycle. Analysis of both signals combined indicate a movement of the piston relative to the crosshead. Maintenance decided to take the machine out of service after the spare was started up and found a loose screw connection at the cross head pin.

Efficiency Optimization

One major goal in operating a plant is to optimize the efficiency and maximize the output. Therefore, the whole process as well as every individual machine should be monitored for efficiency losses.

For reciprocating compressors the monitoring of valve function and losses, clearance volumes, flow balance, compression ratio, indicated power, and, most important, the analysis of the gas dynamics using the p-V diagram are the critical parameters to reduce direct operation cost of the machine.

In addition, direct stress measurements like rod load and rod reversal indicate whether the operation of the machine is still in safe limits or if the overall plant output can be increased by adjusting compressor capacity

PV Analysis

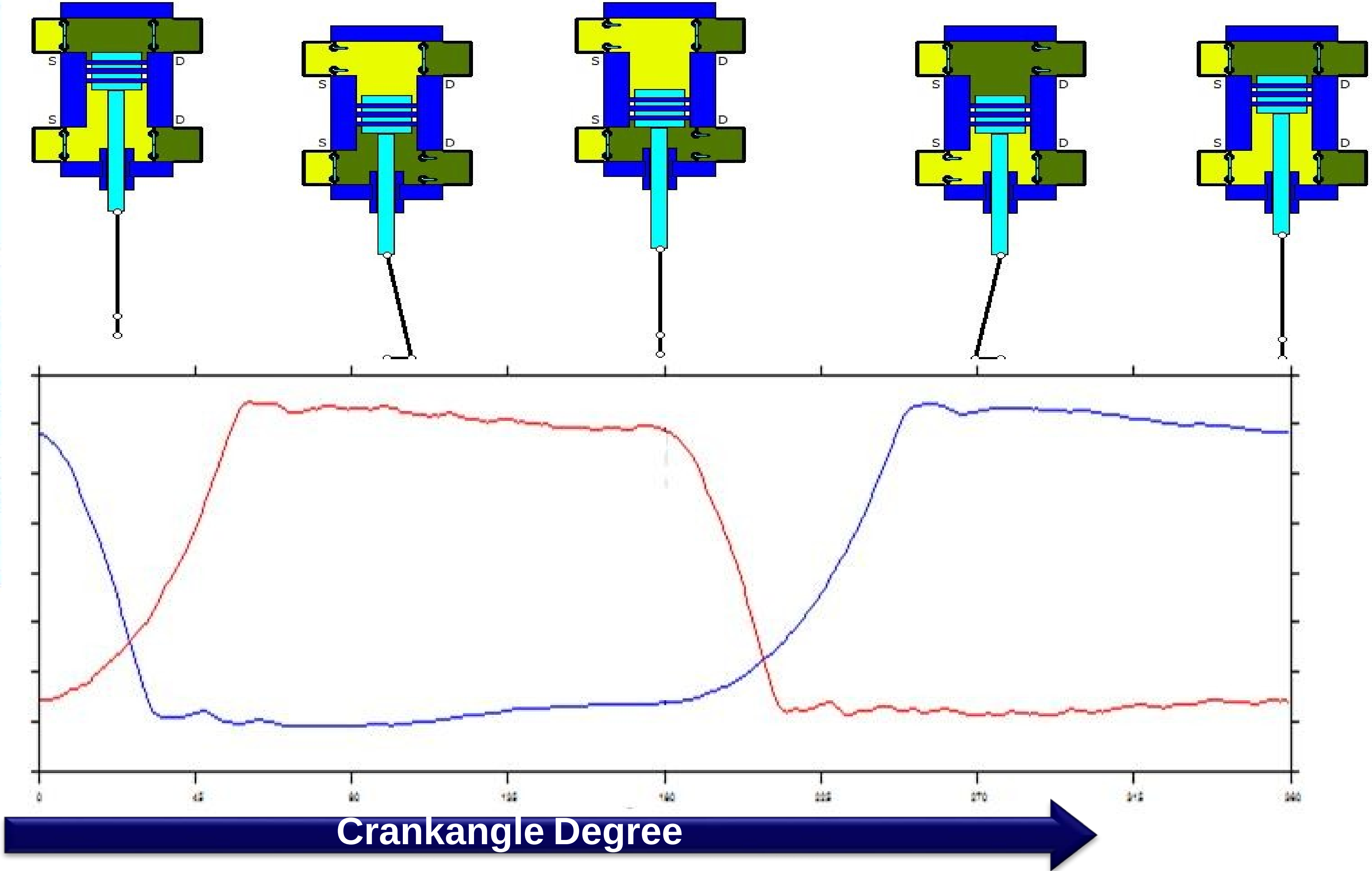
- Pressure velocity (PV) analysis is a technique that has proven to be very effective in assessing the condition of reciprocating machinery .

- Personal computer technology has significantly reduced the cost of this kind of measurement, and improvements in transducer technology have overcome the technical obstacles such that PV analysis is now available online.

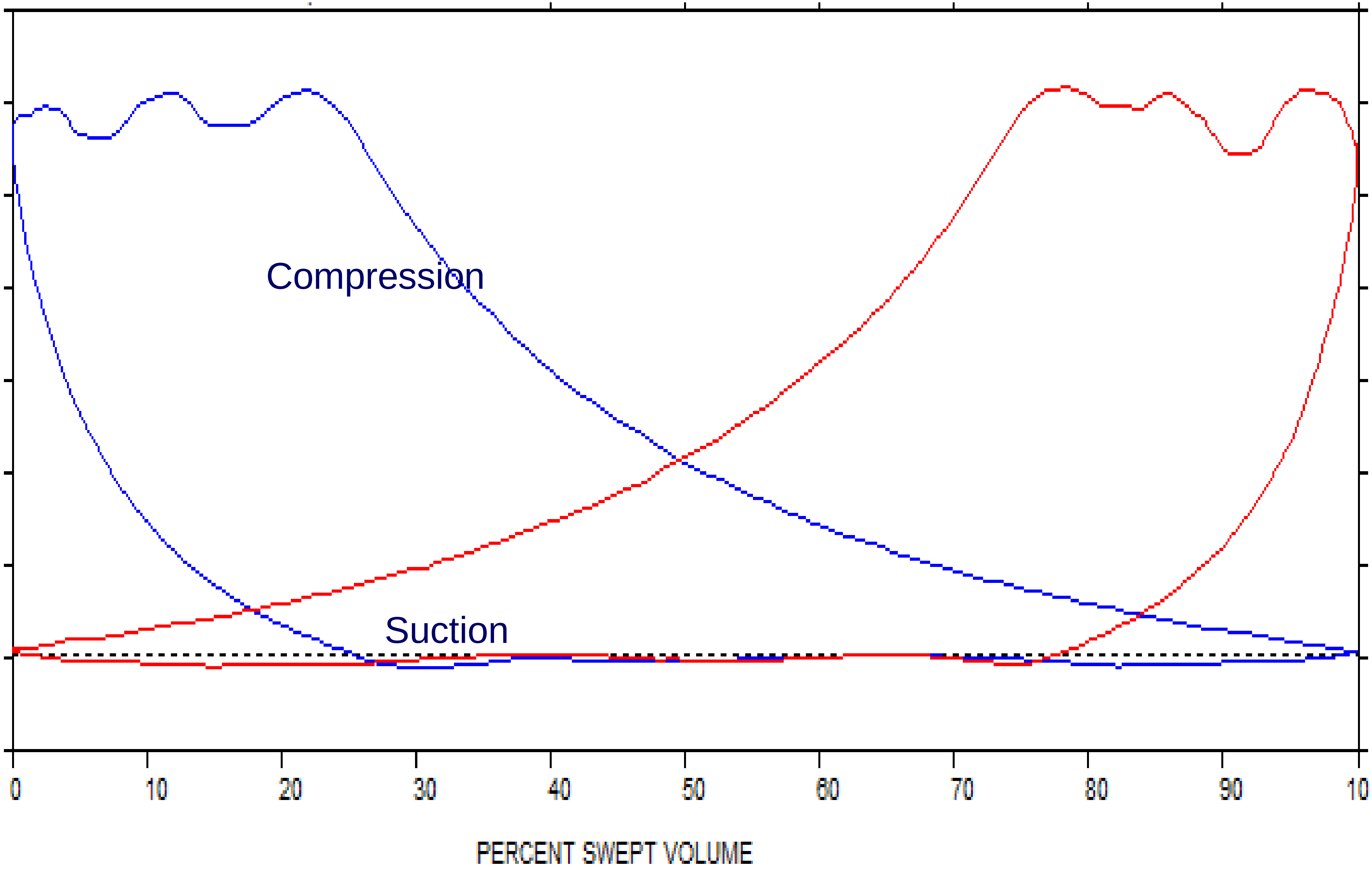
- Dynamic pressure transducers are used to measure the pressure inside the cylinder over the course of the stroke

- This allows the analyst to evaluate the condition of the rings, valves, and packing, while at the same time calculating the dynamic rod load, which is the source of the forces and moments described in the discussion on vibration.

Pressure Traces– Reciprocating



Pressure Volume Curves



Fig

The pressure-volume plot (PV plot)

The pressure-volume plot (PV plot) together with the calculated theoretical PV plot, as shown in Figure, is closely related to the polytrophic exponent function. The PV plot is based on measured dynamic pressure values in the cylinder that are plotted against the corresponding calculated

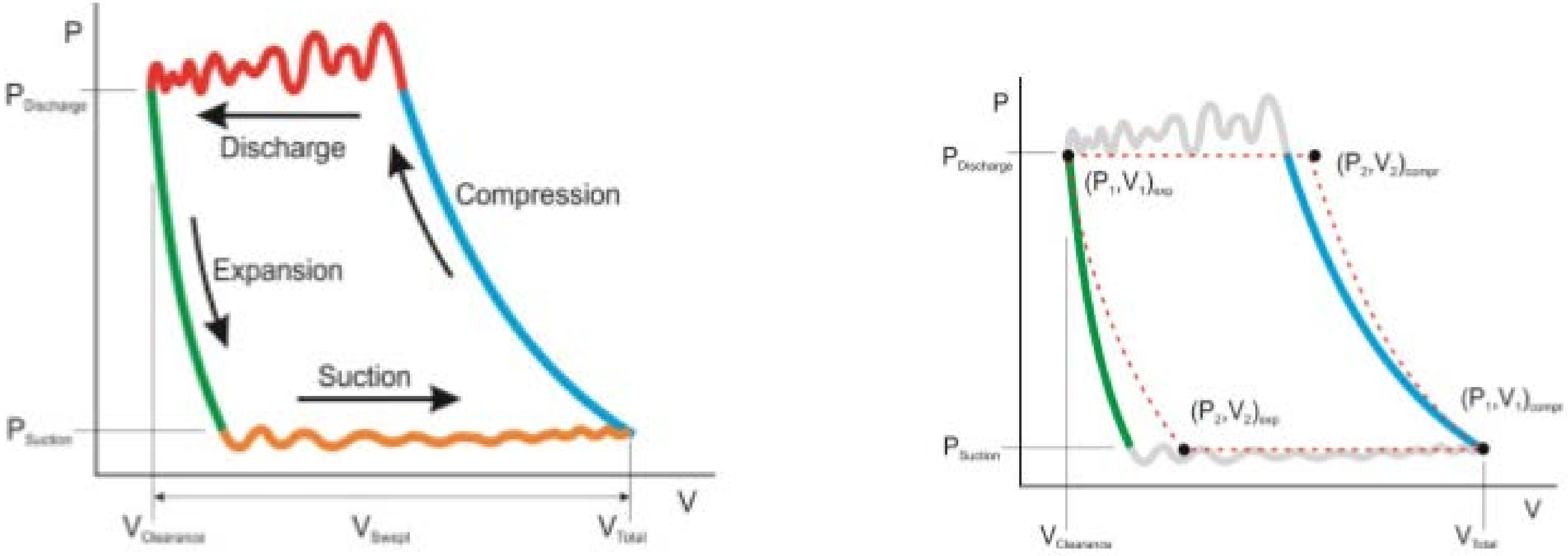


Figure. Left: PV plot showing the four basic compressor cycles. Right: Theoretical PV plot (red) overlying a PV plot. The deviation between the theoretical and actual expansion and compression curves indicate a suction valve leak in this example

Pattern recognition

One proven method for the automatic and “intelligent” evaluation of piston compressors is: Pattern recognition.

