University of Stavanger Faculty of Science and Technology MASTER'S THESIS		
Study program/ Specialization:	Spring semester, 20.1.6.	
Offshore Technology, Industrial Asset Management	Open / Restricted access	
Writer: Tor Olav Stava	(Writer's signature)	
Faculty supervisor: Srividya Ajit External supervisor(s): Ronny Albrechtsen, Gassco AS Thesis title: Implementation of new condition monitoring methods for large variable speed electrical motors into established maintenance management systems Credits (ECTS): Implementation of new condition monitoring methods		
Key words: Asset Management Offshore Technology Electrical Motors Maintenance Management Condition Monitoring Decision Support	Pages:	

Implementation of new condition monitoring methods for large variable speed electrical motors into established maintenance management systems

Master Thesis

Department of Mechanical and Structural engineering and Material Science, Faculty of Science and Technology, UiS

Tor Olav Stava

Faculty supervisor: Professor Srividya Ajit External supervisor: Ronny Albrechtsen, Gassco AS Processing time 1st February until 15th June 2016

Stavanger, June 2016

Abstract

Norwegian export of natural gas to the European continent and United Kingdom depends heavily on large variable speed drive (VSD) electrical motors. These types of motors were viewed as very reliable until multiple unexpected catastrophic failures occurred at various locations. A joint industry research and development project (JIP) was initiated to research new tools and methods for improving the condition monitoring of these large electrical motors.

Section two of this thesis gives and overview of existing technology and methods in use today. This section explains the concepts of maintenance management philosophies and gives a basic introduction to condition monitoring methods and systems, and variable speed drive electrical motors.

Section three presents promising new technology and methods that was matured and tested in the JIP project. Both online and offline methods are discussed.

Section four presents aspects that needs to be considered to successfully implement new tools and methods into existing organisations. Critical issues such as data acquisition, analysis, and reporting are discussed. The importance of having a total system view by considering all aspects and integration of technology, man, and organisation (TMO) is highlighted.

In section five a fault tree analysis (FTA) is presented for the top level failure "short-circuit caused by stator winding insulation breakdown". The contribution from the major fault groups have been estimated and each group and root causes are discussed.

Section six discusses the subjects from the previous chapters and concludes that the new tools and methods from the JIP project represents major improvements in the condition monitoring of large VSD synchronous electrical motors.

Table of Contents

A	ABSTRACTII		
L	IST C	DF FIGURES	IV
A	BBRI	EVIA TIONS	V
1	INT	FRODUCTION AND BACKGROUND	1
	1.1	NEED	2
	1.2	MOTIVATION	
	1.3	SCOPE	3
2	EXI	ISTING TECHNOLOGY AND METHODS	4
	2.1	MAINTENANCE MANAGEMENT PHILOSOPHIES	4
	2.2	COMPONENTS OF A CONDITION MONITORING AND DECISION SUPPORT SYSTEM	5
	2.3	VSD ELECTRICAL MOTORS AND COMPRESSORS	6
	2.4	OFFLINE CONDITION MONITORING METHODS	8
	2.5	ONLINE CONDITION MONITORING METHODS	10
	2.6	EXISTING MAINTENANCE MANAGEMENT SYSTEM	11
3	NE	W TECHNOLOGY AND METHODS	13
	3.1	OFFLINE CONDITION MONITORING METHODS	13
	3.2	ONLINE CONDITION MONITORING METHODS	14
4	IMI	PLEMENTING NEW TOOLS AND METHODS INTO EXISTING SYSTEMS	20
	4.1	SUCCESS CRITERIA	20
	4.2	DATA ACQUISITION AND LOGGING	21
	4.3	DATA ANALYSIS	22
	4.4	Reporting	27
	4.5	INCREASE SENSITIVITY AND CONFIDENCE LEVELS BY AGGREGATING INFORMATION	31
5	AN	ALYSIS	32
	5.1	ELECTRICAL STRESS	34
	5.2	CHEMICAL DECOMPOSITION	35
	5.3	THERMAL AGEING	35
	5.4	MECHANICAL FATIGUE	38
	5.5	EROSION	40
6	DIS	CUSSION & CONCLUSIONS	41
	6.1	DISCUSSION	41
	6.2	CONCLUSIONS	44
	6.3	RECOMMENDATIONS	44
	6.4	LIMITATIONS	44
	6.5	FUTURE SCOPE	45
R	EFEF	RENCES	46

List of Figures

Figure 2: Catastrophic failures due to burnt windings. Image source: JIP project. 2 Figure 3: Illustrative comparison of different maintenance philosophies. Image source: JIP project. 5 Figure 4: Illustration of a condition monitoring and decision support system with improvement feedback loop. 6 Figure 5: Simplified example showing the principle of VSD control of electrical motors. 7 Figure 6: Schematic diagram showing how three-phase sine waves are first rectified to DC and then converted back to AC at the required frequency by the VSD. Image source: Hartman (2014). 7 Figure 7: Overview of the main parts of an electrical motor and the location of important measurement parameters 8 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 17 Figure 19: Partial discharge trend to failure. Image source: Ster IIP project. 16 <td< th=""><th>Figure 1: Endwindings of a large electrical motor. Image source: JIP project</th></td<>	Figure 1: Endwindings of a large electrical motor. Image source: JIP project
project. 5 Figure 4: Illustration of a condition monitoring and decision support system with improvement feedback loop. 6 Figure 5: Simplified example showing the principle of VSD control of electrical motors. 7 Figure 6: Schematic diagram showing how three-phase sine waves are first rectified to DC and then converted back to AC at the required frequency by the VSD. Image source: Hartman (2014). 7 Figure 7: Overview of the main parts of an electrical motor and the location of important measurement parameters 8 Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 16: Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 23 Figure 19: Partial discharge trend to failure. Image source: Ster II (2016). 24	Figure 2: Catastrophic failures due to burnt windings. Image source: JIP project
project. 5 Figure 4: Illustration of a condition monitoring and decision support system with improvement feedback loop. 6 Figure 5: Simplified example showing the principle of VSD control of electrical motors. 7 Figure 6: Schematic diagram showing how three-phase sine waves are first rectified to DC and then converted back to AC at the required frequency by the VSD. Image source: Hartman (2014). 7 Figure 7: Overview of the main parts of an electrical motor and the location of important measurement parameters 8 Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 16: Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 23 Figure 19: Partial discharge trend to failure. Image source: Ster II (2016). 24	Figure 3: Illustrative comparison of different maintenance philosophies. Image source: JIP
Figure 4: Illustration of a condition monitoring and decision support system with improvement feedback loop. 6 Figure 5: Simplified example showing the principle of VSD control of electrical motors	
feedback loop. 6 Figure 5: Simplified example showing the principle of VSD control of electrical motors. 7 Figure 6: Schematic diagram showing how three-phase sine waves are first rectified to DC and then converted back to AC at the required frequency by the VSD. Image source: Hartman (2014). 7 Figure 7: Overview of the main parts of an electrical motor and the location of important measurement parameters. 8 Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 20: Display of temperature trend. Image source: HVPD (2016). 19 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 <td></td>	
Figure 5: Simplified example showing the principle of VSD control of electrical motors7 Figure 6: Schematic diagram showing how three-phase sine waves are first rectified to DC and then converted back to AC at the required frequency by the VSD. Image source: Hartman (2014)	
Figure 6: Schematic diagram showing how three-phase sine waves are first rectified to DC and then converted back to AC at the required frequency by the VSD. Image source: Hartman (2014)	
(2014). 7 Figure 7: Overview of the main parts of an electrical motor and the location of important measurement parameters 8 Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 21: Example of correlation based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support	
(2014). 7 Figure 7: Overview of the main parts of an electrical motor and the location of important measurement parameters 8 Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 21: Example of correlation based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support	then converted back to AC at the required frequency by the VSD. Image source: Hartman
measurement parameters 8 Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 19: Partial discharge trend to failure. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart f	
measurement parameters 8 Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 19: Partial discharge trend to failure. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart f	
Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: 14 Figure 13: Illustration of electrical and process power estimation, and the concept of 14 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of the domains for decisi	
project. 9 Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for	L.
Figure 9: Boroscope inspection. Image source: JIP project. 9 Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of the domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32	
Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: 14 Figure 13: Illustration of electrical and process power estimation, and the concept of 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 19: Partial discharge trend to failure. Image source: HVPD (2016). 19 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: 25 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 24: Suggested flowchart for the top level fault	1 5
monitoring. Image source: Malcolm (2016). 10 Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32 Figure 26: Rouba	
Figure 11: View from boroscope inspection. Image source: JIP project. 13 Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32 Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings. 33 <td></td>	
Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project	
JIP project. 14 Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 19: Partial discharge trend to failure. Image source: JIP project. 23 Figure 20: Display of temperature trend. Image source: Suter II (2016) 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32 Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings. 33 Figure 28: Thermal imaging of windi	
Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. 15 Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016) 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32 Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings. 33 Figure 28: Thermal imaging of winding hot spots. Image source: JIP project. 37	
DeltaPower.15Figure 14: Fibre optic temperature sensor. Image source: JIP project.16Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis.17Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP17Figure 18: Illustration of the different prognosis potential between time interval snapshots and18Figure 19: Partial discharge trend to failure. Image source: HVPD (2016).19Figure 20: Display of temperature trend. Image source: JIP project.23Figure 21: Example of correlation scatter plots. Image source: Suter II (2016).24Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project.26Figure 24: Suggested flowchart for determining required information for reporting and28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
Figure 14: Fibre optic temperature sensor. Image source: JIP project. 16 Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 19: Partial discharge trend to failure. Image source: HVPD (2016). 19 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32 Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings. 33 Figure 28: Thermal imaging of winding hot spots. Image source: JIP project. 37	
Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis. 17 Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 19: Partial discharge trend to failure. Image source: HVPD (2016). 19 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32 Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings. 33 Figure 28: Thermal imaging of winding hot spots. Image source: JIP project. 37	
Figure 17: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project. 17 Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis. 18 Figure 19: Partial discharge trend to failure. Image source: HVPD (2016). 19 Figure 20: Display of temperature trend. Image source: JIP project. 23 Figure 21: Example of correlation scatter plots. Image source: Suter II (2016). 24 Figure 22: Baseline deviation detection based on correlation baselines. 25 Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project. 26 Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system. 28 Figure 25: Illustration of time domains for decision makers and stakeholders. 29 Figure 26: Probability contribution for the top level fault groups in the fault tree. 32 Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings. 33 Figure 28: Thermal imaging of winding hot spots. Image source: JIP project. 37	
project.17Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis.18Figure 19: Partial discharge trend to failure. Image source: HVPD (2016).19Figure 20: Display of temperature trend. Image source: JIP project.23Figure 21: Example of correlation scatter plots. Image source: Suter II (2016).24Figure 22: Baseline deviation detection based on correlation baselines.25Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source:26Figure 24: Suggested flowchart for determining required information for reporting and28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
Figure 18: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis.18Figure 19: Partial discharge trend to failure. Image source: HVPD (2016).19Figure 20: Display of temperature trend. Image source: JIP project.23Figure 21: Example of correlation scatter plots. Image source: Suter II (2016).24Figure 22: Baseline deviation detection based on correlation baselines.25Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source:26Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system.28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings.33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
continuous monitoring using partial discharge analysis.18Figure 19: Partial discharge trend to failure. Image source: HVPD (2016).19Figure 20: Display of temperature trend. Image source: JIP project.23Figure 21: Example of correlation scatter plots. Image source: Suter II (2016).24Figure 22: Baseline deviation detection based on correlation baselines.25Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source:26JIP project.26Figure 24: Suggested flowchart for determining required information for reporting and28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
Figure 19: Partial discharge trend to failure. Image source: HVPD (2016)	
Figure 20: Display of temperature trend. Image source: JIP project	
Figure 21: Example of correlation scatter plots. Image source: Suter II (2016)24Figure 22: Baseline deviation detection based on correlation baselines.25Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source:26JIP project.26Figure 24: Suggested flowchart for determining required information for reporting and28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
Figure 22: Baseline deviation detection based on correlation baselines.25Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source:26JIP project.26Figure 24: Suggested flowchart for determining required information for reporting and28decisions in a decision support system.28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
Figure 23: Illustration of the machine learning concept used on clustered datasets. Image source: 26 JIP project	• • •
JIP project	
Figure 24: Suggested flowchart for determining required information for reporting and decisions in a decision support system.28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings.33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
decisions in a decision support system.28Figure 25: Illustration of time domains for decision makers and stakeholders.29Figure 26: Probability contribution for the top level fault groups in the fault tree.32Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation33Figure 28: Thermal imaging of winding hot spots. Image source: JIP project.37	
Figure 25: Illustration of time domains for decision makers and stakeholders	
Figure 26: Probability contribution for the top level fault groups in the fault tree	
Figure 27: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings	-
in the stator windings	
Figure 28: Thermal imaging of winding hot spots. Image source: JIP project	•
	•
project	
Figure 30: Abrasion caused by loose coil in slot. Image source: JIP project	1 5

