CENTRE FOR MAINTENANCE OPTIMIZATION AND RELIABILITY ENGINEERING

DIRECTOR
CHI-GUHN LEE

SEMI-ANNUAL REPORT
December 2017

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TABLE OF CONTENTS

EXECUTIVE SUMMARY

CHI-GUHN LEE, C-MORE DIRECTOR

INTRODUCTION

The following report summarizes work undertaken between C-MORE and collaborating companies and major changes at C-MORE since the meeting on June 6, 2017.

I took on the role of Director of C-MORE when Professor Mike Kim, the former Director, left the University of Toronto to take a position at the University of British Columbia in July 2017. Coincidentally, Neil Montgomery, Associate Director of C-MORE, also left C-MORE and is now with Canadian Bearings. C-MORE is expecting another loss: Dr. Dragan Banjevic is retiring at the end of 2017 after spending 23 years at C-MORE. Dr. Banjevic agreed to continue his involvement at C-MORE after the retirement. I would like to express our deepest appreciation to him for his dedication over the past 23 years. The three departures have placed C-MORE in a transitional stage and I, as the new Director, have focused on a smooth transition. I have successfully recruited Dr. Janet Lam as a new associate director of C-MORE, and Dr. Elizabeth Thompson as administrative support. Janet will join in January 2018 to fill the position vacated by the departure of Neil, and Elizabeth has been active in C-MORE since October 2017.

I, along with Dr. Andrew Jardine, have visited all the consortium companies between September and November of 2017. We explained the transition that C-MORE was going through and shared our plan for the future. In particular, C-MORE is thrilled that three faculty members have agreed to be officially affiliated with C-MORE: Professor Fae Azhari at MIE, University of Toronto, Professor Scott Sanner at MIE, University of Toronto, and Professor Sharareh Taghipour at MIE, Ryerson University.

THE C-MORE TEAM

PROFESSOR FAE AZHARI

Fae Azhari is an Assistant Professor in the Department of Mechanical and Industrial Engineering, University of Toronto. She received her BSc and MASc degrees in Civil engineering from Isfahan University of Technology and the University of British Columbia, respectively. After working in the industry for a few years, she returned to school and completed her MEng degree in Industrial Engineering and Operations Research at the University of California, Berkeley, and her PhD in Structural Engineering and Mechanics at the University of California, Davis. Fae is interested in structural health monitoring (SHM) and prognosis of engineering systems. Her main areas of research are twofold: (1) sensor development and assessing the performance of novel sensing devices, and (2) developing decision-making frameworks that use probabilistic models to translate collected data into meaningful information and efficient remedial strategies for various infrastructure systems.

PROFESSOR SCOTT SANNER

Sott Sanner is an Assistant Professor in the Department of Mechanical & Industrial Engineering. Previously Scott was an Assistant Professor at Oregon State University and before that he was a Principal Researcher at National ICT Australia (NICTA) and Adjunct Faculty at the Australian National University. Scott earned a PhD in Computer Science from the University of Toronto (2008), an MS in Computer Science from Stanford University (2002), and a double BS in Computer Science and Electrical and Computer Engineering from Carnegie Mellon University (1999). Scott's research spans a broad range of topics from the data-driven fields of Machine Learning and Information Retrieval to the decision-driven fields of Artificial Intelligence and Operations Research. Scott has applied the analytic and algorithmic tools from these fields to diverse application areas such as recommender systems, interactive text visualization, and Smart Cities applications including transport optimization. Scott has served as Program Co-chair for the 26th International Conference on Automated Planning and Scheduling (ICAPS), member of the Editorial Board for the Artificial Intelligence Journal (AIJ) and the Machine Learning Journal (MLJ), and Electronic Editor for the Journal of Artificial Intelligence Research (JAIR). Scott was a co-recipient of the 2014 AIJ Prominent Paper Award.