The application of a system integrated pattern recognition for reciprocating compressors requires some special considerations to allow the exchange experiences of similar machines. When a new critical state occurs, the monitoring system compares the current pattern with all other existing saved in the database and provides the user with a list by similarity.

Pattern recognition is an accepted analysis procedure that supports passive accumulation of experience and also allows operators to compare most varied damage situations and use the percentage match with previous damage situations to make diagnosis as accurate as possible (Figure 2).

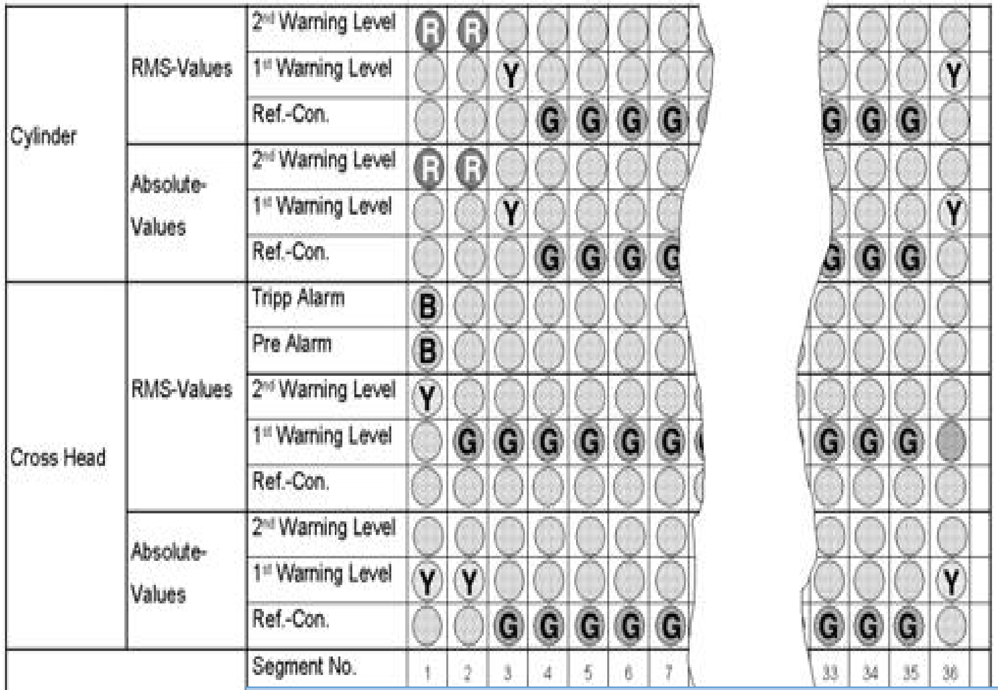
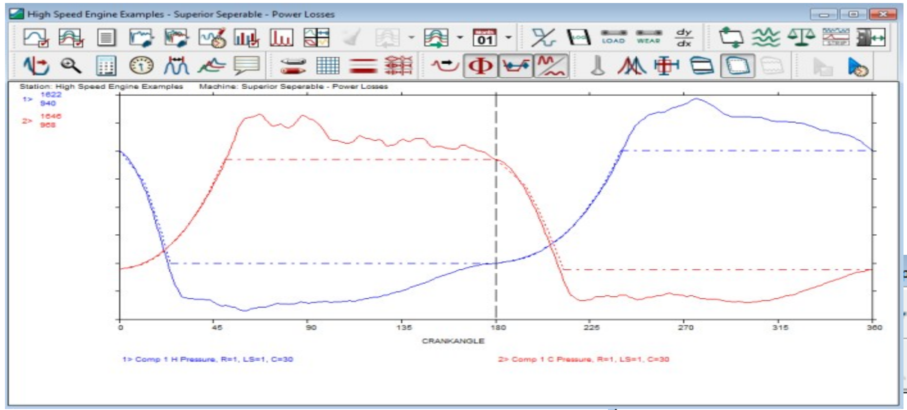
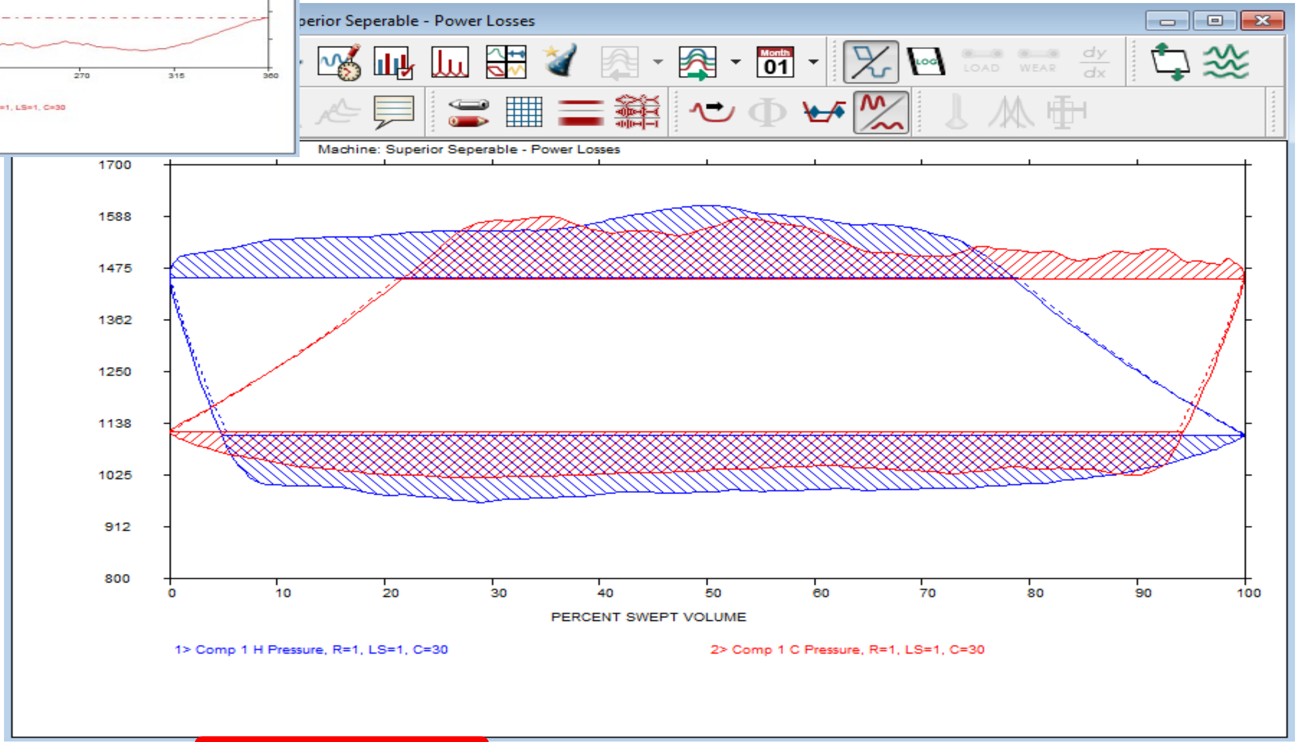


Figure 2. Condition Pattern of Vibration Signals

Calculate Power Losses?



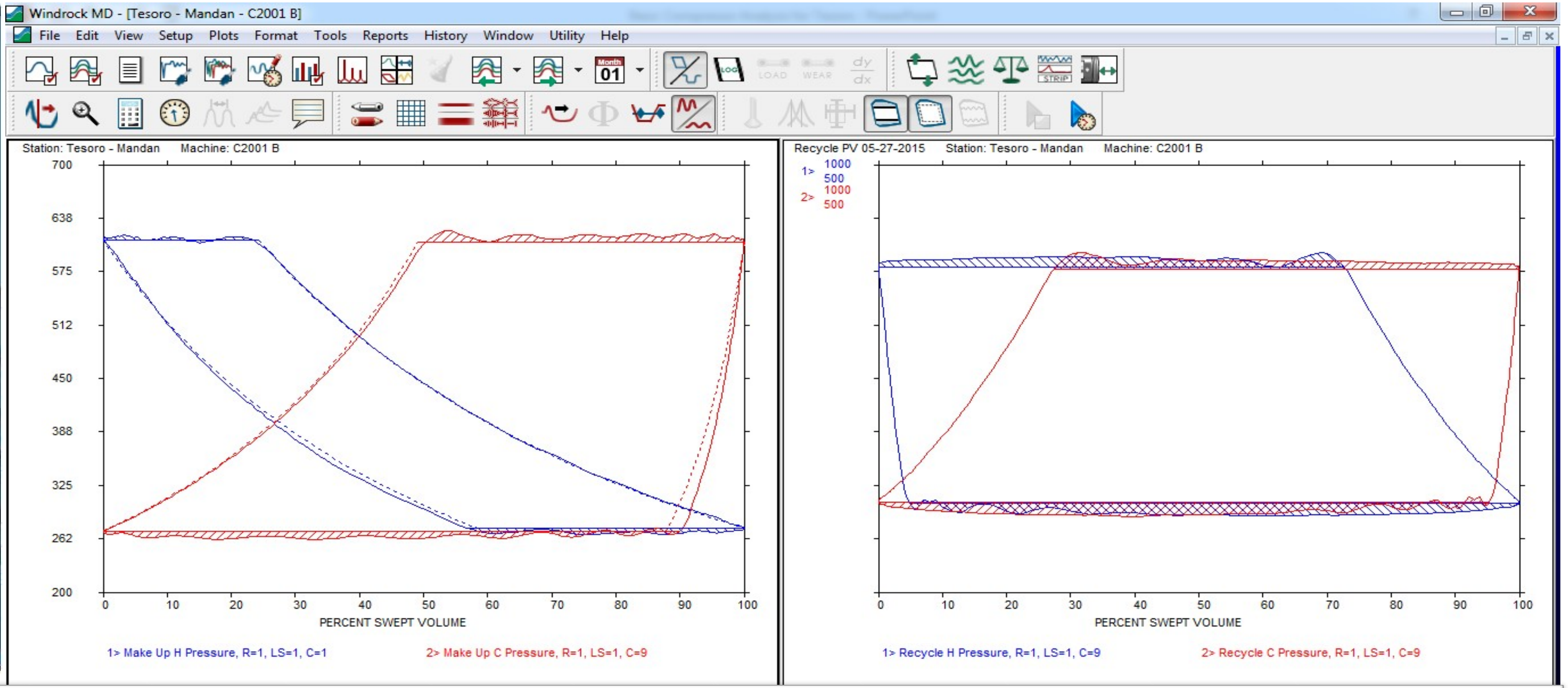
Why is this important?
By reducing valve losses you reduce Horse Power needed to flow gas. Less fuel / amps