Abbreviations

AC	Alternating Current
ACP	Asset Condition and Performance
CAPS	Condition Analysis and Prognosis System
CBM	Condition Based Maintenance
CMDSS	Condition Monitoring and Decision Support System
DC	Direct Current
ESA	Electrical Signature Analysis
FAT	Factory Acceptance Test
FMEA	Failure Mode and Effect Analysis
FTA	Fault-Tree Analysis
IDSS	Intelligent Decision Support System
JIP	Joint Industry Research and Development Project
LCI	Line Commutated Inverter
LEAP	Life Expectancy Analysis Program
MCSA	Motor Current Signature Analysis
MMS	Maintenance Management System
MW	Mega Watt
NCS	Norwegian Continental Shelf
OLPD	Online Partial Discharge
PD	Partial Discharge
PDM	Predictive Maintenance
PM	Preventive Maintenance
PWM	Pulse Width Modulation
RPM	Revolutions Per Minute
PCDA	Process Control and Data Acquisition
SMART	Specific, Measureable, Achievable, Realistic, Time specific
ТМО	Technology, Man, and Organization
VSI	Voltage Source Inverter
VSD	Variable Speed Drive

1 Introduction and background

Norway is a major producer and exporter of natural gas to the European continent and United Kingdom. In 2015 Gassco reported a new record of 108 billion standard cubic meters of natural gas transported from the Norwegian Continental Shelf (NCS) to the Europe and United Kingdom (Gassco, 2015). Millions of homes and families depend on the reliability and stability of the gas supply from the NCS for their heating and cooking needs. Transporting such huge amounts of gas over long distances requires large amounts of compression energy, and most of this energy is in Norway generated by large electrical motors driving export gas compressors. Large electrical motors in the 20-50 MW range have been regarded in the industry as highly reliable equipment and traditionally have not been having much focus when it comes to condition monitoring. The general view has been that it's primarily a static equipment and it's assumed that only the bearings are prone to failure and therefore covered by condition monitoring equipment.

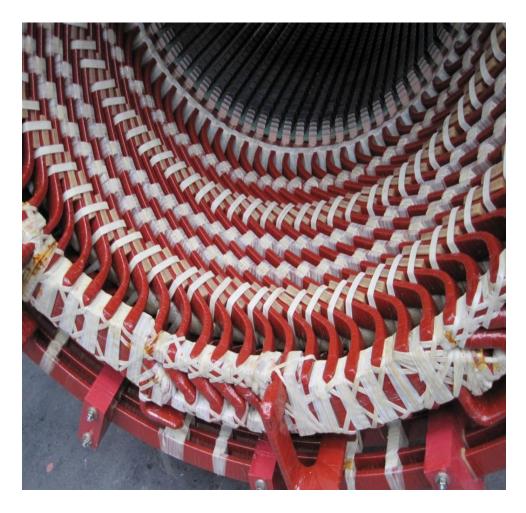


Figure 1: Endwindings of a large electrical motor. Image source: JIP project.

1.1 Need

To great surprise to manufacturers, designers and users, several large variable speed electrical motors in the oil and gas industry have experienced unsuspected breakdowns without any form of pre-warning (ref. incidents at Kårstø and Snøhvit in 2009). These types of electrical motors have been fitted with traditional condition monitoring limited to bearing vibration and temperature monitoring. A Joint Industry Research and Development Project (JIP) consisting of Gassco, Statoil, ABB and Lloyd's Register was established in 2012 to investigate methods for improving reliability of large variable speed electrical motors. The study looked into how the machines were designed and operated and a failure modes and effects analysis (FMEA) was performed early in the project. Several condition monitoring tools and methods were developed, some based on existing technology in different operating equipment and conditions, while others were specifically developed for the specific type of equipment considered by the project.



Figure 2: Catastrophic failures due to burnt windings. Image source: JIP project.

1.2 Motivation

There are several factors that fuels the motivation for this study. The most obvious motivating factor for this study is the economic benefit these improvements may contribute to. From a high-level perspective the business case is quite clear; if it is possible to increase the reliability, decrease maintenance costs, and potentially establish the business as a world-class leader within its field, there is good potential that this will improve the long term bottom line for the business. Other motivational factors are the opportunity to be a part of the development of new research and development projects that may contribute to new methods for improved condition monitoring of large variable speed driven electrical motors.

1.3 Scope

The study presents suggestions on how new technologies and methods for condition monitoring of large variable speed electrical motors can be implemented into existing maintenance management systems (MMS).

A description of the new tools and methods developed by the JIP is presented. Next the focus is on how to implement these tools in the existing condition monitoring and decision support system (CMDSS). Further, the study extends to recent developments in methodologies and technologies that can be utilised to achieve world-class predictive maintenance for large electrical motors. Value creation potential with implementation of the new tools and methods will be attempted identified and described.

For the sake of simplicity, the descriptions and discussions have been limited to a large, medium voltage synchronous motor driven by a line commutated inverter (LCI) variable speed drive (VSD). A basic description of this system is presented in section 2.3.

2 Existing technology and methods

2.1 Maintenance management philosophies

A brief overview of the most common maintenance philosophies are presented here Mobley (2004) and Mobley et al. (2008)

2.1.1 Run-to-failure maintenance

Run-to-failure maintenance is when equipment is allowed to fail, and where the maintenance personnel replaces or repairs it only after it has failed. True run-to-failure is rarely used, especially on critical equipment Mobley (2004). Even under this philosophy some minimal maintenance is usually performed, like for example periodic cleaning, replacing oil and lubricants, and visual inspections. Run-to-failure is challenging for a maintenance organisation since it is not possible to know when equipment will fail, and the organisation needs to be prepared for any event possible at any given time. Procedures, personnel and spare parts needs to be readily available in order to minimize downtime. The lack of ability to plan the work ahead of time and the requirement for a large number of spare parts makes this philosophy less than desirable and generally not recommended.

2.1.2 Preventive maintenance

There "... are many definitions of preventive maintenance, but all preventive maintenance management programs are time driven. In other words, maintenance tasks are based on elapsed time or hours of operation." Mobley (2004). Preventive maintenance (PM) is typically the majority of the planned maintenance on large electrical motors. Common examples of work performed during PM are: visual inspections, cleaning, analysis and changing of bearing oil, and partial discharge analysis. PM intervals are usually specified by the manufacturer of the equipment and may sometimes be adjusted for specific operating conditions and operating experience. For equipment critical for the operation and reliability of the process the PM also needs to correspond to planned maintenance windows. In many cases this will lead to maintenance being performed before it is necessary or the PM may be deferred to the next maintenance window even if it stretches beyond the recommended interval, increasing the statistical risk of equipment failure before next PM.

2.1.3 Condition based maintenance

Condition based maintenance (CBM) takes into account the current condition of the equipment in order to enable maintenance to be performed when necessary instead of going by fixed time intervals. Depending on the equipment health and operating conditions CBM could lead to both increased and decreased length of intervals between maintenance. The important point is that to the extent possible all maintenance should only be performed when required, based on the actual condition of the equipment.

2.1.4 Predictive maintenance

Predictive maintenance (PDM) is taking CBM to the next step, where the condition data for the equipment is analysed and predictions about the future condition of the equipment are performed. The predictions can be based on simple statistics, or complicated combinations of statistics, previous history, expert knowledge and machine learning systems. Predictive maintenance has been in use for many years, and as such is nothing new. However, the accuracy and confidence in the predictions have scope for great improvements in order to establish the "correct" maintenance based on the actual condition of the equipment. Modern computer technology and understanding of failure modes is expected to contribute significantly to the future development of predictive maintenance systems.

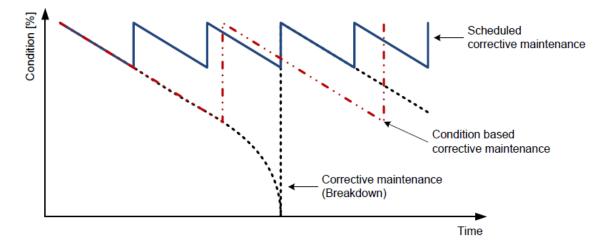


Figure 3: Illustrative comparison of different maintenance philosophies. Image source: JIP project.

2.2 Components of a condition monitoring and decision support system Main components of a CMDSS:

- Data acquisition
- Data analysis
- Results reporting
- Decisions and actions
- Results and improvement

The three first components are what we commonly refer to as the monitoring system, and are described by Uday Kumar (1990) as *Measuring, Diagnosing,* and *Informing*. These three areas are critical for the CMDSS, but do not cover the important aspects of decision making, results

evaluation and system improvements. These items need to be added to the system in order to make it dynamic, continuously updating and improving based on the users' experiences and the results achieved.