PROFESSOR SHARAREH TAGHIPOUR

Professor Taghipour is an Associate Professor at the Department of Mechanical and Industrial Engineering at Ryerson University. Before her appointment at Ryerson, she worked as a postdoctoral fellow at C-MORE. She obtained her PhD in Industrial Engineering from the University of Toronto, and her BSc in Mathematics and Computer Science and her MASc in Industrial Engineering from Sharif University of Technology, Iran. Her research interests include reliability engineering, inspection and maintenance optimization, stochastic operations research, statistical analysis, and novel applications of maintenance optimization models, such as optimization of cancer screening. She holds a status-only Associate Professor appointment in the Department of Mechanical and Industrial Engineering at the University of Toronto and has collaborated with C-MORE on a number of projects. Sharareh has well-established partnerships and research collaborations with various industry partners from healthcare to energy, mining, transportation, utilities, and manufacturing including the Toronto General Hospital, Admira Distributed Hybrid Energy Systems Inc., Vale Canada Ltd. CHEP Canada, Fiix, Alstom France, Nova Chemicals, Manitoba Hydro, and ArcelorMittal Dofasco.

NEW RESEARCH GRANTS / PROJECTS

NEW CONSORTIUM MEMBER – BARRICK GOLD

C-MORE was delighted to have Barrick Gold re-join as a consortium member in January 2017. Dragan Banjevic has begun working on a case study to analyze remaining useful life of the Barren pumping system at Barrick’s mine in South America. We are looking forward to a productive collaboration in 2018 and beyond.

NEW PROJECTS: PRINCESS MARGARET HOSPITAL – THESIS AND CAPSTONE DESIGN PROJECT

C-MORE has been collaborating with Princess Margaret Hospital (PMH) to understand the flatness of Linear Accelerators (LINAC). Two teams of students have been formed: a thesis team involving Mozam Syed Shahin and Daniel Duklas and a Capstone team involving Tonglin Jin, Yuheng Lin, Xuehan Wang and Yuze Li. The thesis team has focused on analyzing 11 LINAC machines in terms of the flatness trend as a function of various parameters adjusted automatically as well as manually and maintenance performed, whereas the Capstone team has examined the design of maintenance procedure of the machines.

C-MORE ACTIVITIES WITH CONSORTIUM MEMBERS

Since June 2017, C-MORE lab members have been working on research, participating in conferences, and meeting with Consortium members. C-MORE is currently involved in the following projects with industry partners:

MINISTRY OF DEFENCE UK

A new project on flying incidents in Squirrel helicopters fleet was started after discussions at the June meeting. Tim Jefferis sent historical data for 2011-2017 for preliminary analysis. Dragan has worked on a plausible mathematical model for testing incidence occurrences. The key problem was uncertainty in collecting flying hours (FHs) and possible under reporting of dangerous incidents. The current results will be presented at the meeting. Tim was able to find data on FH in November; this will be useful for validation of underlying assumptions and further analysis and comparison.

TECK

Justin Cvetko Lueger proposed a survey of online condition sensor technology. Teck is interested in incorporation of this technology to improve certain engine maintenance interventions. Graeme Dillon, author of Teck engine asset health reports, will be the main contact for this project. The initial findings will be presented. Jeff Sutherland also sent a sample of Teck Greenhills oil transformer data for preliminary analysis to investigate a feasibility of a possible project with C-MORE. Preliminary findings are included in the report. Finally, Kevin Hatch is seeking feedback on his approach to the effective age of major mobile equipment components. At present there is a planned preventive removal at 25,000 hours, but perhaps the removal should be earlier due to events during the life of the component such as “fuel”, “glycol” etc. that would impact the useful life of the component. A conference call with Teck and C-MORE has been arranged in early December.

TORONTO TRANSIT COMMISSION

Neil Montgomery had started a project on the optimal frequency and schedule of subway track inspections continued. An analysis of the BD line has been performed. The analysis of two other lines, YUS and SHP, is ongoing. TTC is going to send NDT MOWIS results (non-destructing tests results) for the past three years for analysis and reporting. An important question is whether major repair and maintenance actions performed three years ago on TTC subway lines made positive differences. The main goal of the study is to optimize inspection frequency with respect to expected number of incidents and limited resources.

TORONTO HYDRO

Chi-Guhn Lee and Andrew Jardine visited Toronto Hydro in October to explore options for projects. There was already a plan to expand and generalize previous work on asset hazard function estimation problems.

BARRICK GOLD

Barrick renewed its interest in collaboration with C-MORE. Andrew Jardine presented C-MORE software EXAK and SMS to a distinguished group of Barrick engineers interested in reliability and maintenance. Discussions of possible projects are under way. A WebEx meeting has been planned on a case study: Veladero Pumping System.