Compressor Calculations

Comp	IHP	RPM	Toe	Press	%Vol	Ef	%Pow	Loss	Flow	Clear	%	
Cyl			Pd	Ps	Dis	S c	Dis	Suc	Bal	Set	Cal.	
1> CH1	198.42	899.1	1453.7	1109.4	78.4	95[illegible]1	16.7	21.5	1.[illegible]4	27.4	24.7	3-26-15 11:35:42
2> CC1	142.52	899.1	1450.3	1118.5	78.4	94[illegible]4	15.0	18.0	1.[illegible]5	33.2	30.0	3-26-15 11:37:12

Valve Losses on C2001 B



Compressor Calculations

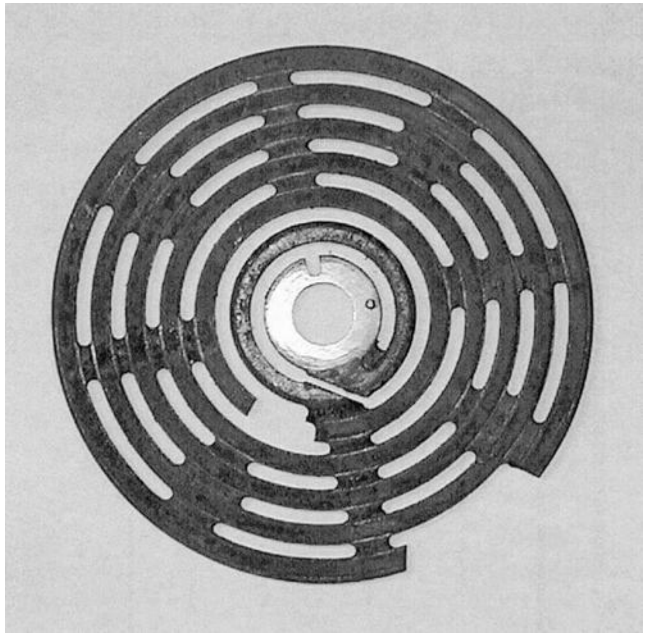
Comp Cyl	IHP	RPM	Toe Press Pd	Ps	%Vol Eff Dis	Su	%Pow Loss Dis	Suc	Flow Bal	Clear Set	% Cal.	
1> CH1	66.32	396.7	611.6	274.6	23.4	43.0	0.4	1.7	.08	81.4	79.4	5-27-15 10:10:57
2> CC1	130.93	396.8	609.7	271.1	49.6	90.0	1.4	2.1	.06	16.7	13.8	5-27-15 10:17:23

Faults in Suction Valves and Discharge Valves

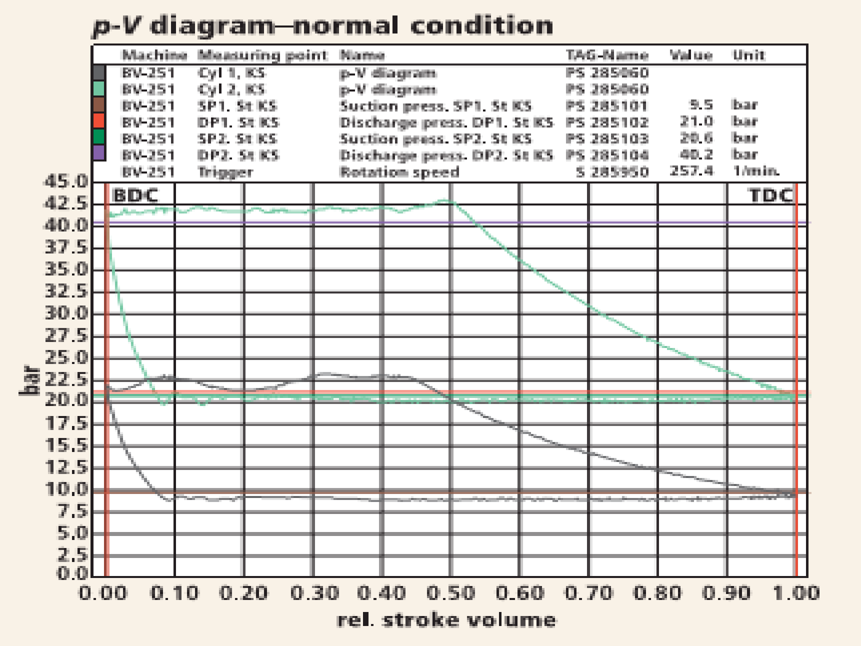
Faults in suction valves and discharge valves count among the most frequent reasons for an unplanned outage of reciprocating compressors.

The status inside the compressor can be evaluated directly by permanent measurement of pressure in the cylinder by PV diagram.

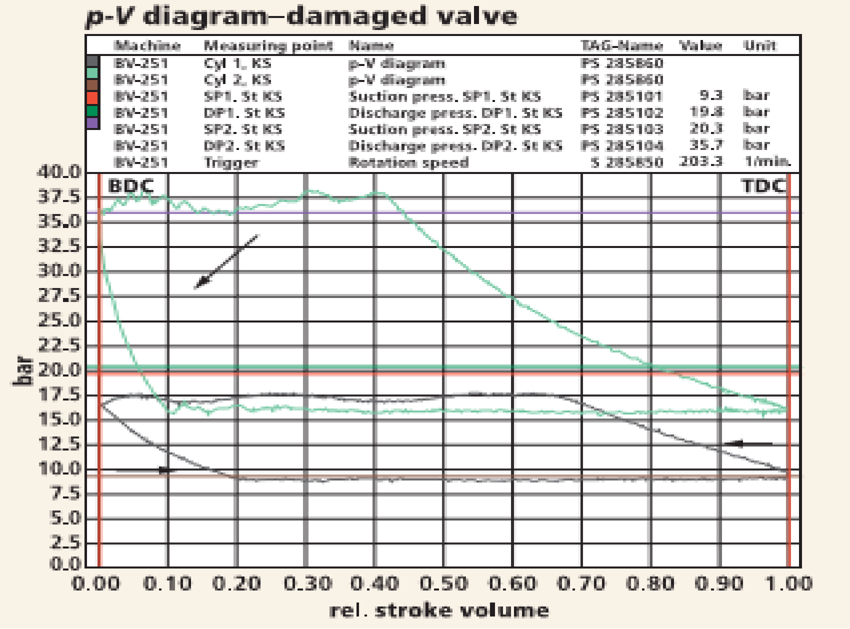
Additional condition information on these valves is provided by measurement of vibration in the cylinders, which is analyzed in 36 segments for every crank cycle with each 10 degrees of crank angle and monitored in relation to limiting values



Comparison of a good valve with a damaged valve.



P-v diagram of first and second stage cylinder with properly operating discharge valve



P-v diagram of first and second stage crank End cylinder with faulty first stage crank End discharge valve

The first-stage p–V diagram is visibly distorted and no longer reaches the target intermediate pressure

Faults in Suction Valves and Discharge Valves

The monitoring system signalled exceeding of the vibration limits in the first stage cylinder and disturbance of the p-V characteristic values of the crank-end compression chamber.

Figure 6 reproduces the vibration characteristics and pressure characteristics recorded at the time of the alarm. There is increased vibration in the cylinder here during almost the entire revolution of the crank, less vibration being evident only within the discharge phase (70 to 180 degrees crank angle) of the crank-end compression chamber.

Compression now rises more steeply and re-expansion is distinctly flatter than before, beginning about 10 degrees later .The changes are even more obvious in comparison with the first and second stage p-V diagrams (Figure 7).

Faults in Suction Valves and Discharge Valves

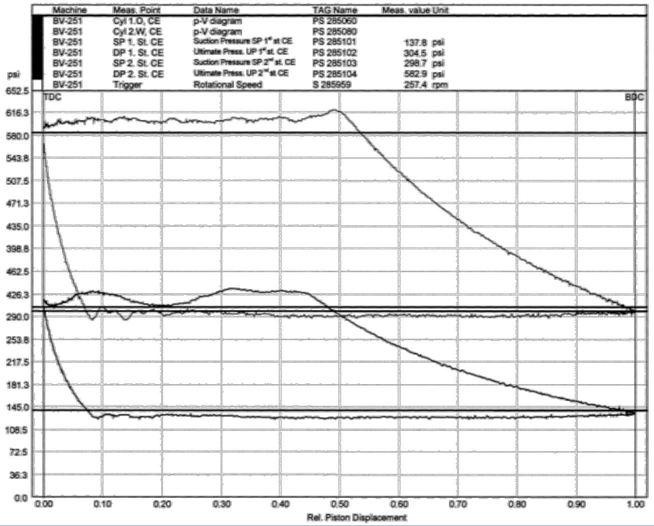


Figure 5. p-V of Crank-End Cylinder Side in First and Second Stage with Pressure Valves Working Normally

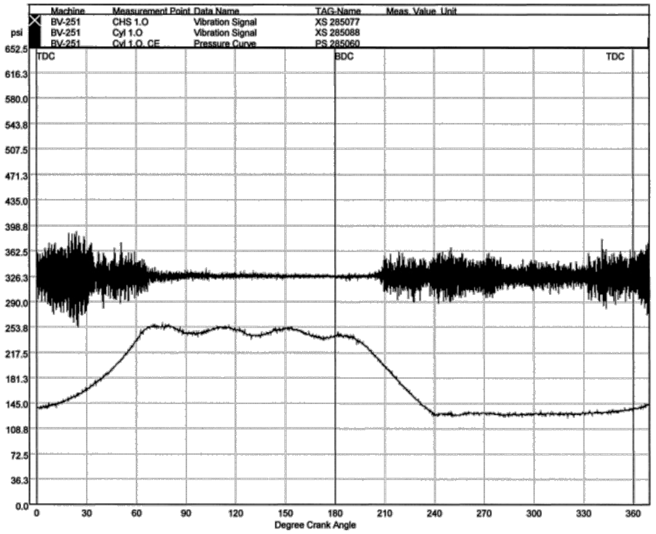


Figure 6. Crank-End Cylinder Pressure Characteristic and Vibration Characteristic in First Stage Cylinder with a Faulty Crank-End Pressure Valve.