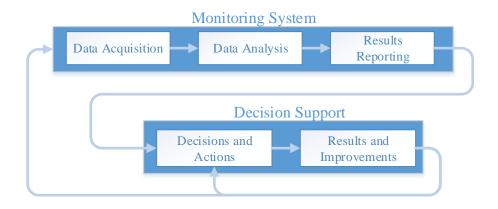


Figure 4: Illustration of a condition monitoring and decision support system with improvement feedback loop.

The data acquisition consists of the actual sensors that are fit on the equipment and which measure the raw data for key parameters. Sensors are normally constructed as simple as possible in order to reduce their probability of failure since they are commonly operating in harsh environments. The data analysis part of the monitoring system performs necessary filtering and conversion of raw data, performs calculations, parameter correlation and analysis. Kumar (1990) also defines transmitting and storage functions (i.e. network and historian) as part of the data analysis function. Results reporting as presented by Kumar (1990) covers the critical questions of *who, what* and *how* when it comes to presenting and reporting the information from the monitoring system. The three questions are closely interlinked and need to be considered together in a holistic manner for each decision identified.

The main purpose of a monitoring system is to support decision making. Therefore, the monitoring system should be considered as part of the total decision making loop, and not just as a stand-alone part of the overall system. For such a system to achieve optimal performance a holistic system perspective needs to be considered. Figure 4 illustrates the complete loop from an overall system perspective.

2.3 VSD electrical motors and compressors

The majority of the land-based natural gas export from Norway is powered by large VSD electrical motors driving centrifugal gas compressors. The exported gas is transported through several kilometre-long pipeline from the NCS to receiving terminals in Europe and United Kingdom. The supply of gas from the gas production fields, and the demand for gas at the

customers' locations varies throughout the day, which requires that the gas flow can be controlled according to the fluctuations in flow requirements. Although the speed control could be performed by the use of alternative methods, for example a gearbox, electric VSDs are generally more energy efficient than the mechanical solutions. The maintenance requirements are also in general lower for electrical equipment than large mechanical equipment.

The basic principle of an electric VSD is to control the frequency of the current supplied to the motor. A commonly used method to achieve this is to convert, or rectify, the AC power from the power grid to DC power, which then the VSD feeds to the electrical motor in carefully timed intervals and sequences to the motor windings. In a synchronous electrical motor, the rotor rotates at the same speed as the magnetic field induced by the AC current in the windings, and the speed is thereby controlled by the frequency output from the VSD.

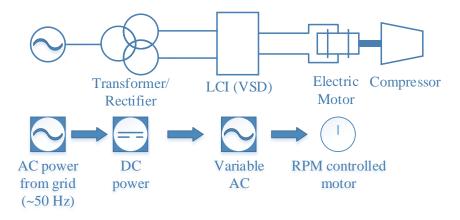


Figure 5: Simplified example showing the principle of VSD control of electrical motors.

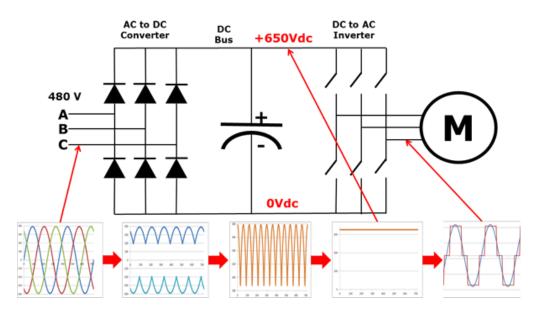
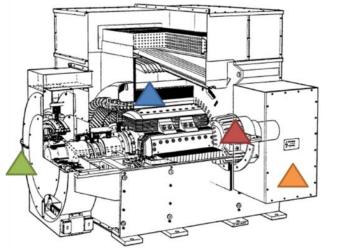


Figure 6: Schematic diagram showing how three-phase sine waves are first rectified to DC and then converted back to AC at the required frequency by the VSD. Image source: Hartman (2014).

Figure 7 shows the main components of a large electrical motor with the critical monitoring locations indicated on the figure:

- Temperature monitoring of windings (blue)
- Mechanical vibration monitoring of bearings (red)
- Electrical ESA/MCSA analysis (orange)
- Driven equipment monitoring, e.g. compressor and process parameters (green)



Temperature Mechanical Electrical Driven equipment

Figure 7: Overview of the main parts of an electrical motor and the location of important measurement parameters. Image source: JIP project.

2.4 Offline condition monitoring methods

2.4.1 Partial discharge

Partial discharge (PD) activity occurs in small voids in the insulation between the windings in an electrical motor. Under certain conditions gas inside these voids can get charged by the potential energy difference between the windings (Tavner et al., 2008). Next the gas breaks down and releases the energy by emitting heat, light, sound and releasing electrons and ions. This process erodes the insulation surrounding the void and further deteriorates the insulation. Partial discharge is one of the most critical measurement to determine the current condition of the winding insulation in an electrical motor. Offline partial discharge analysis is a wellestablished method for analysing the current condition of the motor windings. However, the requirement to take the equipment offline often leads to relatively long measurement cycles. Given that this is then generating snapshots of the current condition it is not possible to determine at what point the deterioration first started to be detectible between the two measurement points. The results from the PD analysis are usually presented as a report by the company performing the analysis.

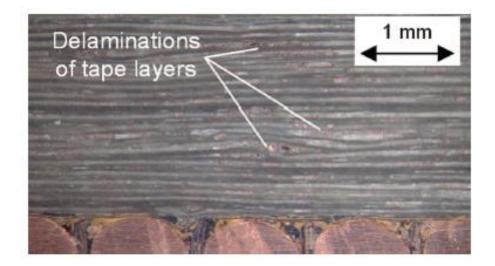


Figure 8: Voids in winding insulation due to delamination of tape layers. Image source: JIP project.

2.4.2 Visual inspections

Visual internal inspections are performed during routine maintenance at specified intervals. The intervals are initially specified by the vendor of the equipment and is typically every 2 years. The inspection procedure includes removal of maintenance hatches on the equipment frame and visual inspection of the end windings, with focus on the integrity of the windings and fixtures, insulation, dust build-up and moisture.



Figure 9: Boroscope inspection. Image source: JIP project.

2.4.3 Recycle performance test

Each time a compressor train is taken offline for preventive maintenance it is a common practice to perform a recycle performance test. For this test, the compressor train is run at a number of predetermined fixed speed operating points and allowed to stabilize while available performance data are logged. The log data are then compared with previous performance tests or baseline data gathered from performance test after compressor overhaul. The test data analysis allows for trending of spot data which can give indications of the current condition of the machine and the rate of degradation. Although these tests provide valuable data about the current condition and development, a performance test can only be performed when the machine is offline, giving only data snapshots, and relies heavily on the knowledge of the experts performing the analysis.

2.5 Online condition monitoring methods

This section briefly describes the current methods used for online condition monitoring of the large variable speed drive electrical motors which is the focus for this thesis.

2.5.1 Vibration monitoring

The electrical motors are fitted with a conventional setup for vibration monitoring of the sleeve bearings using two orthogonally mounted proximity probe sensors for each bearing. This is currently the main method for condition monitoring of the electrical motors. However, the current diagnostic function is limited to setting alarm and trip levels. The vibration monitoring data are available in the Process Control and Data Acquisition (PCDA) system and historical data can be retrieved from the data historian.

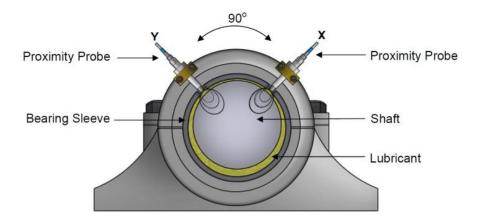


Figure 10: Illustration of typical orthogonal X and Y proximity probe installation for vibration monitoring. Image source: Malcolm (2016).

2.5.2 Temperature monitoring

The electrical motor is currently fitted with localized temperature monitoring of the stator windings. Monitoring is also carried out for the cooling air inlet and outlet temperatures, cooling water inlet and outlet temperatures, and the bearing oil temperature. The common feature for all of these monitored variables is that the diagnostic functions are currently limited to setting alarm and trip levels. The data are available in the PCDA system and historical data can be retrieved from the data historian.

2.5.3 Tribology

Large electrical motors are commonly designed with hydrodynamic bearings, while smaller sized motors are typically running on rolling element bearings. The oil in the closed hydrodynamic bearing system have temperature monitoring on the inlet and outlet. The current diagnostic function is limited to setting alarm and trip levels. The oil temperature data are available in the PCDA system and historical data can be retrieved from the data historian.

2.6 Existing maintenance management system

Maintenance management systems are continuously evolving, from run-to-failure, scheduled preventive maintenance, condition based maintenance, and in recent years into predictive maintenance. Although predictive maintenance is not new and is already in use for some critical equipment, there are improvements to be made with regards to condition monitoring and prediction for large variable speed electrical motors with special focus on electric breakdown.

2.6.1 Maintenance philosophy

The maintenance philosophy currently implemented for the electrical motors is predominantly calendar- or time-based preventive maintenance (PM), with fixed intervals for inspections, tests, and overhaul. These inspection intervals are specified by the manufacturers based on statistical data and can be given in form of for example calendar months or hours in operation, or a combination of both. However, since much of the maintenance needs to be done with the equipment offline, the available maintenance windows are often dictated by the long term planned maintenance periods. These planned maintenance periods are again set with an overall system and network perspective and will in most cases differ from the recommended intervals set by manufacturers. Knowing that the degradation of electrical motors is directly depending on the operating conditions, the pre-determined schedules from the supplier and the planned maintenance windows may not be the most optimal schedule for performing necessary maintenance.

2.6.2 Decision-makers and stakeholders

In a complex organisation and processing plant there are several levels of decision-makers with potentially multiple interfaces. In addition, there are a large number of stakeholders ranging from the field operators, via middle level management, up to top level operators and owners. Some of these stakeholders will also be decision-makers, while others may have a high level of influence on the decision-makers. Examples of strong influencers without direct decision-making authority can be systems experts, economic advisors and owners.

Important decisions regarding the operation and maintenance of large electrical motors are often challenging to make, especially if there is not much available supporting information, due to the severe impact they normally have on the process operations. The complexity of interactions and responsibilities of decision-makers can present a challenge to get a complete overview of the holistic decision-making system, and to ensure that the system is in line with the overall goals and strategies. The general impression is that the immediate decisions regarding day-to-day operations and maintenance are well-defined and managed, but as we get further away from the immediate operation, the definitions and responsibilities tends to become a bit unclear.

3 New technology and methods

This section presents an overview of the tools and methods matured in the JIP project that has been demonstrated to be feasible and having potential for improving current condition monitoring and prognostic systems.

3.1 Offline condition monitoring methods

3.1.1 Standardized inspection procedures and reporting

It was discovered during the JIP project that there was a need for establishing a uniform method of inspection and reporting for the compressor drives. Although several inspections reports existed from previously performed inspections, they could not readily be compared and hence condition development could not be tracked in a reliable manner. The reason for this could be that different companies performed the different inspections, and even that the same company used different methods and report formats from one inspection to the other.