C-MORE STAFF AND STUDENTS

C-MORE STUDENTS

Ya-Tang Chuang, PhD Candidate: Ya-Tang continued his PhD research on "Failing to Learn: Information Boost in Maintenance Optimization." He has finished his literature review for the project, and he is now working on developing an approximation algorithm to solve the maintenance problem.

Michael Gimelfarb, PhD Candidate: Michael began the MASc program in September 2015 under supervision of Mike Kim, and recently finished his thesis studies on "Thompson Sampling for the Control of a Queue with Demand Uncertainty." He is now in the PhD program under the co-supervision of Professor Scott Sanner and Chi-Guhn Lee on Bayesian reward shaping for reinforcement learning algorithms, which will be an essential tool for maintenance optimization when the models are unknown.

C-MORE STAFF

Dragan Banjevic, C-MORE Project Director: Dragan is retiring from his position at C-MORE, after 23 years of work, as the first staff member of the lab, called CBM Lab at that time. Dragan's input has been invaluable to all students and postdoctoral fellows associated with the program.

Neil Montgomery, Senior Research Associate: Neil left C-MORE in July 2017 for a leadership role at Canadian Bearings, Toronto. The extent of his contribution to C-MORE over the years cannot possibly be overestimated. I am sorry to lose him but congratulate Canadian Bearings on its acquisition.

Janet Lam: Dr. Janet Lam will begin her role as Associate Director of C-MORE in January 2018. Janet is very familiar with C-MORE; she acquired her doctorate while at C-MORE and then worked as a postdoctoral fellow. I am very happy to welcome her back.

C-MORE EDUCATIONAL PROGRAMS

Andrew Jardine has continued to offer courses in asset management around the world. Since June 2017, he has been involved in the following:

AUGUST 20-24: Five-day course "Certificate in Physical Asset Management," Abu Dhabi, UAE

NOVEMBER 6-15: Eight-day course "Certificate in Physical Asset Management," University of Toronto.

CONCLUSION

I have been most fortunate to join an outstanding team of colleagues, most notably founding director Andrew Jardine, who continues to be very much involved in our work and provides valuable insights and advice, as well as Dragan Banjevic and Elizabeth Thompson. I am particularly excited to collaborate with three affiliated faculty members. I am already co-supervisor of Mike Gimelfarb with Professor Scott Sanner on a machine learning project and anticipate expanding my collaboration to include other affiliated faculty members. I am also looking forward to working closely with all of our collaborating companies in 2018 and learning more about their specific needs so that C-MORE can add value to their organizations. I am confident C-MORE will continue to maintain the support of current industry members through the hard work and dedication of its staff and students.

Chi-Guhn Lee
December 2017

C-MORE LAB ACTIVITIES JUNE 2017 - DECEMBER 2017

VISITS AND INTERACTIONS WITH CONSORTIUM MEMBERS AND OTHERS

JULY 2-6, 2017
Dragan Banjevic attended the 10th International Conference on Mathematical Methods in Reliability (MMR 2017) at Grenoble, France, and presented a joint paper with Janet Lam, "A Non-periodic Inspection Policy with Amortized Preventive Maintenance Costs."

SEPTEMBER 1, 2017
Chi-Guhn Lee, Dragan Banjevic, and two students visited Daniel Letourneau, Professor at the Department of Radiation Oncology, University of Toronto, at UHN (University Health Network) to discuss the project "Capstone on Data Analysis."

SEPTEMBER 18, 2017
Chi-Guhn Lee and Andrew Jardine visited Teck at Sparwood, BC.

SEPTEMBER 20, 2017
Chi-Guhn Lee and Andrew Jardine visited TTC.

OCTOBER 11, 2017
Chi-Guhn Lee and Andrew Jardine visited Toronto Hydro.

OCTOBER 12, 2017
Chi-Guhn Lee and Andrew Jardine visited Barrick Gold.

OCTOBER 22-25, 2017
Michael Kim presented a join paper with PhD student Ya-Tang Chuang at INFORMS Annual Meeting, in Houston, Texas.

NOVEMBER 10, 2017
Dragan Banjevic visited Aleksandar Urosevic and associates from TTC to discuss further steps in TTC Track Inspection Case Study.

NOVEMBER 16, 2017
Chi-Guhn Lee, Andrew Jardine, and Dragan Banjevic visited Barrick Gold at its Toronto office. Andrew gave a presentation on C-MORE software EXAKT and SMS.