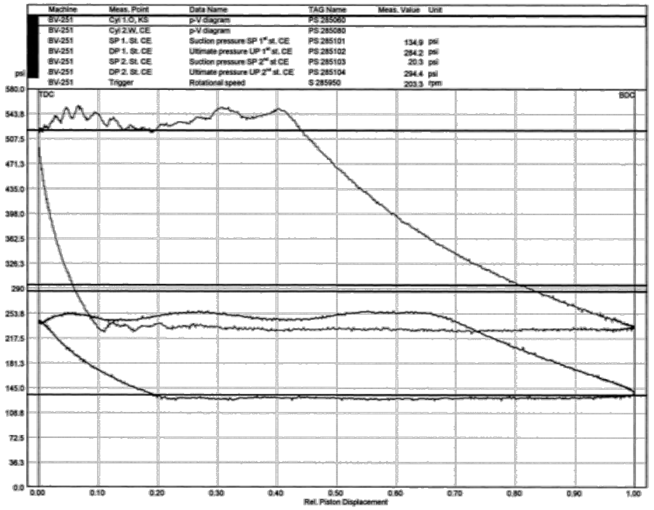
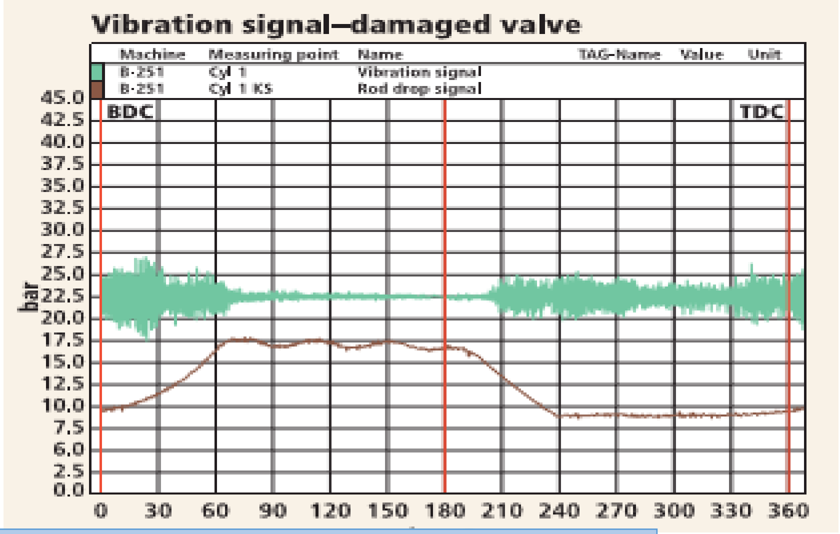


Figure 7. p-V Diagrams (Volume Display) of Crank-End Cylinder Spaces in First and Second Stage with Faulty First-Stage Crank-End Pressure Valve.

Faulty crank-end discharge valve.

There is increased cylinder vibration during almost the entire crank stroke, less vibration being evident only within the discharge region (70° to 180° crank angle) of the crank-end compression space. The changes are even more obvious on comparison with the first- and second-stage p–V diagrams.



Crank-end first-stage cylinder pressure and Vibration characteristics with a faulty crank-end discharge valve.

Faulty Stuffing-Box

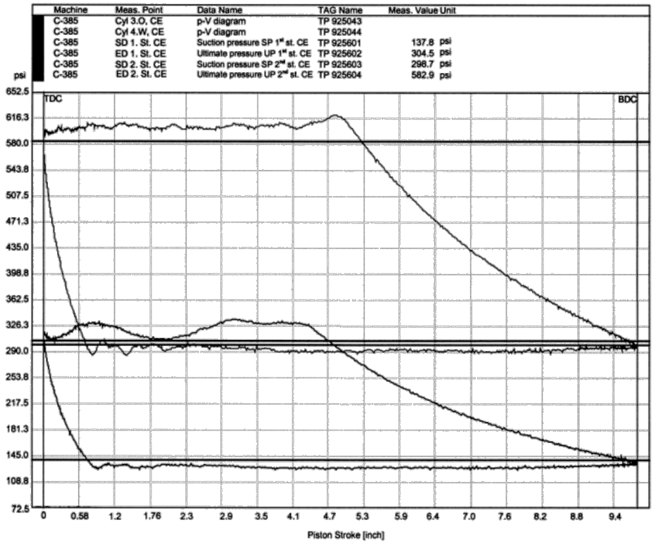


Figure . p-V Diagrams (Volume Display) of Crank-End Cylinder Spaces in First and Second Stage with Stuffing-Box Packing in Good Working Order

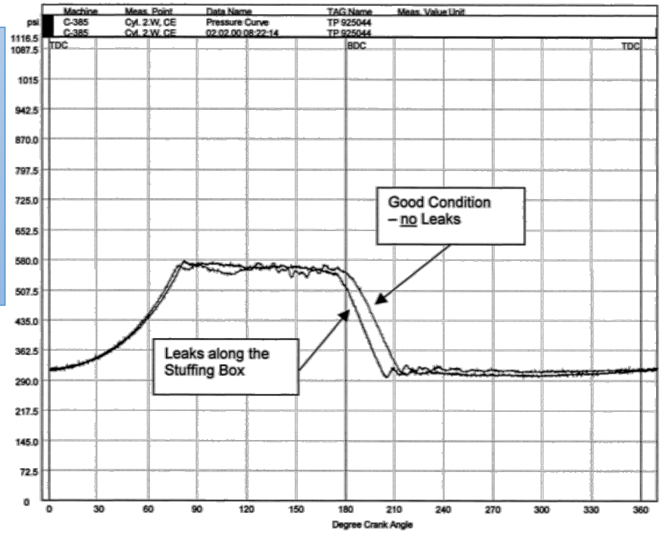


Figure . Cylinder Pressure Curves for Crank-End Cylinder, Second Stage, With and Without Leakage along the Stuffing-Box Packing, in One Revolution of the Crank (360 Degrees Crank Angle).

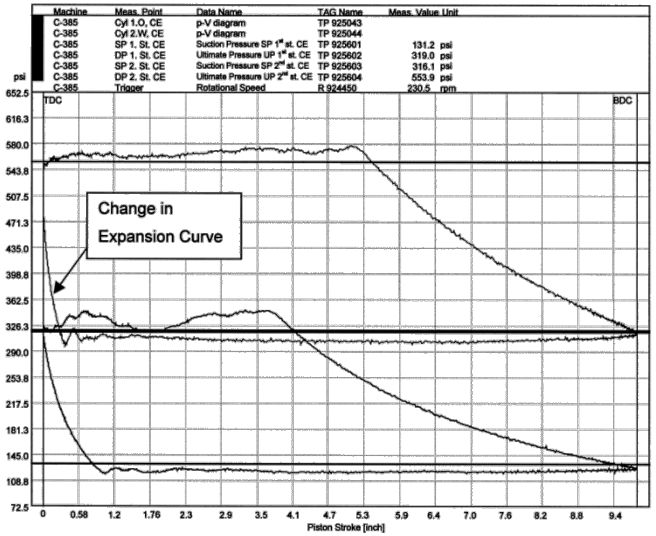
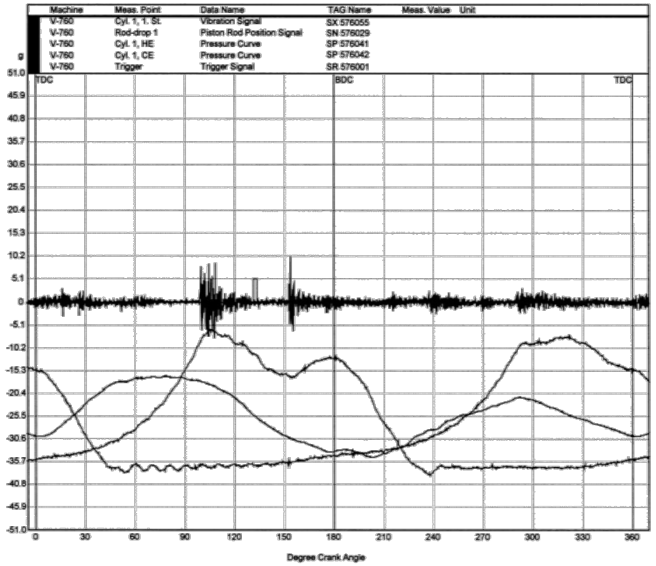


Figure . p-V Diagrams (Volume Display) for Crank-End Cylinder Spaces in First and Second Stage, with Leakage along the Second-Stage Stuffing-Box Packing

Piston Ring Wear

Figure 12. Development of Segments 1, 9, 18, and 27 (Hourly Mean Values) of Rod-Drop Analysis During the Six Weeks Before Shutting Down the Machine.



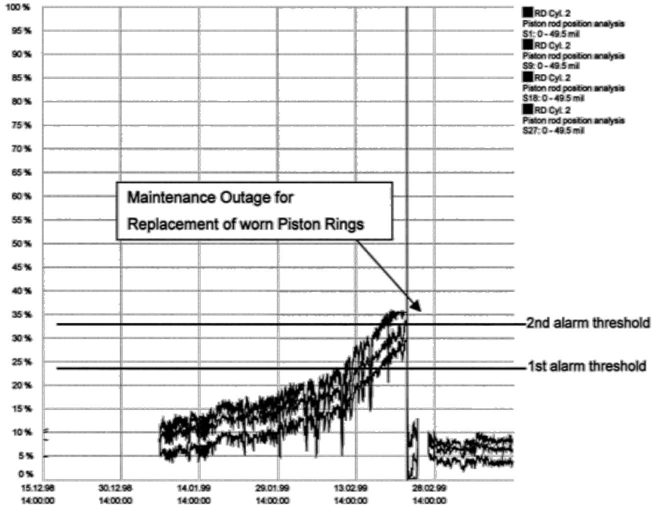
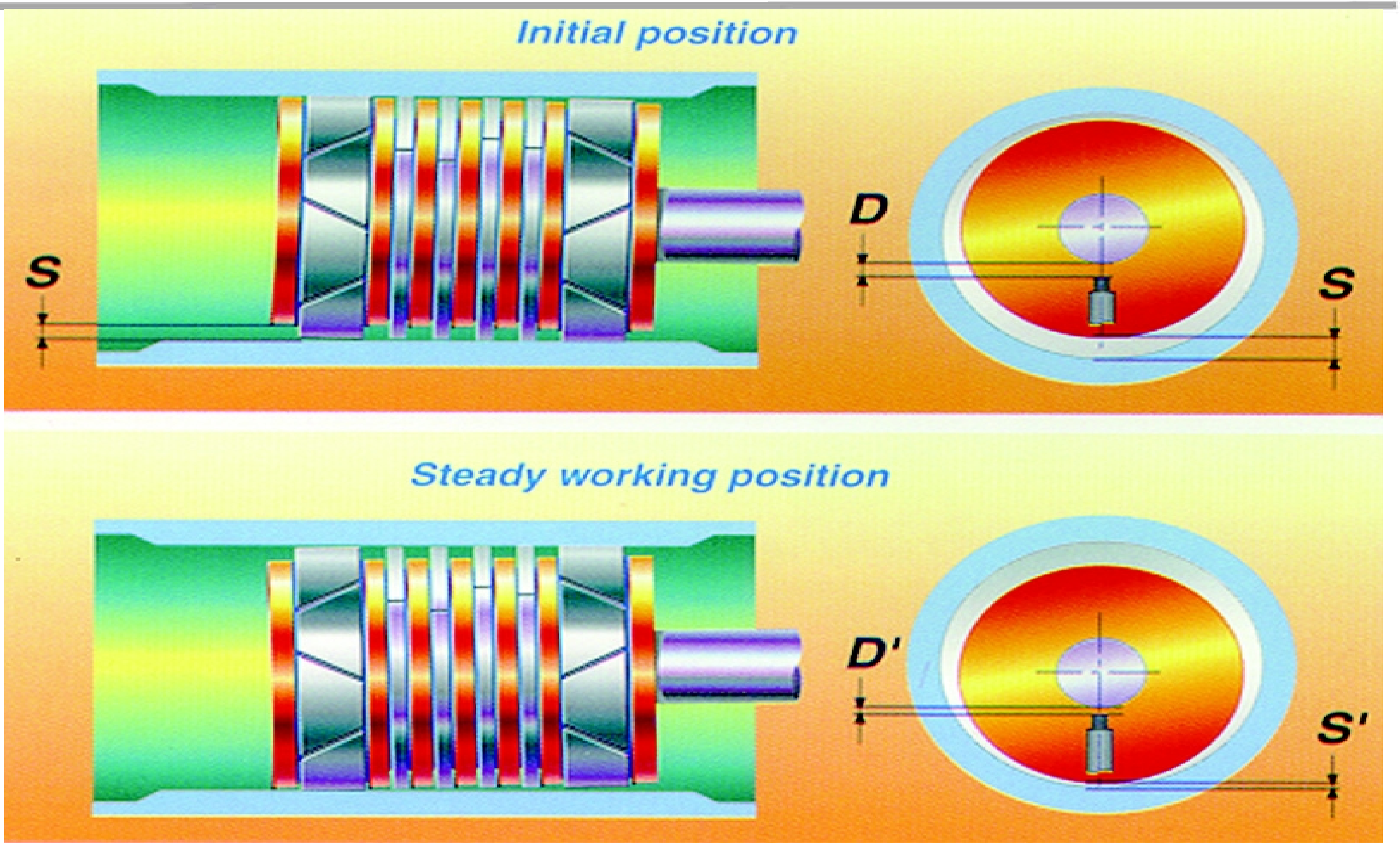