The JIP developed a suggested inspection guideline that included which equipment elements to be tested, how they should be tested, and how the results should be reported. This will allow for better tracking of the condition development of the equipment between inspections. It could also allow for easier comparison of condition between the different drives, i.e. which drive has experienced more degradation than another. This could prove useful in the maintenance planning when deciding which equipment needs to be prioritized for maintenance.

3.1.2 Advanced visual/boroscope inspections

Boroscope inspections is an established technique for equipment such as turbines and large generators, but is currently not an established method for inspecting electrical motors. This method can give access to areas that would otherwise require major dismantling, but require the possibility to open inspection hatches or remove parts of the motor housing. Boroscope inspections can provide good pictures and valuable information for the accessible areas, but will not be able to give any information about inaccessibly parts of the motor.



Figure 11: View from boroscope inspection. Image source: JIP project.

Important information from this type of inspection can for example be the presence and amount of dust, as well as the colour and location of the dust. The presence of dust can be an indicator of insulation breaking down inside the motor. Boroscope inspections can be of great benefit when paired with PD analysis, in which PD measurements can indicate insulation breakdown and also give a general location of this breakdown. The visual inspection can then target the area identified by the PD analysis in order to confirm the presence of dust, discoloration, hot-spots, or other visual indicators.

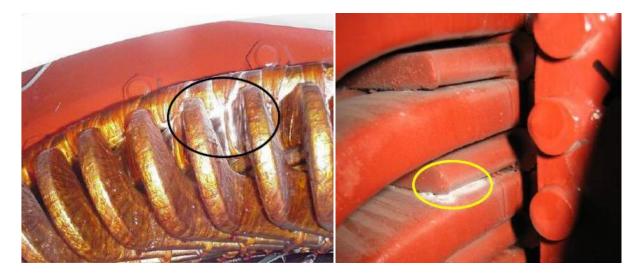


Figure 12: Examples of visual indicators detectable using boroscope inspections. Image Source: JIP project.

3.1.3 Stator winding insulation investigation

The integrity of the stator winding insulation is critical for the health of the motor. During operation the winding insulation have to withstand a number of destructive stresses such as thermal, electrical, and mechanical. Monitoring the integrity of the winding insulation is an effective way to identify incipient problems, and a valuable tool to help plan for maintenance before a critical breakdown will occur. The JIP identified existing methods for performing stator windings insulation tests in the ABB Life Expectancy Analysis Program (LEAP) which is a solution for offline winding testing (ABB, 2016). The JIP project further helped define a standard procedure for performing this offline test, including measures to secure storing of log data that could be retrieved and used later for trending, correlation, and other relevant analysis.

3.2 Online condition monitoring methods

The JIP project investigated several methods for new online methods for condition monitoring of large electrical motors. The methods that have been demonstrated to give good results and being evaluated for normal installation are listed in this section.

3.2.1 Improved power estimation

Accurate and repeatable power estimation is an important factor for monitoring the condition and degradation of electrical motors. Ideally the electrical power should be identical to the compression power for an electrical motor driven compressor. However, due to inaccuracies in the available data this is not the case in real systems. The JIP project introduced the concept of *DeltaPower* as the difference between the electrical and the gas power in a compressor system as shown in Figure 13.

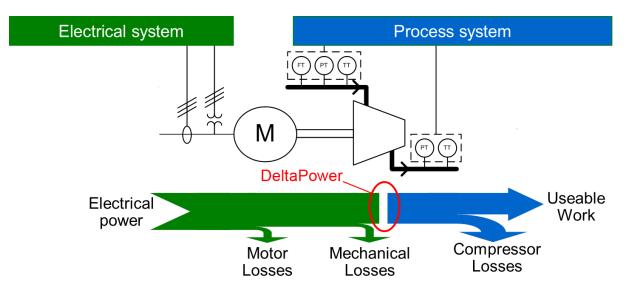


Figure 13: Illustration of electrical and process power estimation, and the concept of DeltaPower. Image source: JIP project.

The JIP project demonstrated high accuracy and repeatability of the electrical power estimation, within 1% of rated power. However, deviations were identified between the electrical and process power. Although there are multiple sources for this inaccuracy the main contribution is expected to be the gas composition. Since the gas composition is not continuously monitored it needs to be estimated in the calculations, which leads to inaccuracies between the model and real operation.

It is expected that by combining the DeltaPower solution with existing process and compressor monitoring it will be possible to reduce the effect of inaccuracies in the results. Further, by using signature analysis of DeltaPower, head and efficiency characteristics, the project demonstrated promising results in identifying which sensor contributes to the inaccuracies. This could enable the system to identify faulty sensors in addition to being able to monitor electrical power with high accuracy.

3.2.2 Comprehensive temperature monitoring

Temperature can give early indication of incipient failures and the JIP project performed a pilot installation by retrofitting temperature sensors to a test machine. Although the installation and testing of the sensors were successful, it is known that there are some deviations between the measured and the real temperature due to the sensor distance from the measured object caused by the insulation material.



Figure 14: Fibre optic temperature sensor. Image source: JIP project.

3.2.3 ESA/MCSA monitoring system

Electric Signal Analysis (ESA) and Motor Current Signature Analysis (MCSA) are well known and established methods for monitoring electrical motors. However, the technology was not available for synchronous VSD-driven motors. The JIP project helped in developing enhancements and improvements of ESA/MCSA-based fault diagnostic for a broader range of machines and faults. Parameters that are relevant for the condition of the motor are calculated based on extracted information from the current and voltage waveforms. In addition, vibration data are included in the system analysis for added fault detection capabilities. The parameters are monitored over time. If a change is observed this will reflect a physical change in the machine. An important prerequisite for this method to work is that the calculated parameters can be monitored with high accuracy and repeatability.

The calculated parameters from this method are:

- Commutation inductance
- Voltage unbalance
- Harmonic voltages
- Control unbalance
- Temperature monitoring

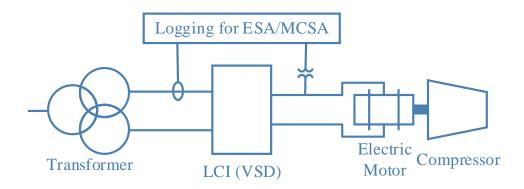


Figure 15: Measurement points for voltage and current for the ESA/MCSA analysis.

The monitoring system can be used to identify several issues, such as:

- Rotor winding defects
- Mechanical unbalance, misalignment, and looseness
- Bearing problems
- Power supply quality

3.2.4 Stator end-winding monitoring

The stator end-windings experience oscillating magnetic forces at twice the driving frequency caused by the power frequency current. These vibrations induce stresses that may cause mechanical damage in the form of insulation fatigue cracking and abrasion. The JIP project performed a pilot sensor installation of new fibre-optic sensors and a solution for online monitoring of end-winding vibration and temperature. The results from the pilot were very promising and the sensors were confirmed working after 1 year in service. The technology is currently being reviewed for implementation in technical requirements for new large electrical motors.



Figure 16: Stator endwinding deformation due to electromagnetic forces. Image source: JIP project.

3.2.5 Online partial discharge

Online partial discharge (OLPD) has been developed by the JIP project for use on large electrical motors, and successfully tested as a pilot sensor installation. OLPD enables detection of changes in partial discharge activity and can be a valuable tool in predicting the remaining lifetime of the machine.

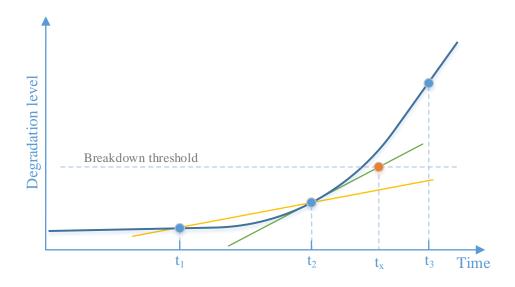


Figure 17: Illustration of the different prognosis potential between time interval snapshots and continuous monitoring using partial discharge analysis.

The advantage of having continuous PD analysis compared to offline snapshots can be seen from Figure 17. The blue curve represents the actual degradation level as a function of time for a hypothetic electrical motor. The times t_1 , t_2 , and t_3 represents planned maintenance periods where offline partial discharge analysis would be performed, and t_x represents the time when breakdown would occur as predicted by the online monitoring system. The dashed line represents the degradation level where complete motor breakdown is expected, while the yellow and green lines represents the prognosis vector based on offline and online PD, respectively at the time t_2 . Thus, performing continuous PD analysis would make it possible to predict the time when breakdown would occur. From Figure 17 it can be seen that online condition monitoring (green line) would predict that breakdown would occur at the time t_x , well before the next planned maintenance window at t_3 , while the offline prediction indicates that the machine would survive until the next planned maintenance window.

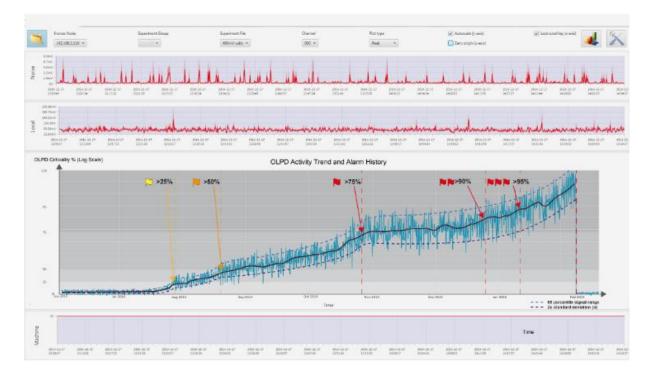


Figure 18: Partial discharge trend to failure. Image source: HVPD (2016).

The online monitoring and analysis system could also make it possible to predict the increased degradation rate as illustrated by the graph. At the time t_2 , both the first and second derivative are positive, which indicated that the degradation rate is rising, and that the rate if degradation is increasing. This type of information would be impossible to extract when using only offline methods.

The new methods presented here are suggested to be incorporated with the existing systems and presented in the following chapter.

4 Implementing new tools and methods into existing systems

Introducing new tools and methods in existing organisations and CMDSS poses several challenges, like potential need for additional manpower, increased workload on the existing maintenance organisation, lack of managerial understanding of the potential value creation. Additional challenges are present due to multiple vendors, standalone systems, expert knowledge requirements, and non-uniform interface designs across the various vendors and systems. These challenges require that the introduction of the new tools and implementation into existing systems are thoroughly planned for and aligned with both the operational and managerial part of the organisation. This section outlines areas that needs to be evaluated and further detailed in order to make the best use of the new tools and methods for condition monitoring of electrical motors.