NOVEMBER 23, 2017
Chi-Guhn Lee and Andrew Jardine visited Tim Jefferis at DSTL.

DECEMBER 4, 2017
Tim Jefferis (DSTL) visited C-MORE to discuss possible new projects with Dragan.

DECEMBER 4, 2017
Chi-Guhn Lee and Dragan had a conference call with Kevin Hatch from Teck on effective age problem.

C-MORE PUBLICATIONS AND PRESENTATIONS 2017

JOURNAL PAPERS PUBLISHED OR ACCEPTED

[1] Jiang Z., Banjevic D., and Li B. 2017. "Optimizing the re-profiling policy regarding metropolitan train wheels based on a semi-Markov decision process," *Journal of Risk and Reliability* 231: 595-507.

[2] Jiang Z., Banjevic D., and Jardine A.K.S. 2017. "Remaining Useful Life Estimation of Metro Wheel Considering Measurement Error," *Journal of Quality in Maintenance Engineering*, accepted.

[3] Lee M., Kwon, R.H., Lee C.-G., and Anis A. 2017 "Decentralized Strategic Asset Allocation with Global Constraints," *Journal of Asset Management*, online July 1, 2017.

JOURNAL PAPERS SUBMITTED OR UNDER REVIEW

[1] Banjevic D., and Kim M., 2017 "Thompson Sampling for Stochastic Control: The Continuous Parameter Case," under review.

[2] Sahba P., Balcioglu B, and Banjevic D. 2017. "Multilevel Rationing Policy for Spare Parts When Demand is State-Dependent," *OR Spectrum*, under second review.

[3] Chuang Y.-T., and Jong K.M. 2017. "Sequential Bayesian Maintenance Optimization: Failing to Learn via Exploration Boosts," submitted to *Operations Research*.

[4] Wang, J., and Lee, C.-G. 2017. "Bayesian Economic Change Detection with Multiple Change Types," *European Journal of Operational Research*.

[5] Najafi S., Lee C.-G., Najafi-Asadolahi S. and Nahmias S. 2017. "Dynamic Pricing under Consumer's Sequential Search," *Management Science*.

[6] Momodu A., and Lee C.-G. 2017. "Valuation of Israeli Options Using a Projected Successive Over Relaxation Algorithm," *Journal of Derivatives*.

[7] Tat R., Taleizadeh A.A., and Lee C.-G. 2017. "Cooperation on Capacitated Inventory Situations with Permissible Delay in Payments," *International Journal of Production Economics.*

[8] Yeung N., and Lee C.-G. 2017. "An MDP Model for Dynamic ICU Admission and Discharge Control," *Service Science*.

[9] Lee C.-G., Liu L. and Kim J.-S. 2017 "Optimal Distribution of a Perishable Food with Quality Requirements and Delivery Time Windows," *International Journal of Production Economics*

CONFERENCE PAPERS IN PROCEEDINGS

[1] Banjevic D., and Lam S. 2017. “A Non-periodic Inspection Policy with Amortized Preventive Maintenance Costs,” MMR 2017, July 3-6, 2017, Grenoble, France.

CONFERENCE PRESENTATIONS

[1] Chuang Y.-T., and Kim M.J. 2017. “Failing to Learn via Exploration Boosts,” 2017 INFORMS Annual Meeting, October 22-25, Houston, Texas.

C-MORE LEADERSHIP ACTIVITIES

CHI-GUHN LEE, C-MORE DIRECTOR

Chi-Guhn Lee is the Director of the Centre for Maintenance Optimization and Reliability Engineering (C-MORE). He is also a Professor at the Department of Mechanical and Industrial Engineering, at the University of Toronto. He received his Ph.D. in the area of Industrial & Operations Engineering from the University of Michigan, Ann Arbor, and joined the University of Toronto faculty in 2001. Before his Ph.D. studies, he spent over three years at Samsung SDS in Seoul, Korea, leading a project on the re-usable OOP library for fast prototyping of system integration software.