Figure 13. Cylinder Pressure Characteristics, Rod-Drop, and Vibration in Cylinder 1 in Good Condition

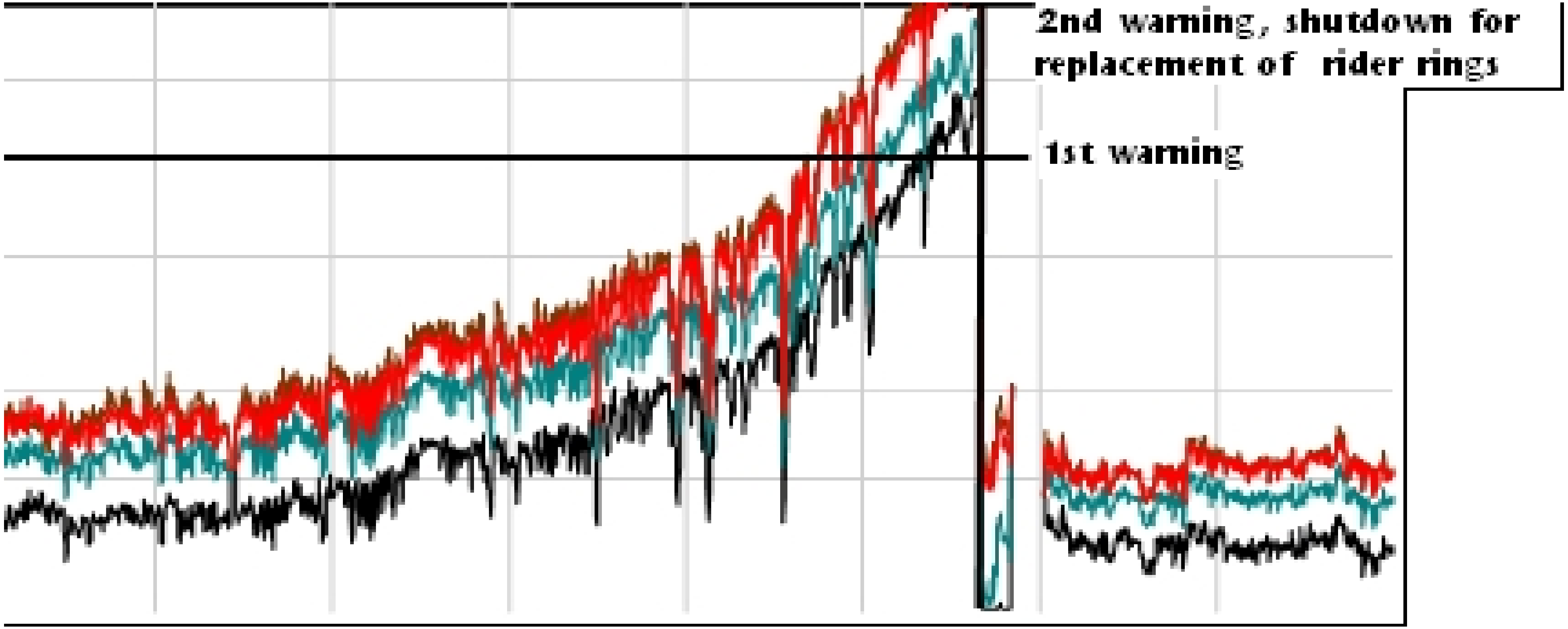
ROD DROP MONITORING

- The piston rod assembly drops during operation due to normal rider band wear .
- Sometimes due to high temperature of the the gas stream , cylinder valve problem, insufficient lubrication for prolonged period can cause drastic reduction in rider band life.
- Replacement of rider bands solely an hours of operation is not the most efficient method



PISTON ROD DROP BY RIDER RING WEAR

BROKEN RIDER RING



Rod drop values prior to the shutdown for replacement of the worn rider rings

Table 1- RIDER RING CONDITIONS- input variable 1

Set	Vriable	Description	Range
1	Extremely high deficiency level	Major mission degradation which can affect other components also	3-4 mm
2	high deficiency level	Major mission degradation or major system damage	4-6 mm
3	average deficiency level	Minor mission degradation, or minor system damage	5-8 mm
4	low deficiency level	Less than minor mission degradation, or minor system damage	8-10 mm

Table -2 - OPERATING TEMPERATURE CONDITIONS- input variable 2

Set	Vriable	Description	Range
1	strong deviation	Strong deviation fom normal condition	140-150
2	slightly deviation	slight deviation fom normal condition	135-140
3	less severe operation,	Less deviation fom normal condition	130-135
4	no change	No change fom normal condition	110-130

fuzzy inference systems

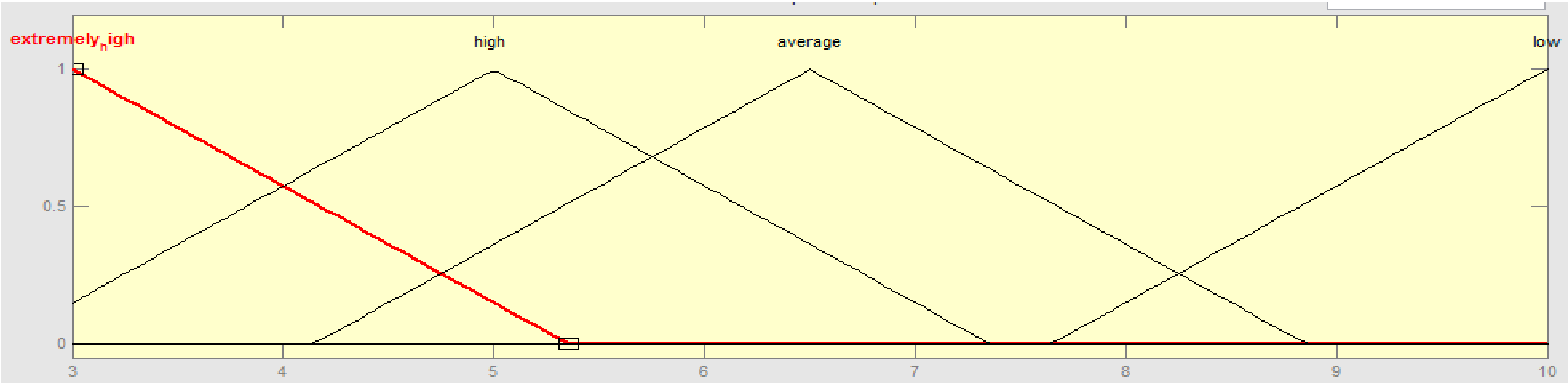
The steps performed by fuzzy inference systems when processing inputs are:

1. Compare the input variables with the membership functions of the premise part to obtain the membership values of each linguistic terms this step is called fuzzification

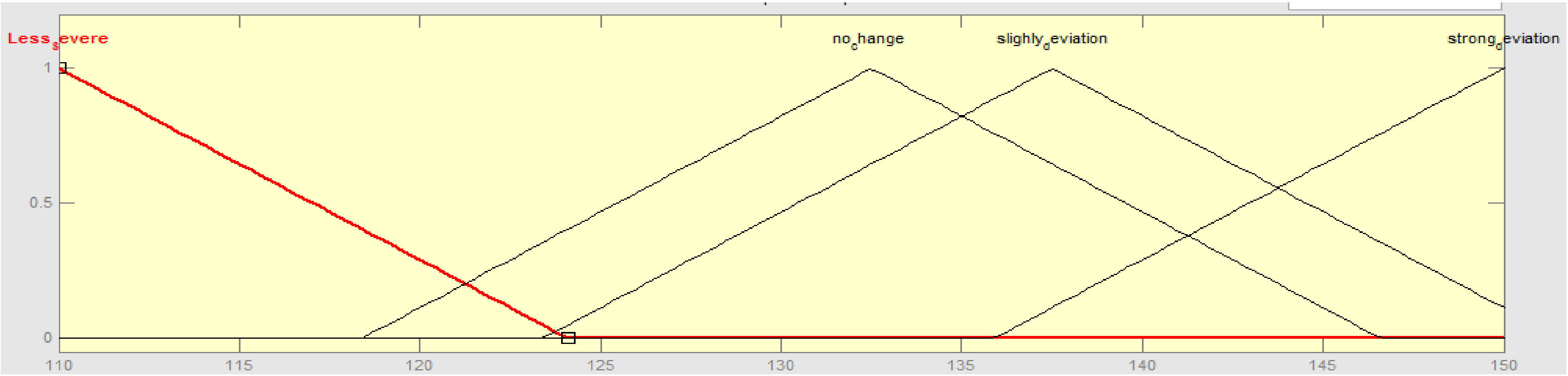
2. Combine the membership values of the premise part to deduce firing strength of each rule using the selected operator