4.1 Success criteria

Clearly defined success criteria should be established early in the planning process to enable a successful outcome when integrating the new tools and methods in the existing CMDSS. This will help to keep the focus on the overall success, and can also help identify any conflicting goals. A simple set of preliminary success criteria can for example be:

- Reduced maintenance and operational cost for the selected electrical motors
- Increased reliability of the selected electrical motors

These simple success criteria may seem to be conflicting and mutually exclusive. A hypothetical detailed analysis could end up showing that the maintenance cost would actually increase due increased maintenance of the additional equipment and sensors being installed for condition monitoring. However, a small increase in the reliability of the equipment may by far outweigh the increase in maintenance costs. In this example the first success criteria could be rewritten to something like "Maximum 3% increase in maintenance costs for the selected electrical motors".

When determining these success criteria, it is recommended to follow the SMART (Specific, Measureable, Achievable, Realistic, Time specific) principles for goal setting. In addition, the criteria should be analysed with respect to conflicts as mentioned previously. Finally, the main focus should be on determining the appropriate success criteria, and trying to limit the actual number of criteria.

4.2 Data acquisition and logging

4.2.1 Data resolution

A challenge with existing systems and historian log data is that the systems in some cases are outdated and they are using various methods of reduced data logging, for example by the use of dead-bands, averaging or data compression. Experience from the JIP project showed that the limits imposed, by for example dead-bands, on the available log data severely limited the usefulness of the log data for later analysis purposes.

In order for modern condition monitoring, analysis and prediction to be useful a lot of data is required at high resolution. This is not provided by the old logging systems, and it will be necessary to look into what can be done to improve the data logging. Technology improvements during the last couple of decades has made data storage cheap and easily available, and network protocols have improved significantly compared to the 80's and 90's when several of the systems were designed, which are considered in this thesis.

The technical aspect of upgrading outdated equipment is in most cases not expected to be big challenge. However, it could prove cost prohibitive and could potentially need to be evaluated against the overall benefit achievable by performing a holistic analysis.

4.2.2 Big data

After the technical aspect of data resolution and transfer has been solved, the next challenge will be to store and organize all this data, which brings us into the field of big data. New sensors and modern systems that demand data with high resolution will increase the load on the existing, and sometimes outdated, data and communication systems. Especially electric sampling data can tend to have very high sampling frequency requirements compared to normal process operation requirements. The ESA/MSCA method presented in section 3.2.3 is based on sampling frequencies of 4 kHz for vibration monitoring and 40 kHz for electrical measurements. If it is desired to store this raw data at full resolution it is clear that log data spanning several sources and sensors would quickly fill up huge amounts of storage. Although storage costs have become very low in the last decade, there are still challenges related to how the data should be stored and made retrievable.

Decentralization of computing and storage resources away from large datacentres and into substations closer to the actual equipment and sensors being logged, may help solve some of the biggest challenges when it comes to for example pulling new network cables over long distances in a live plant. However, this could possibly also limit the future benefits of the data since it may not be readily made available for fast data retrieval in big data analysis.

Another solution that could be useful when introducing new sensors and equipment is to utilise wireless equipment. This could potentially reduce, or even eliminate, the need for pulling new network cabling. However, there may be other issues with respect to wireless communication that may reduce the usability of the signals, like for example loss of signal, interference, bandwidth limitations, and time delay.

4.3 Data analysis

4.3.1 Trending and prognosis

Trending of log data is a very common form of data presentation and analysis today. In its simplest form trending only presents logged data as a function of time. Although this is not directly a form of analysis, it is a well-used tool by operators and equipment experts to get an impression about the historical and current condition, in addition to the trend of the condition development.

Prognosis, or forecasting, can sometimes be implemented as part of the trending system, and in some cases it will be performed by dedicated equipment experts based on their knowledge and available data that will make an educated forecast about the future condition development. It is the forecasting part of this analysis that may have significant room for improvements by implementing online measurements and advanced forms of software analysis, such as for example machine learning that will be discussed later.

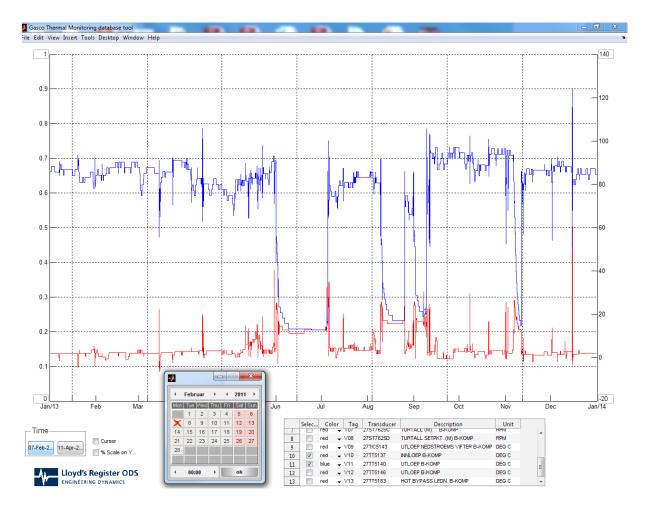


Figure 19: Display of temperature trend. Image source: JIP project.

4.3.2 Correlation detection

As a part of the data analysis it is required to incorporate a self-learning correlation detection routine, that will enable to retrieve all the data from the big data storage centre and perform continuous correlation detection on the data. The purpose of this is, partly to identify any unknown correlations in the overall system using the complete set of data available, and also to warn about changes in any of the variables of the already known correlations.

An example of correlation detection is shown by the use of scatter plots in Figure 20. The leftmost plot shows practically no correlation between the variables x and y (r = -0.04). The middle plot shows a slight negative correlation between the variables (r = -0.37), and the rightmost plot shows a strong positive correlation between x and y (r = 0.86). Identifying correlations in a system will enable the prognostic system to take advantage of these data and perform predictions about the future development of a variable based on the correlated variable. It may also be used to identify if variable deviates from the known correlation pattern, which

could indicate that something has changed in the system and could trigger the need for investigation.

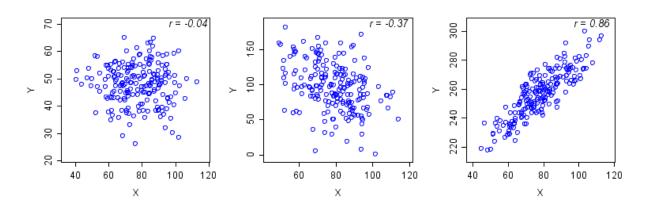


Figure 20: Example of correlation scatter plots. Image source: Suter II (2016)

Common practice with system parameters correlations in existing systems is that the correlations are pre-defined based on input from system engineers and equipment experts. This practice is most likely based on the limited computing power and software available during the establishment of design practices in the 80s and 90s. By exploiting the massive computing power and advanced software available today it might be possible to identify hidden opportunities that can improve condition monitoring and forecasting capabilities.

Some suggested variables that should be considered for correlation analysis are:

- Temperature and flow rate
- System load and vibration
- System load and flow rate
- Power consumption and work output

The correlations can in some cases be used directly to indicate problems in the machine or system depending on which correlation are considered. However, the additional benefit from utilising correlations can be that by combining several correlations it can be used to pinpoint or rule out specific failures.

4.3.3 Baseline deviations

A common and relatively simple form of equipment analysis is to detect deviations from a defined normal condition. The normal condition can be based on for example a known pattern, or log data from equipment test runs such as for example during Factory Acceptance Tests (FAT) or after maintenance and major rebuilds.

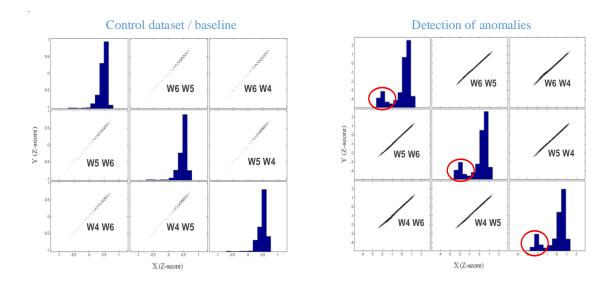


Figure 21: Baseline deviation detection based on correlation baselines. Image source: JIP project.

A challenge with this form of analysis is that it may not be suitable for dynamic systems, such as VSD controlled electrical motors on compressors. For such a system there may not be a clearly defined baseline, unless it is possible to normalize the specific variables used in the analysis. Alternatively, a compromise may be suggested where several baselines are established depending on operating point, and where the deviation detection are based on interpolating between the baselines closest to the current operating point. It should however be expected that such a method would decrease the sensitivity of the analysis, and therefore may not be applicable in some situations.

For variables where it is possible to establish a defined baseline the method in most cases be very useful and easily understandable by system users. For online condition monitoring the trending of deviations from the baseline can give valuable information about the health and condition development of the equipment.

System variables that are good candidates for baseline deviation detection are for example:

- Temperature
- Power consumption
- Flow rate
- Vibration

However, as mentioned above, all of these variables are affected by the current operating point, and will need to somehow be normalized or made valid for only a specified operating envelope.

4.3.4 Pattern recognition

Pattern recognition can be a useful tool if the failure mechanisms are well known, and when they exhibit identifiable patterns in the waveform or frequency spectrum. Traditional pattern recognition normally relies on empirical data, or predefined models, such as factors of natural frequencies in rotating machinery.

An example of successful use of pattern recognition in a condition monitoring and prognosis system can be seen at PROGNOST (2015), who have specialised in identification of mechanical faults in reciprocating machinery. The system is based on a large database of known failure patterns which enables automatic diagnostics and clear text message describing the fault type and location of the failing component. Although the PROGNOST system is only applicable for identification of mechanical faults in reciprocating compressors and gearboxes, it represents a good example of what can be possible to achieve using this method if it can be adapted to a wider range of machinery.

4.3.5 Machine learning

Machine learning is the science of making computers and machines able to learn. It is considered a subarea of artificial intelligence, and is already in use in areas such as facial recognition, voice recognition, credit card fraud detection, and spam filtering (Schapire, 2008). Pattern recognition can be a challenge for new systems with no previous data log of known failures, as there is no known pattern to match the current data to. This is where machine learning can be beneficial as this will be able to detect patterns using several classification methods, and thereby be able to learn characteristic patterns related to the specific equipment and system. By enabling computers to learn automatically it can be possible to solve complex tasks that would have been practically impossible to program in a traditional manner.

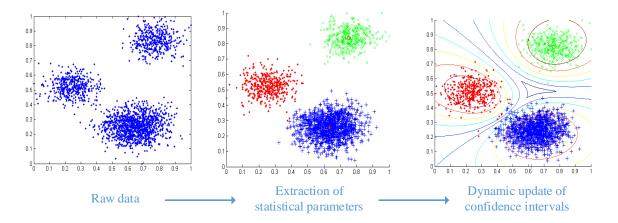


Figure 22: Illustration of the machine learning concept used on clustered datasets. Image source: JIP project

4.4 Reporting

Reporting process of the results is a critical part of the decision support system that requires careful planning, and requires the ability to be easily updated and adapted to new situations, knowledge and experiences. Provisions should be made available to the organisation that enable easy access to feedback and improvement tools for all the system stakeholders, such as for example end-users, contributors, decision makers, and system responsible.