3. Generate the consequence or results of each rule

4. Aggregate the results or consequences to produce a crisp output – this step is called defuzzification



Input Memembership Function for Rider Ring condition

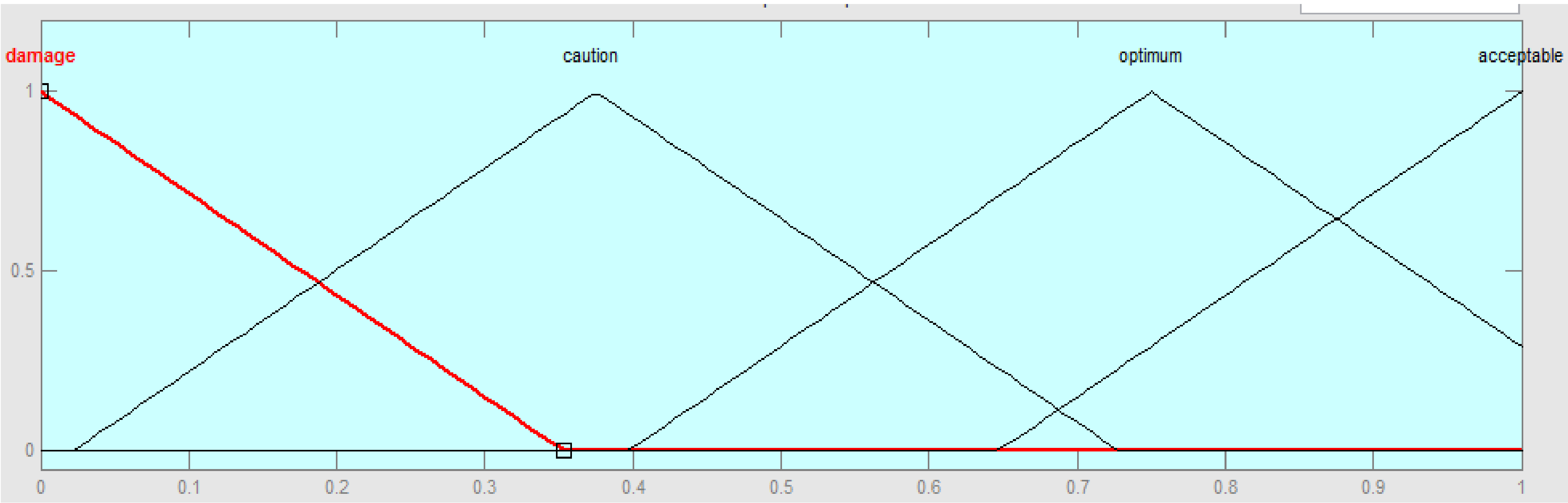


Input Memembership Function for Operating Temperature condition

Table -4 - output variable - Suggested compressor maintenance decision

Set	Membership function	Description	Range
1	**Damage**	**Immediately replace the component**	**0-0.25**
2	**Caution**	**Replace in the next opportunity maintenance schedule Before next inspection- less than one year**	**0.25 - 0.5**
3	**Optimum**	**Can run till next inspection –more than one year**	**0.5-1**
4	**Acceptable**	**Can run further – more than two years**	**1**

Output Membership

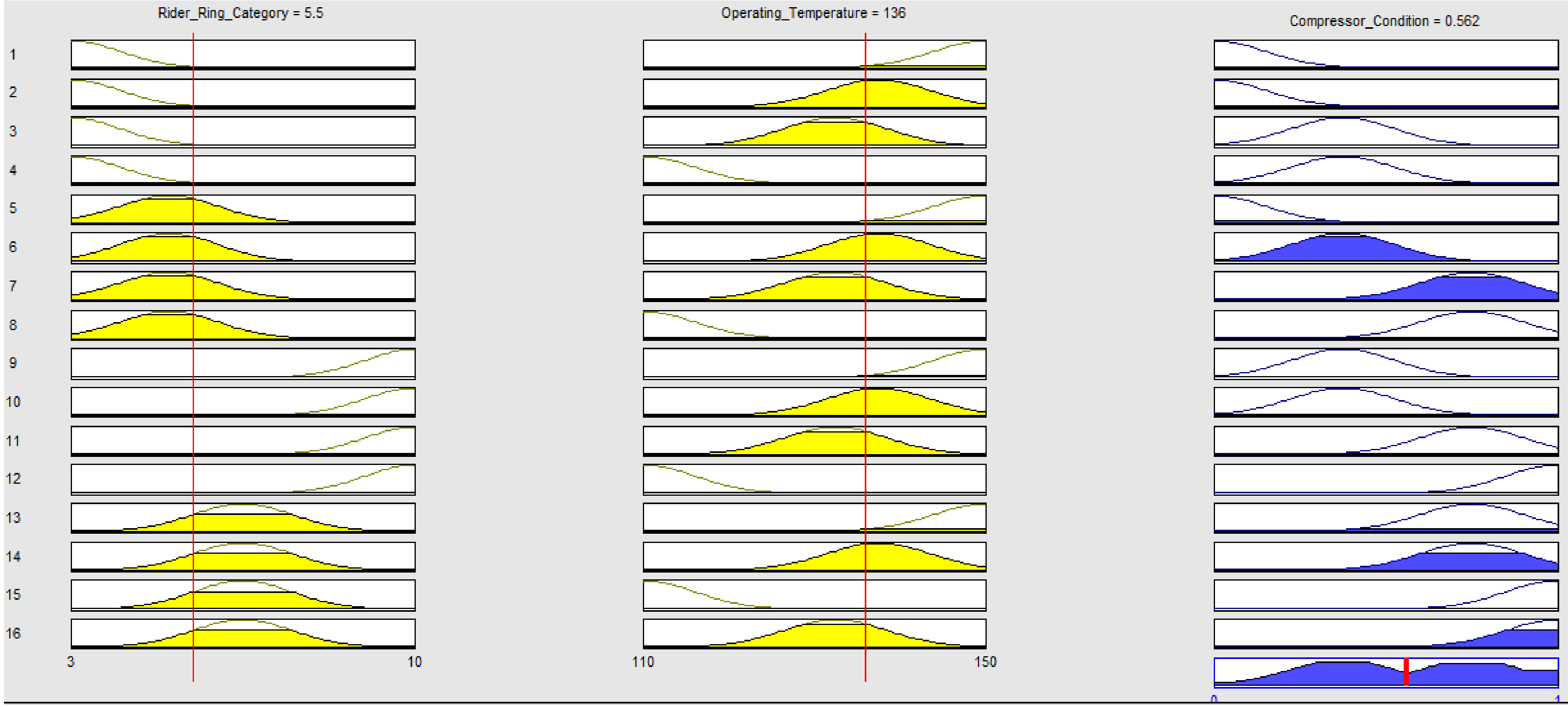


Output Membership Functions for Compressor Condition

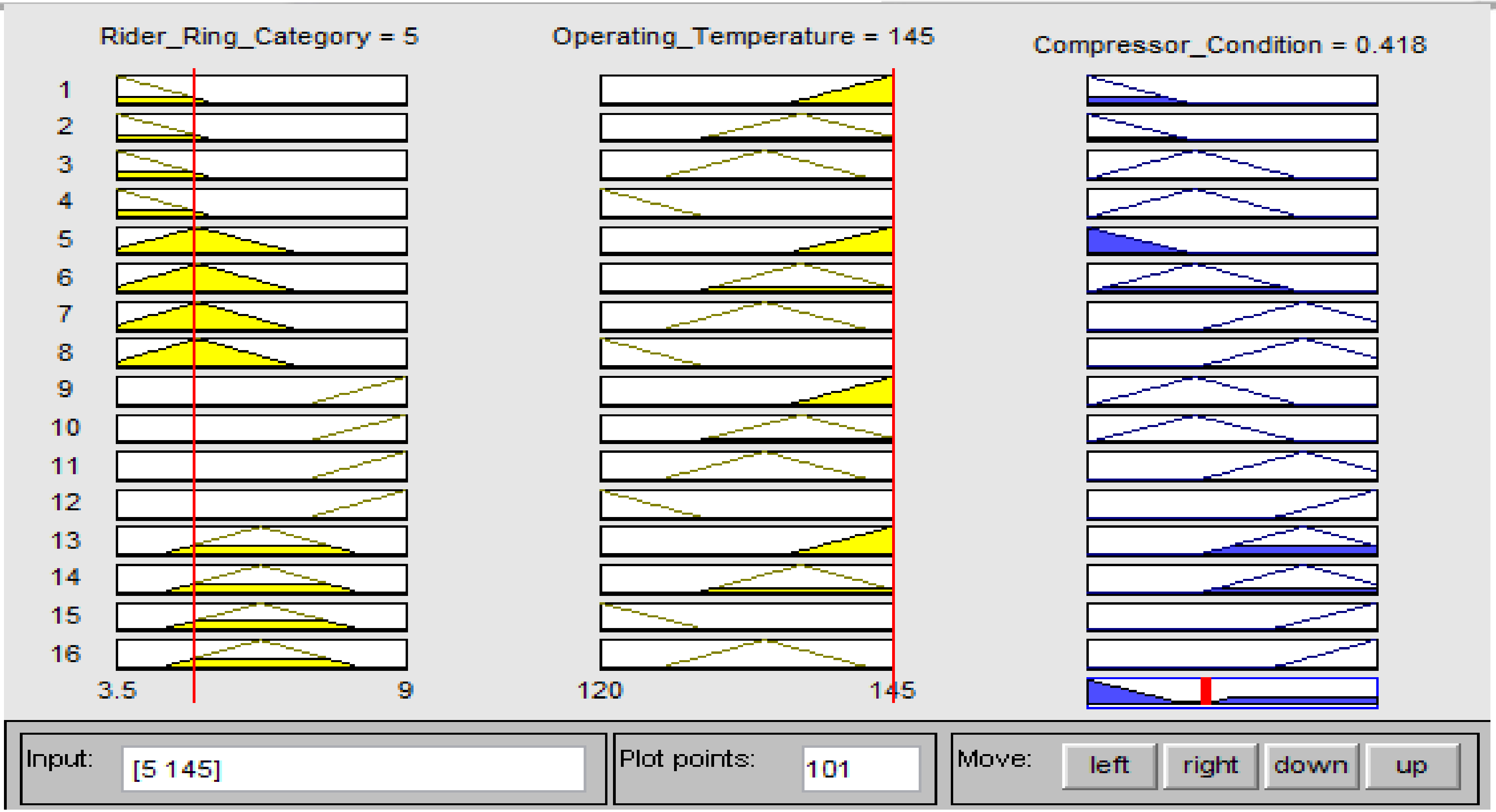
IF-THEN Rules - fuzzy inference system

Rule	IF	Last inspect result	AND	Operating Condition	THEN	Maintenance practice
1		low		strong deviation		optimum
2		low		slightly deviation		acceptable
3		low		no change		acceptable
4		low		less severe operation		acceptable
5		average		strong deviation		optimum
6		average		slightly deviation		acceptable
7		average		no change		acceptable
8		average		less severe operation		acceptable
9		high		strong deviation		damage
10		high		slightly deviation		optimum
11		high		no change		acceptable
12		high		less severe operation		acceptable
13		Extremely high		strong deviation		damage
14		Extremely high		slightly deviation		damage
15		Extremely high		no change		caution
16		Extremely high		less severe operation		caution

SAMPLE 1- Rider Ring Thickness- 5.5mm   Temperature- 136C

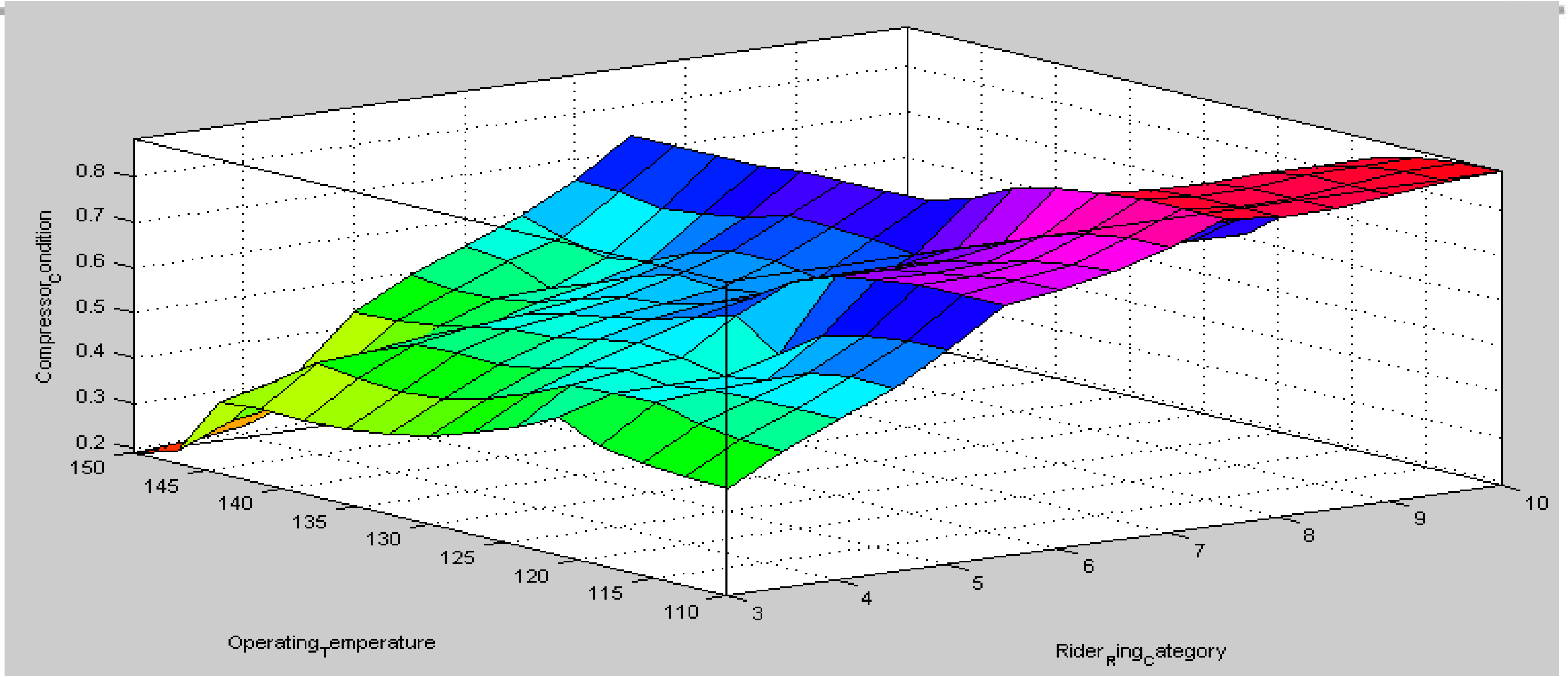


A sample case is taken when the rider ring thickness is 5.5 mm and the operating temperature is 136 deg C ,the compressor Condition in MATLAB tool box output comes out to be 0.562 which means maintenance decision taken should be optimum and compressor can run till next inspection. Hence no maintenance action need to be taken for one year



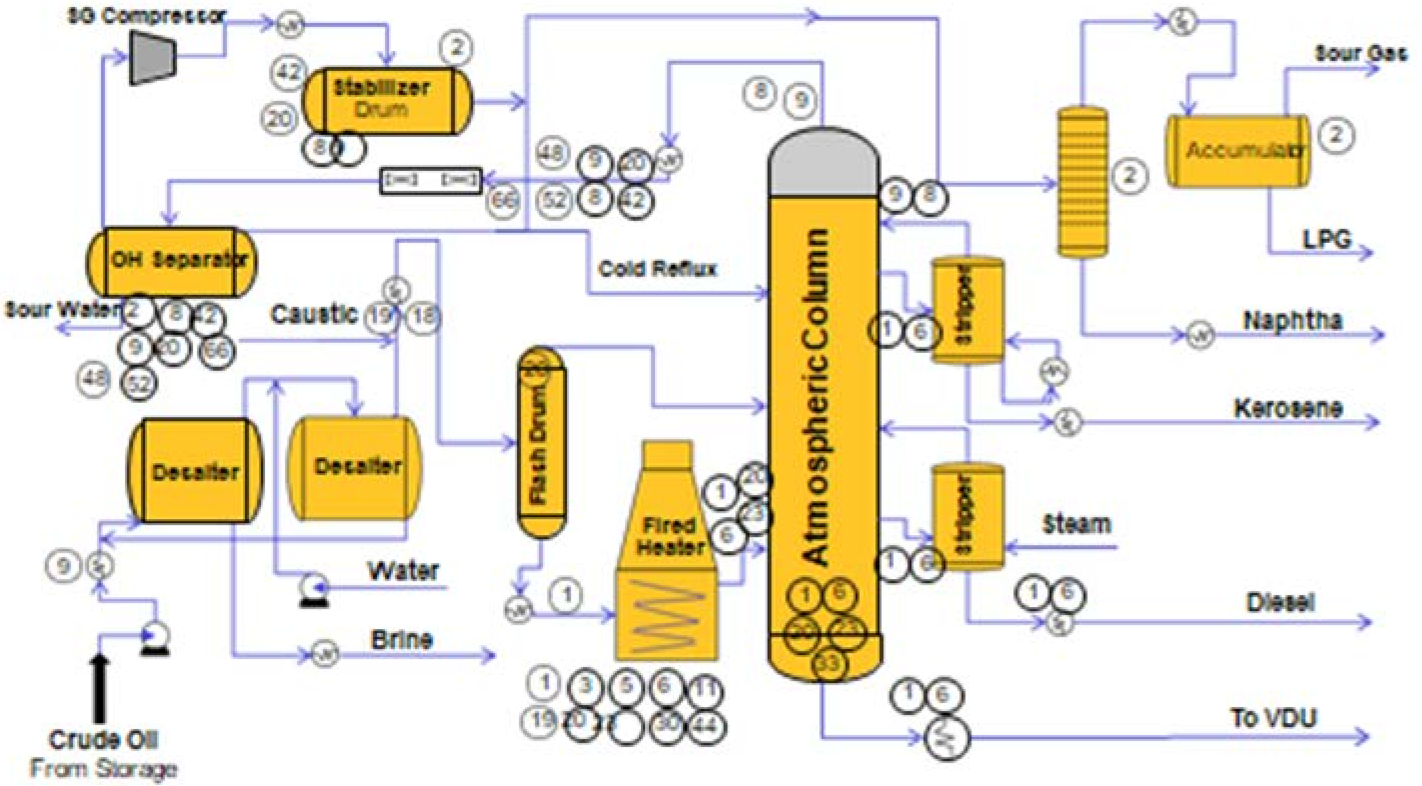
In this case the rider ring thickness is 5 mm and the operating temperature is 145 deg C ,the compressor Condition in MATLAB tool box output comes out to be 0.418 which means maintenance decision is caution. Replace in the next opportunity maintenance schedule before next inspection-(one year)

Surface Viewer



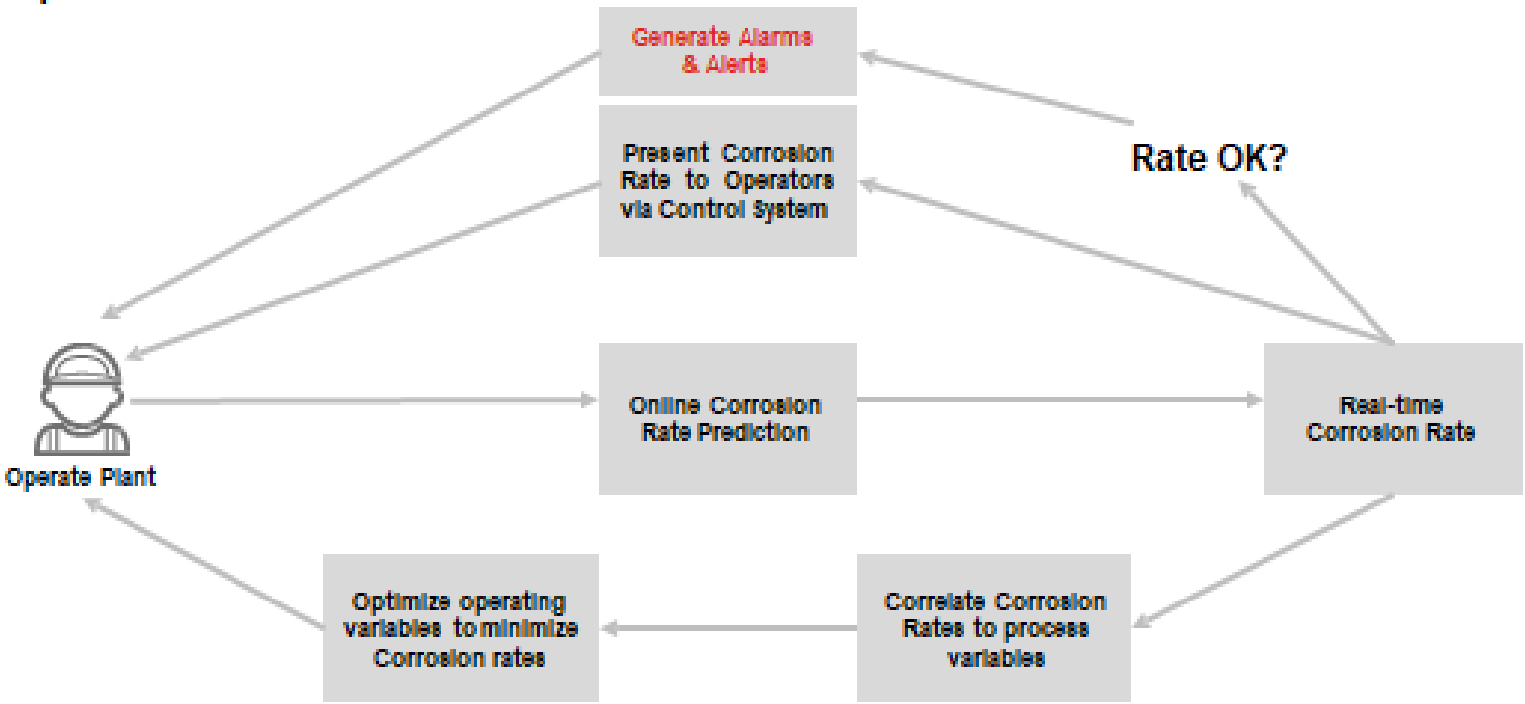
A surface viewer is created in MATLAB , Upon opening it , you see a three-dimensional curve that represents the mapping input and output . Because this curve represents a two-input one-output, you can see the entire mapping in one plot. It helps to view the dependency of one of the outputs on any one or two of the inputs (Fuzzy user guide 2012). If we provide arbitrarily two values of the variables of ring thickness and temperature , just by placing the cursor in the 3D plot we will be able to predict the severity and take maintenance decision.