Figure 23 shows a suggested flowchart that can be used to determine critical information required for decision making, reporting and the decision support system. As described by Taylor (2012) it is important to start the process with the decision in mind. Further it should be focused on keeping the reports and information contained therein focused on what is necessary to make a well informed decision, while still avoiding information overload.

In the process of establishing the decision support system it will be critical to involve several parts of the organisation to ensure a successful system design and implementation. There needs to be a total system view which includes all aspects of Technology, Man, and Organisation (TMO). All three parts needs to be designed together for maximum benefit of such a system. Bad data or a low quality report may not be of any use for anyone (Technology). A fantastic report will be of no use if no-one will read it or act on it, and if the report is given to someone in the organisation that don't have the proper foundation to interpret it (Man), critical decisions may not be taken with potentially severe consequences. Further, if the organisation is not prepared to make the necessary decisions, or if roles and responsibilities are unclear, the decisions may not be made in time (Organisation). Finally, even if each of these elements are optimised and perfected, it will still be critical to ensure smooth interaction and communication between the relevant roles in the organisation.

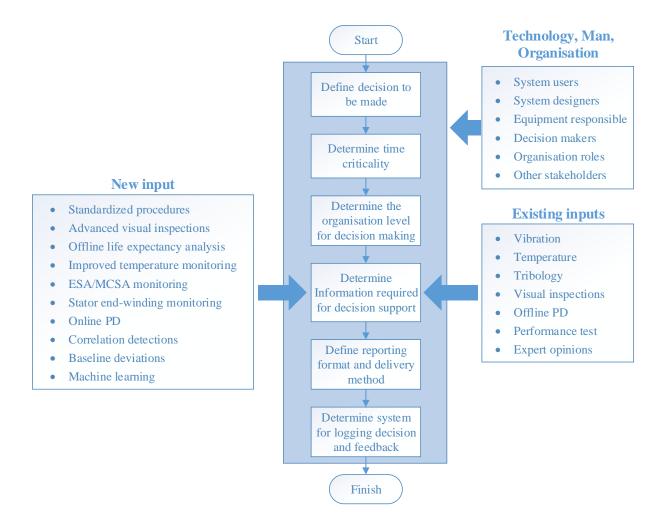


Figure 23: Suggested flowchart for determining required information for reporting and decisions in a decision support system.

4.4.1 Format, level of detail, and timing

For all the available data, condition status and prognosis, it is necessary to establish which information has to be presented, to whom, and how to present the specific information. During this process it will be important to carefully consider who the recipient will be and what information they require to do their job. With so much information available it is likely to fall in the information overload trap, where one includes all information with the idea that it will give the end-user a better understanding of the system. However, this may often lead to information overload and decision paralysis. Therefore, it's important to only include the information required for the specific decision that is to be made at that specific point in time by a specific decision maker.

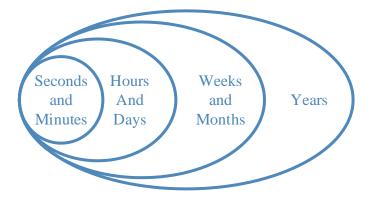


Figure 24: Illustration of time domains for decision makers and stakeholders.

The timing criticality of the information and required decisions may also sometimes dictate in which format the specific data needs to be presented. Some decisions may need to be automated, and will only display the automated decision results on the operators' systems display. The next level could be to display a warning, and possibly a recommendation, on the operator screen on which the operators would need to make the decision. Moving further up the hierarchy and to less time-critical decisions, the data and recommendations could be sent as email, work-orders, of pre-defined printed reports and presentations.

For the short-term decisions there may not be much choice, as the decisions needs to be made close to the actual operations and equipment in questions. For medium- to long-term strategic decisions with potentially large economic consequences there may be some lack of clarity with respect to where the decision authority is located. If such lack of clarity exists, it needs to be clarified as part of the system, so that when a decision needs to be made no-one questions where the responsibility is located.

4.4.2 Contributors

Depending on the purpose and the recipient of the reports a number of internal and external contributors may need to be involved in the information input, interpretation and preparation of the reports. As with the format, content, and recipients of the reports, the required contributors and their contributions should be evaluated and defined depending on the purpose of the decision to be made based on the information in the report. This means that the required contributors may vary widely depending on the holistic view of the decision to be supported. For the shortest time periods which usually involves the direct system operators, there may only be time for automated contributions, which will then require immediate information from the

monitoring and analysis system. Recommended actions should be presented, or potentially preprogrammed depending on the criticality.

For longer term decisions there may be a wide range of input required to be gathered from equipment experts, system responsible, operators and maintenance personnel. Again the necessity to clearly define the required input, and make every contributor aware of the purpose for the information they provide may assist in avoiding information overload.

4.4.3 Organisation levels and decision makers

When it comes to decision making related to the equipment condition there are several factors that needs to be evaluated and defined. The first question to ask is which decisions needs to be made? According to Taylor (2012) when establishing a decision making system, the first action should always be to start with the specific decision in mind.

Determining at which organisation level a specific decision shall be made depends on factors such as the time criticality of the decision, the economic and political impact, defined responsibilities, technical knowledge and experience. A common trait for most decisions are that the more time-critical the decisions are closer to the equipment the decisions should be made. The most critical decisions should be pre-programmed or hardwired, and in most cases it would involve the manufacturer equipment protection and safety systems, where no active operator decisions are needed. The less time-critical decisions will normally move progressively up the organisation hierarchy, in which long term strategic decisions are made, and where more time can be devoted to analyse the particular situation.

4.4.4 Automating decisions

In order to increase the efficiency and limit the organisation load related to decision making and providing manual decision support information, it could be of great advantage to automate as much of the decision making process as possible. According to Taylor (2012) decisions that should be considered for automating are characterized by the following traits:

- Repeatable A decision that is performed on a regular basis, with the same set of options, based on similar set of data, is a good candidate for automation.
- Nontrivial Decisions that are complex in nature, or require substantial amount of work to consider are prime candidates for automating as this will improve organisation efficiency. Trivial decision on the other hand will normally not be candidates for automation due to the cost overhead of maintaining such a decision system will be higher than the cost required for a person to make the decision.

- Measurable business impact Since establishing and maintaining an automated decision system will require capital investment and operational expenses it will be important to show the business impact of making the decisions.
- Candidate for automation These must be consensus and willingness in the organisation to accept the automated decisions, trusting the system, and continuously working to monitors and improve the decision system. There is no point in developing a system if the organisation will not accept it and use it as intended.

4.5 Increase sensitivity and confidence levels by aggregating information

The JIP project identified this as a potential but due to time-constraints this opportunity was saved for future work. The purpose of aggregating information is to take advantage of the system data in a manner that has not been effectively utilised before. The common practice seems to be that use of system condition data has been divided between areas of expertise, system limitations, and dependencies on specific suppliers. This means that there is a system for process monitoring, which is mostly used by system operators and system responsible. There are mechanical monitoring systems such as vibration monitoring, which is mainly used by mechanical equipment experts. There are electric monitoring systems that are used by electric system operators, experts and maintenance personnel.

There may be many reasons for the existing segregating of information, some if which may seem to be linked to system and technological limitations that existed at the time when the original systems were designed. In may also seem that condition monitoring systems could benefit from a more multidiscipline approach in order to identify more of its potential. It is expected that the overall confidence of the prognosis and forecasting can be increased by combining and aggregating several sources of information, such as electrical, vibration, temperature, process, and environmental monitoring data.

In order to facilitate future possibility to include this system improvement provisions should be made when implementing new measurements that the data are made available and stored in such a manner that it will be easily accessible at a later date. This would include interface to access live data, and the establishment or inclusion of log data in a database. Standalone or segregated systems without networking or interfacing capabilities should be avoided, as this would limit the future usability of the data.

5 Analysis

The fault-tree shown in Figure 26 are based on FMEA sessions performed in the JIP project and is valid for phase-to-phase short circuit, turn-to-turn short circuit, and short circuit to ground. The fault tree analysis (FTA) can be used as a starting point for a thorough analysis of the effect on the reliability improvements in the various areas can have on the total system. The probabilities given in Figure 26 have been based on information from the FMEA sessions and expert opinion. The top level groups probability contribution have then been calculated and the results are presented in Figure 25, which shows that thermal ageing is the biggest contributor to stator winding failure.

It should be expected that complex interactions and dependencies between events and root causes will be identified upon further detailed analysis. For example, vibrations and thermal cycles can cause friction and erosion, but are still listed as independent causes and consequences in the fault tree. It could therefore be argued that erosion could be classified as mechanical fatigue. Dependencies and interactions between different root causes and consequences have only been briefly mentioned here, and will need to be further studied if deemed necessary for a more detailed FTA. Some of the root causes presented may also be possibly argued that they are not true root causes, but rather a consequence of other root causes. More detailed information can be obtained from Tavner et al. (2008).

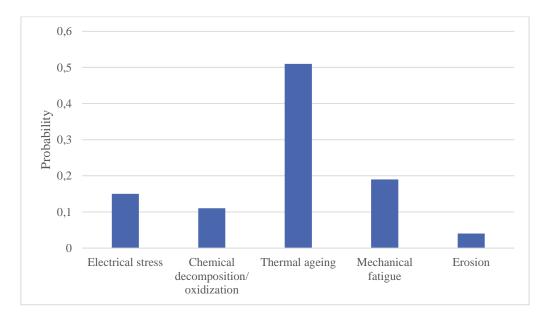


Figure 25: Probability contribution for the top level fault groups in the fault tree.

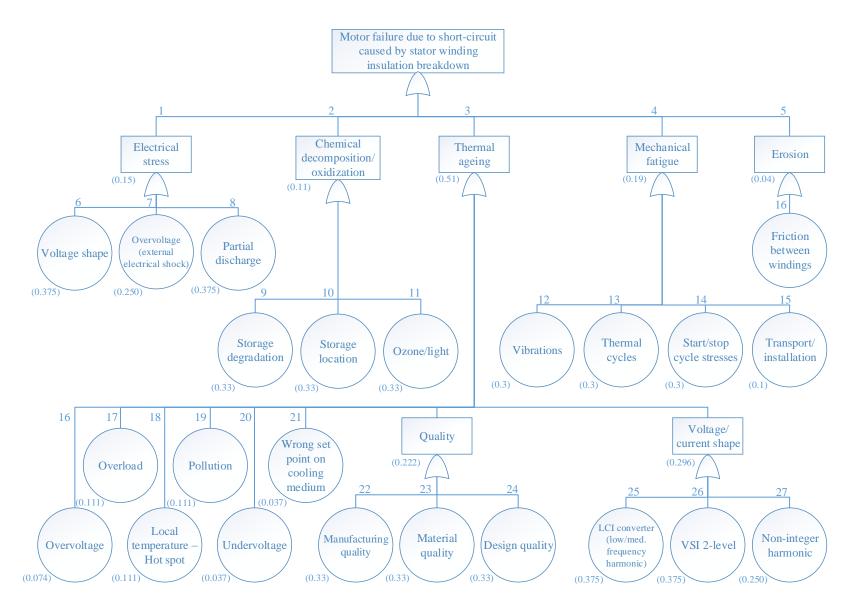


Figure 26: Fault-tree for motor failure due to short-circuit caused by breakdown of insulation in the stator windings.

5.1 Electrical stress

Node 1 in the fault-tree contains a group of three root causes (node 6-8) that has been identified to potentially cause an electrical stress event that can lead to insulation breakdown and shortcircuit between the windings. The three root causes for this event are:

- Voltage shape
- Overvoltage
- Partial discharge

The first two root causes, voltage shape (node 6) and overvoltage (node 7), are mainly related to how the VSD controls the voltage and current supplied to the electrical motor. It could be expected that improving or replacing the current technology for speed control may reduce these issues. There have been much development and improvement of Pulse Width Modulated (PWM) VSDs the last few decades (Billard et al., 2014). This is generally considered a better technical solution for VSD control of electrical motors, but have not been commercially available for large synchronous electro motors due to technical limitations. There could be potential benefit in replacing the old LCI technology with newer PWM technology if it will be available for large synchronous electrical motors. It should be noted that node 6 and 7 are also represented by node 25 and 16 respectively, and that this dependency should be further clarified. Currently the voltage is monitored and the equipment protected by setting alarm and trip limits.

Partial discharge (node 8) can be described as small sparks inside the winding insulation causing voids inside the insulation (Tavner et al., 2008). This process contributes to degrading the insulation and may eventually lead to short-circuit between the windings. Tools and methods exists that are well-established and give good results regarding the partial discharge condition of electrical motors. However, there have been no methods available for online monitoring of partial discharge on large VSD controlled synchronous electrical motors. The pilot installation of online PD monitoring in the JIP project showed promising results. This method is expected to contribute to increased knowledge about the partial discharge activity in the winding insulation of large VSD controlled synchronous electrical motors during normal operation. Although there is no way to recover from the increased partial discharge, by obtaining better knowledge of the status the probability of having any *unsuspected* breakdowns can be reduced. This increased knowledge about current condition and expected remaining lifetime may allow for maintenance personnel to plan for the work required to either overhaul of replace the motor component.

5.2 Chemical decomposition

Node 2 in the fault-tree contains a group of three root causes (node 9-11) that has been identified to potentially cause chemical decomposition that can lead to insulation breakdown and short-circuit between the windings. The three root causes for this event are:

- Storage degradation
- Storage location
- Ozone/light

These three root causes (node 9 and 10) are mainly related to storage conditions. It should be noted however, that the failure of the components, i.e. short-circuit between windings, would most likely only be noticed after a degraded component was put into service. Storage degradation mechanism can be related to atmospheric conditions such as humidity, temperature variations and the presence of destructive chemicals, which can cause degradation of the winding insulation material (Tavner et al., 2008). Although no specific method was developed by the JIP to address this issue, the project recommended for future work that manufacturers and owners established detailed procedures for long term preservation of the equipment. Further it was recommended to evaluate the use of Nitrogen as protective atmosphere for storage, and applying direct current to the equipment during storage instead of using space heaters for a more even heat distribution.

5.3 Thermal Ageing

Node 3 in the fault-tree contains a group of twelve root causes (node 16-27) that has been identified to potentially cause thermal ageing that can lead to insulation breakdown and short-circuit between the windings. The twelve root causes for this event are:

- Overvoltage
- Undervoltage
- Overload
- Pollution
- Local temperature Hot spot
- Wrong set point on cooling medium
- Quality
 - Manufacturing quality
 - Material quality
 - Design quality
- Voltage/current shape

- LCI-converter (low/medium frequency harmonics)
- o VSI 2-level
- Non-integer harmonic

Thermal aging describes the mechanism of insulation breakdown due to excessive temperature which can cause permanent physical degradation of the insulation material. Damages to the winding insulations related to temperature cycling are defined under the mechanical fatigue event (node 4).

Insulation life, h	Temperature, °C
20000	165
10000	175
5000	185
2500	195
1250	205
625	215
312	225

Table 1: Estimated insulation lifetime depending ontemperature. Source: JIP project.

Overvoltage, undervoltage, and overload (nodes 16, 17, and 20) are closely connected to the root causes listed under the electrical stress event (node 1). Interactions and dependencies may exist between the causes and events that should be more closely examined. Of these three root causes undervoltage is considered as low probability of causing damage to the winding insulation, while overload and overvoltage are categorised as high probability. Overvoltage may occur as a consequence of the drive regulation technique in addition to the potential of letting power grid disturbances through to the motor. Applying filtering and monitoring of the voltage should be considered in order to reduce the probability of applying overvoltage and to increase the knowledge about the operating conditions of the motor. Overload may occur as a consequence of process operation disturbances, operator error, or wrong control functions. It should be ensured that the potential for running machines into overload is minimal.

The root causes 'local temperature – hot spots' (node 18) and 'wrong set point on cooling medium' (node 21) can be considered having close interactions and dependencies. Defining what is the right or wrong set point for cooling medium may also not always be straightforward

since the cooling medium temperature will only reflect the overall temperature balance, and cannot identify local hot-spots. Although there are temperature sensors installed in the windings on the motor focused on in this thesis, there are only one sensor per winding, and therefore inadequate to identify local hotspots unless they are closely located to the physical sensor location. Thermal imaging camera for identifying hot spots was suggested by the JIP project, but due to limited field of vision the idea wasn't considered feasible. Other suggestions from the project involved using the existing temperature sensors to compare the winding temperatures with each other, and including the cooling water temperature as a factor in the analysis. Although this method cannot directly identify hot-spots, it could be a useful tool to gain better knowledge about the internal temperatures in the motor.

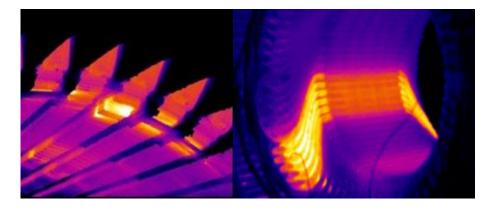


Figure 27: Thermal imaging of winding hot spots. Image source: JIP project.

Three root causes (nodes 22-24) are related to quality, considering manufacturing, material and design quality. Common for these causes are that while the consequences of low quality can take a long time to emerge, the possibility to control these quality related issues exist mainly during the design and production at the manufacturer. The suggestion was therefore that suppliers should provide customers with option for "highest quality" bid on materials and design margins, and that adequate quality assurance processes were implemented.

Voltage/current shape (node 25-27) are concerned about the control and regulation functions for variable speed driven electrical motors, and the ability of the equipment to filter out any disturbances from the power supply grid. The technical details regarding these root causes are beyond the scope of this thesis, but it was identified during the FMEA sessions in the JIP project that the voltage and current shape produced by the variable speed drives can cause local temperature hot-spots in the electrical motor windings. It was recommended to evaluate the type of drive selected for new equipment with respect to temperature and hot-spot issues. Further it was recommended to measure the wave shape during normal operation, which is

expected to be possible by using the same equipment and methods as introduced by ESA/MCSA presented in section 3.2.3.

5.4 Mechanical fatigue

Node 4 in the fault-tree contains a group of four root causes (node 12-15) that have been identified to potentially cause mechanical fatigue that can lead to insulation breakdown and short-circuit between the windings. The four root causes for this event are:

- Vibrations
- Thermal cycles
- Start/stop cycle stresses
- Transport/installation

Common for these four root causes are that they all cause relative motion between insulating components, causing mechanical damage to the insulation (Tavner et al., 2008). Similar to some of the other root causes presented it can also here be discussed if these are true root causes, or if there are interdependencies that should be identified.

Vibrations (node 12) can cause abrasive motions causing erosion of the insulation material, so there is a clear link to node 5 – Erosion. Additionally, vibrations can appear as a consequence of unbalanced current applied to the motor windings, lack of winding support blocks, bad design, and potentially several other reasons. In large electrical motors it is especially the large end-winding overhang that can be subject to excessive vibrations. The JIP project performed a pilot and tested retrofitting of vibration sensors that will enable online monitoring of end-winding vibrations, (see section 3.2.4). The results from the pilot was positive, and if combined with existing vibration monitoring (see section 2.5.1) and ESA/MCSA monitoring (see section 3.2.3) the condition monitoring of vibrations can be greatly enhanced.

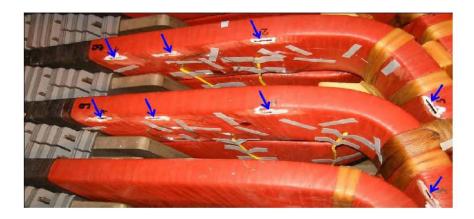


Figure 28: Retrofitting of fibre optic vibration sensors on end-windings. Image source: JIP project.

Thermal cycles (node 13) causes expansion and shrinking of the machine components, and can lead to abrasive movements causing degradation of winding insulation. To minimize the damaging effects of thermal cycles it will be important to avoid rapid changes in temperature and to keep the temperature changes evenly distributed in the machine components to allow for equal expansion and shrinking movements during temperature changes. The JIP project performed a pilot test and tested retrofitting of temperature sensors that will enable online monitoring of end-winding vibrations, (see section 3.2.2). The results from the pilot test were positive, and could be combined with existing temperature monitoring in order to have better control of the temperature cycles and heat distribution. Additionally, having a history log of the temperature cycles of a machine, and should be considered for implementation in a future decisions support system.

Start/stop cycles (node 14) causes mechanical stress in the motor components which can lead to relative motion between insulation components causing degradation. However, since the motors considered in this thesis are VSD controlled, the start and stop sequences are programmed by the manufacturer to keep the stresses in the motor within acceptable limits. The primary concern as noted by the JIP project was the stress experienced by the motor during a trip. Although it may not be possible to limit the stresses on the motor during a trip, it could prove beneficial for a prognostic and decision support system to include information about the number of trips experienced by the motor, and if enough information is also available on the level of stresses for each individual trip could contribute to increased knowledge about the remaining lifetime of the motor.

Transport/installation (node 15) is concerned about how the motor parts are handled during transport and installation when they are sent for inspection and overhaul. Handling during the removal and installation phase is also a concern since it is a delicate procedure with small margins moving several tons of equipment, like when removing the motor stator from the housing. Wrongful handling or lack of proper bracing during transport could potentially allow the windings to move or vibrate in such a way as to damage the winding insulation. The JIP project registered this as a low risk since established procedures exist, and only recommended to review the current procedures in order to identify if there is a need for improving the procedures for transport and installation.