Making the complex and invisible.....



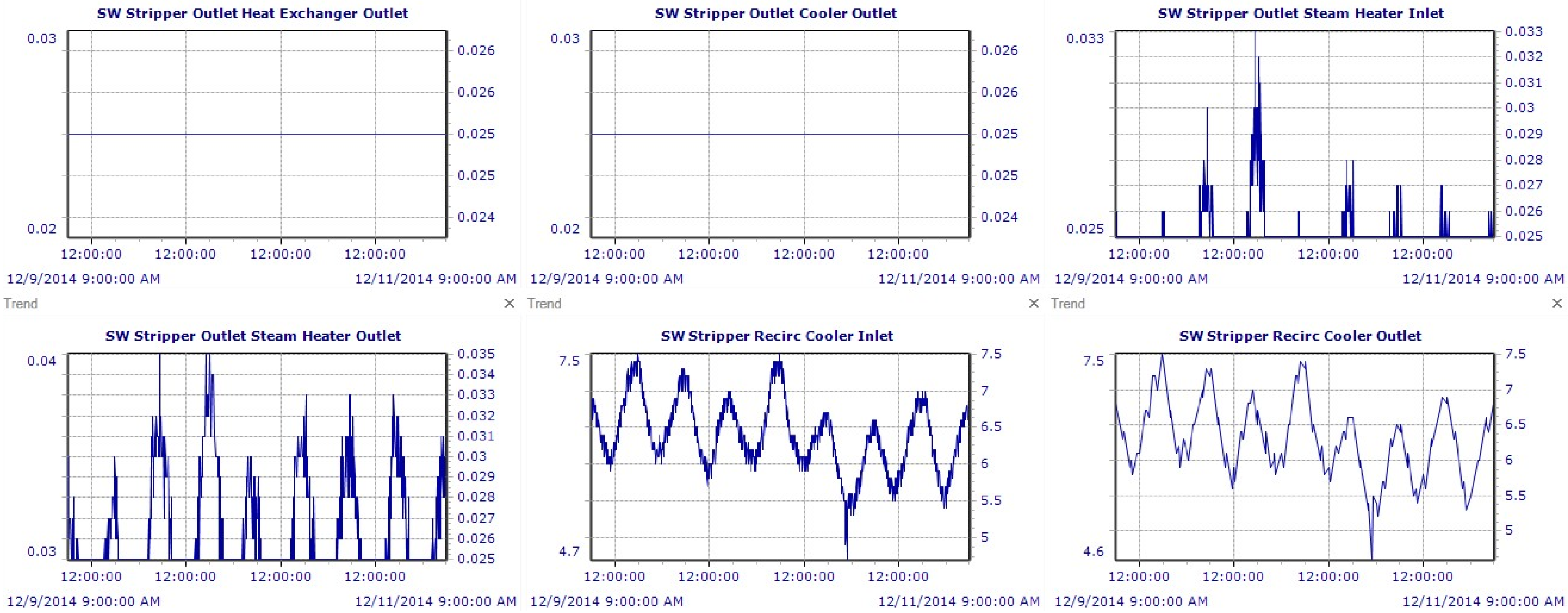
1 – Sulfidation; 2 – Wet H2S Damage (Blistering/HIC/SOHIC/SSC; 3 – Creep / Stress Rupture; 5 – Polythionic Acid Corrosion; 6 – Naphthenic Acid Corrosion; 8 – Ammonium Chloride Corrosion; 9 – HCl Corrosion; 11 – Oxidation; 18 – Caustic Cracking; 20 – Erosion/Erosion Corrosion; 23 – Cl SCC; 30 – Short term Overheating / Stress Rupture; 33 – 885F Embrittlement; Dissimilar Metal Weld Cracking; 42 – CO2 Corrosion; 44 – Fuel Ash Corrosion; 48 – Ammonia Stress Corrosion Cracking; 52 – Liquid Metal Embrittlement; 66 – Organic Acid Corrosion

Making Corrosion Actionable by Operations

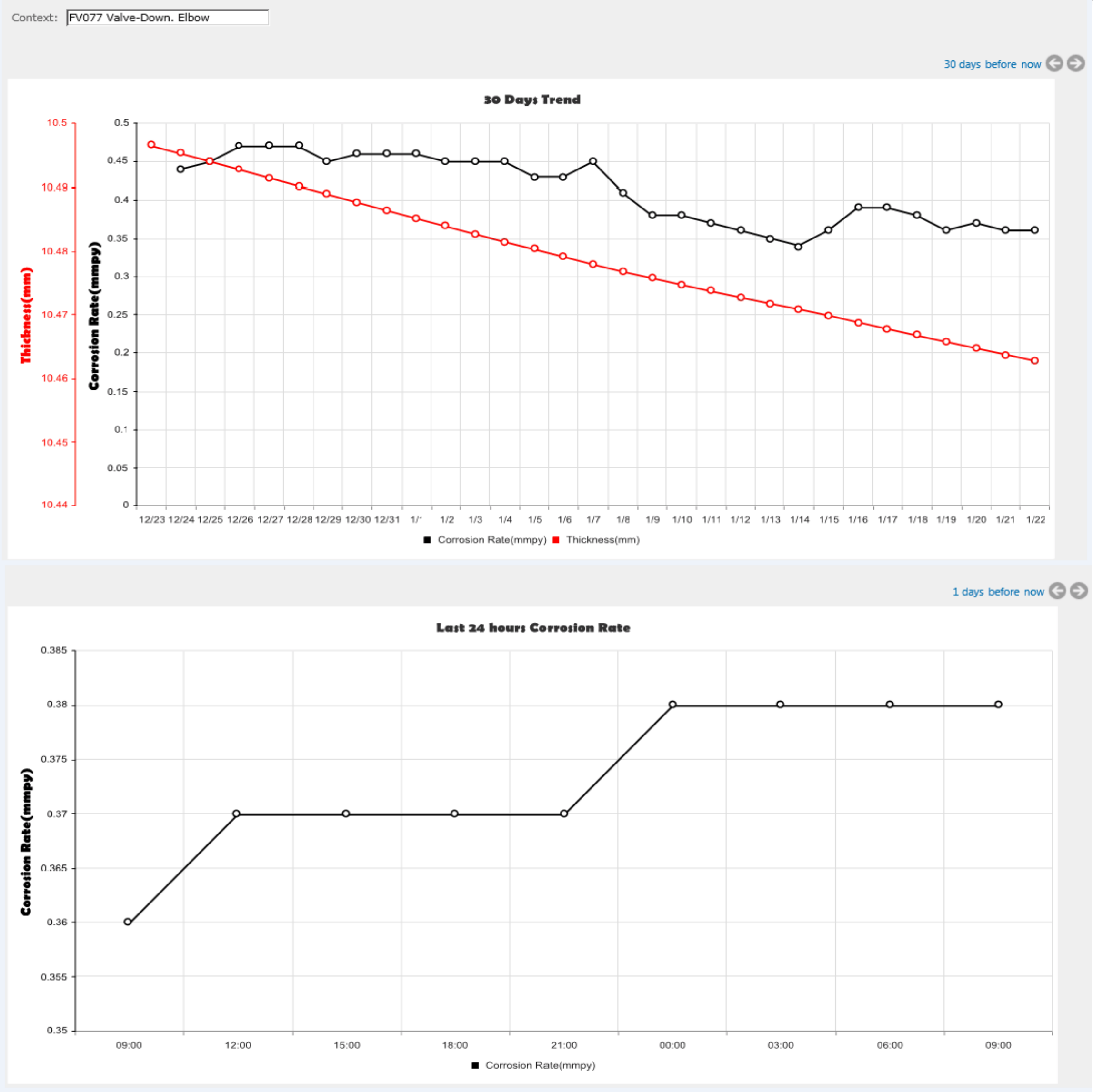


Honeywell
THE POWER OF CONNECTED

Real Time Analytics…Monitor Rates at Multiple Locations



provides a real time quantified picture of unit and piping integrity; transforming your data into knowledge.



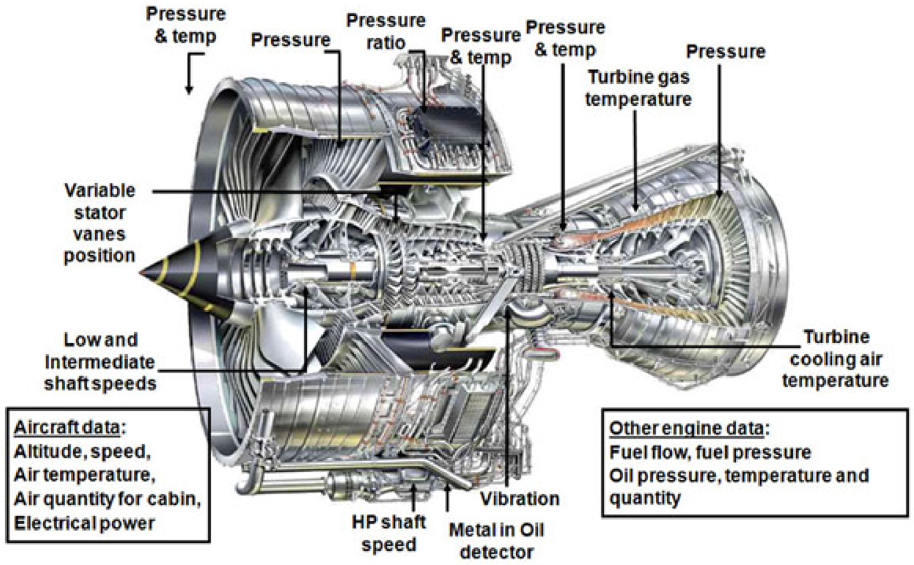
- RT corrosion rates in line with measured rate
- Ability to see remaining thickness and cumulative metal loss

IoT and Predictive Maintenance

Rolls Royce uses Engine Health Management (EHM) to track the health of thousands of engines operating worldwide, using onboard sensors and live satellite feeds in real-time.

EHM is a pro-active technique for predicting when something might go wrong and averting a potential threat before it has a chance to develop into a real problem. EHM covers the assessment of an engine's state of health in real time or post-flight and how the data is used reflects the nature of the relevant service contracts.

EHM uses a range of sensors strategically positioned throughout the engine to record key technical parameters several times each flight



ROLLS ROYCE

To sum up

Dr. Trinath Sahoo

More Data doesn´t just let us see more

More data allow us to see **new**

More data allow us to see **better**

More data allow us to see **different**