5.5 Erosion

Node 5 in the fault-tree contains a single root cause (node 16) that has been identified to potentially cause erosion that can lead to insulation breakdown and short-circuit between the windings. The root cause for this event is:

- Friction between windings

It can be discussed if this is actually a root cause or if it should be considered an effect due to other root causes, since friction damage is caused by movement of windings against insulation. The main causes for these types of movement would be expected to be vibrations, thermal expansion, and the mechanical stresses during start/stop cycles, which are all covered under node 4 – Mechanical fatigue.



Figure 29: Abrasion caused by loose coil in slot. Image source: JIP project.

6 Discussion & Conclusions

6.1 Discussion

The oil and gas processing industry have relied heavily on the use of gas turbines as drivers for gas export compressors. Limited experience exists in the industry with large VSD electrical motors. The design of these large electrical motors has mainly been based on generator designs and converted to motor service. This means that the design may not be properly optimized for the intended service, and only limited testing may have been performed since the finished motor is in essence its own prototype. Since electrical motors of the size considered in this thesis often are one-of-a-kind products not much experience exist to base the designs on. Recent years' experience shows that even relatively new motors have broken down suddenly and unexpected, potentially due to reduced design margins in order to minimize the initial capital investment for the equipment. In addition to the limited operating experience with large VSD electrical motors the condition monitoring technology available for the equipment have been limited, and often dependent on taking equipment offline. Online condition monitoring and prognostic methods will be necessary to improve reliability and predictability of large VSD electrical motors in the gas export market.

It can be argued that predictive maintenance is already in use for some major equipment components in processing plants. However, it has been shown that there is room for improvement when it comes to condition monitoring and prognosis of large variable speed electrical motors. By increasing focus on critical components and variables that have previously not been included or fully utilised in the condition monitoring systems, there is additional potential for extending the prognosis system to also include connected components through correlations and machine learning, like for example the driven equipment and connected utility systems. By including multidiscipline data measurements and expert knowledge in knowledge based decision making systems there may be potential for synergetic effect that can improve the accuracy of condition monitoring and prognostics.

Further improvements can be expected by using the improved prognosis capabilities and couple with automated decision making systems. Current methods for decision support tend to be rather simple systems, like setting alarm and trip limits and information on operator screens, or they tend to be time-consuming, require equipment downtime and access to experienced personnel to perform analysis and recommendation. Large amounts of log data are in many cases already stored and can be accessed by condition analysis and prognosis systems (CAPS). However, it has yet to be seen a CAPS that can combine the available data from multiple sources

and perform all the functions required for a condition monitoring and decision support system (CMDSS). Even though promising technological solution may exist, it has not been possible to identify a successful implementation of such a system that includes the total system from condition monitoring, through human operators, and in to the organisational levels. An example of successful technical implementation of CMDSS can be found in Yam et al. (2001) where it is referred to as intelligent decision support system (IDSS).

New technologies and data may open up for improvements in the prediction ability of the CMDSS. Previously unknown correlations may be discovered when the new data is analysed in combination with already existing data, and possibilities that was not originally intended may be discovered. These types of correlations may be classified in a few categories:

- Known correlations but not considered of value for condition monitoring purposes
- Known by experts but currently not viable due to lack of data
- Unknown and undiscovered due to complex variable interactions

As the equipment monitored by the CMDSS can potentially be expanded to a large variety of equipment and vendors, there may be a need for a software system that is independent of suppliers and vendors, and that can access the data from all the various sensors and systems for further analysis. This could be required to perform correlation analysis and machine learning algorithms on a combination of data, from amongst others: electrical motor drive system, electrical motor mechanical condition monitoring, compressor condition monitoring, and process parameters.

Based on the information presented in this thesis, reference documents, and the experience form the JIP project, it has been shown that technology is available that can facilitate great improvements for the reliability and predictability of critical equipment. Some of the basic technology have been available for years, but haven't been utilised in a holistic method to establish a CMDSS with focus on automation, modern technology and methods, and synergistic effects. Other technology specific for the VSD electrical motors in this thesis have just been developed and piloted, and are showing positive results. Continued work on the technical solutions and integrations are likely to show even more promising results.

Further work in the field of CMDSS will be required, and more opportunities likely exist, either previously unachievable, or unknown. An iterative learning approach would be critical in order for systems and organisation to evolve and take advantage of synergistic effects. Implementing

such a system is only the beginning, and the real benefits will be realised with continuous feedback and improvement.

Having the technology and methods available is only part of the solution. In order to take full advantage of the available technology it will be necessary to consider the holistic view that includes technology, man, and organisation (TMO). Figure 23 gives a suggested workflow for how the TMO aspect could be included in the total system design when establishing a decision support system. If new technologies are just added to existing systems but fail to consider the total aspects of TMO, there will be high risk that the implementation of the system will fail. Even the greatest technology will not do any good if the man and organisation factor is not in alignment and acceptance with the technology. Failing to consider this aspect will likely lead to failed investment in promising solutions. It should also be noticed that great technologies are made by great engineers and technologists, not salespeople or business organisation experts. However, a successful implementation of new technology and new work methods require the involvement of all these experts, and all stakeholders and affected people in the organisation to include third party organisations and stakeholders.

The biggest challenge faced by the industry at this point seems to be the actual implementation of technology and the changes required in existing work methods and organisations. Human fear and scepticism can often be a challenge when faced with new and unfamiliar technology. Changes can many times be seen as something negative, and thereby resistance grows in the organisation. Focus on solving the TMO aspect of CMDSS implementation will be critical for a successful outcome.

6.2 Conclusions

Technical solutions for condition monitoring of VSD electrical motors have been developed and tested in the JIP project, and are showing promising results. Three technical solutions that have been successfully tested in the JIP project and that are worth mentioning specifically are:

- Online partial discharge monitoring
- ESA/MCSA analysis
- End-winding vibration monitoring

Compared to the current situation, these technologies represent great leaps forward when it comes to condition monitoring of large VSD electrical motors. It is expected that successful implementation of the new technology and methods will contribute to higher reliability and predictability for the equipment and thereby for the gas export that they power. Figure 23 gives a suggested framework for how to successfully design a decision support that takes into account both existing and new technology, as well as the technology, man, and organisation (TMO) aspect.

6.3 Recommendations

Based on the results from the JIP and the discussions in this thesis it is recommended to continue developing the technologies that have shown positive results with respect to condition monitoring of large VSD electrical motors. Prerequisite technologies should also be identified and if necessary developed to enable use of new condition monitoring and prognostic systems, especially with focus on online condition monitoring and prognostics. In relation to this evaluation should be made to understand the need for independent analysis and decision support systems that can be vendor agnostic and utilise all the available signals and log data in the analysis algorithms.

Further, it is recommended that the TMO aspect is carefully considered in view of a holistic decision support system. Development of such as system should start with the decision in mind and should cover all aspects affecting the decision making process (Taylor, 2012). Changing organisations, responsibilities and established work systems can be a long and painful process and it is recommended that this process is started early and involve all relevant stakeholders.

6.4 Limitations

The thesis has been limited to a single variable speed driven synchronous electrical motor since this was the primary focus of the JIP project that was the basis for this thesis. Some methods that has been presented and discussed may be applicable for a wider range of machines and equipment. For example, discussion concerning decision support systems, machine learning, and automated decisions are of a more general nature, and can be extended to include many other types of equipment. Further, some of the methods and technologies discussed in this thesis are already in use for other types of equipment, but have not been available for large VSD controlled electrical motors.

6.5 Future scope

Recommendations for future scope:

- Evaluate requirements for big data. Some systems considered in this thesis are old, and may not be adequate to handle the increase in data handling required to utilise a modern CMDSS.
- Evaluate if any existing CMDSS exist that can perform the desired functions, or if such a system should be specifically developed for the purpose at hand.
- Evaluate required interactions between equipment and vendors, and if the CMDSS should be established as a fully vendor agnostic system, or as a system that could include data, information, recommendations from multiple vendors.
- Evaluate the possibility and economical potential for reducing over-maintenance of critical equipment by performing major maintenance activities based purely on condition monitoring and prognostics. Assuming improved condition monitoring and prognostic methods are implemented.

References

- ABB. 2016. *Life Cycle Assessment* [Online]. Available: <u>http://new.abb.com/motors-</u> generators/service/maintenance/life-cycle-assessment [Accessed June 3 2016].
- BILLARD, T., LEBEY, T. & FRESNET, F. 2014. Partial discharge in electric motor fed by a PWM inverter: off-line and on-line detection. *Dielectrics and Electrical Insulation*, *IEEE Transactions on*, 21, 1235-1242.
- GASSCO. 2015. *Leveranserekord i 2015* [Online]. Available: <u>http://gassco.no/media/nyheter/Leveranserekord-i-2015/</u> [Accessed July 2 2015].
- HARTMAN, C. 2014. Available: <u>http://www.vfds.com/image/data/resources/what-is-vfd/inverter-circuit.png</u> [Accessed June 3 2016].
- HVPD. 2016. *HVPD Kronos Monitor Partial Discharge Trend to Failure* [Online]. Available: <u>http://www.hvpd.co.uk/files/6214/3229/3274/HVPD_Kronos_Monitor_</u> <u>Partial Discharge_Trend to Failure.png</u>.
- KUMAR, U. 1990. *Reliability analysis of load-haul-dump machines*. 1990:88 D, Division of Mining Equipment Engineering, Luleå University of Technology.
- MALCOLM, J. 2016. Condition Moitoring On-Line System.
- MOBLEY, R. K. 2004. Maintenance Fundamentals, United States: Butterworth Heinemann.
- MOBLEY, R. K., HIGGINS, L. R. & WIKOFF, D. J. 2008. *Maintenance engineering handbook*, New York, McGraw-Hill.
- PROGNOST. 2015. *Failure Detection* [Online]. Available: <u>http://www.prognost.com/products/nt/early-failure-detection</u> [Accessed May 15 2016].
- SCHAPIRE, R. 2008. COS 511: Theoretical Machine Learning. Available: http://www.cs.princeton.edu/courses/archive/spr08/cos511/scribe_notes/0204.pdf.
- SUTER II, G. W. S.-A., P.; CORMIER, S.M. 2016. *CADDIS Volume 4: Data Analysis* [Online]. United States Environmental Protection Agency. Available: <u>https://www3.epa.gov/caddis/images/Fig1scatterplots750pxw.png</u> [Accessed June 4 2016].
- TAVNER, P., RAN, L., PENMAN, J. & SEDDING, H. 2008. *Condition Monitoring of Rotating Electrical Machines*, Stevenage, The Institution of Engineering and Technology.
- TAYLOR, J. 2012. Decision management systems : a practical guide to using business rules and predictive analytics, Upper Saddle River, N.J, IBM Press/Pearson plc.
- YAM, R. C. M., TSE, P. W., LI, L. & TU, P. 2001. Intelligent Predictive Decision Support System for Condition-Based Maintenance. *The International Journal of Advanced Manufacturing Technology*, 17, 383-391.