Professor Lee has done both theoretical and applied research in dynamic optimization under uncertainty. His theoretical work involves accelerated value iteration algorithm for Markov decision processes, progressive basis-function approximation for value function space, multi-variate Bayesian control chart optimization, and optimal learning using the Multi-armed Bandit Model. His interest in application is diverse, ranging from supply chain optimization to financial engineering, to dynamic pricing and healthcare optimization. In recent years, he and his team have actively adopted machine learning algorithms into their research portfolio. In particular, he is currently active in reinforcement learning, inverse reinforcement learning, and deep reinforcement learning.

Professor Lee is an associate editor for *Enterprise Information System* and *International Journal of Industrial Engineering* and is a member of several other editorial boards.

ANDREW K.S. JARDINE, PROFESSOR EMERITUS

Andrew Jardine, Principal Investigator, Evidence Based Asset Management, and C-MORE's Founding Director, continues to liaise with Director Chi-Guhn Lee and company representatives. His wide network of contacts, gathered over more than 20 years with C-MORE, remains a valuable asset.

Andrew has also continued his active role in C-MORE educational programs. He co-presented a five day certificate-granting course in Physical Asset Management in Abu Dhabi, UAE, August 20-24, 2017. He also co-presented the extremely popular University of Toronto certificate program in Physical Asset Management, November 6-15, 2017.

DRAGAN BANJEVIC, C-MORE PROJECT DIRECTOR

Dragan continued collaboration with members of C-MORE Lab, in particular with former PDF Janet Lam, currently teaching inspection intervals at a US university. He recently took on a main role in collaboration with companies with the departure of Neil Montgomery. He has continued collaboration with Mike Kim on Thompson sampling and decisions under uncertainty.

SHARAREH TAGHIPOUR, RYERSON, EXTERNAL COLLABORATOR

Professor Taghipour is an Associate Professor at the Department of Mechanical and Industrial Engineering, Ryerson University. Before her appointment at Ryerson, she worked as a postdoctoral fellow for about a year at C-MORE. She obtained her PhD in Industrial Engineering from the University of Toronto; before that, she received her BSc in Mathematics and Computer Science and her MASc in Industrial Engineering from Sharif University of Technology, Iran. Her research interests include reliability engineering, inspection and maintenance optimization, stochastic operations research, statistical analysis, and novel applications of maintenance optimization models, such as optimization of cancer screening. She holds a status-only Associate Professor appointment in the Department of Mechanical and Industrial Engineering, University of Toronto, and has collaborated with C-MORE on a number of projects. Professor Taghipour has well-established partnerships and research collaborations with various industry partners from healthcare to energy, mining, transportation, utilities, and manufacturing including the Toronto General Hospital, Admira Distributed Hybrid Energy Systems Inc., Vale Canada Ltd. CHEP Canada, Fiix, Alstom France, Nova Chemicals, Manitoba Hydro, and ArcelorMittal Dofasco.

SCOTT SANNER, UNIVERSITY OF TORONTO

Scott Sanner is an Assistant Professor in the Department of Mechanical & Industrial Engineering. Previously Scott was an Assistant Professor at Oregon State University and before that he was a Principal Researcher at National ICT Australia (NICTA) and Adjunct Faculty at the Australian National University. Scott earned a PhD in Computer Science from the University of Toronto (2008), an MS in Computer Science from Stanford University (2002), and a double BS in Computer Science and Electrical and Computer Engineering from Carnegie Mellon University (1999). Scott's research spans a broad range of topics from the data-driven fields of Machine Learning and Information Retrieval to the decision-driven fields of Artificial Intelligence and Operations Research. Scott has applied the analytic and algorithmic tools from these fields to diverse application areas such as recommender systems, interactive text visualization, and Smart Cities applications including transport optimization. Scott has served as Program Co-chair for the 26th International Conference on Automated Planning and Scheduling (ICAPS), member of the Editorial Board for the Artificial Intelligence Journal (AIJ) and the Machine Learning Journal (MLJ), and Electronic Editor for the Journal of Artificial Intelligence Research (JAIR). Scott was a co-recipient of the 2014 AIJ Prominent Paper Award.

FAE AZHARI, UNIVERSITY OF TORONTO

Fae Azhari is an Assistant Professor in the Department of Mechanical and Industrial Engineering, University of Toronto. She received her BSc and MASc degrees in Civil engineering from Isfahan University of Technology and the University of British Columbia, respectively. After working in the industry for a few years, she returned to school and completed her MEng degree in Industrial Engineering and Operations Research at the University of California, Berkeley, and her PhD in Structural Engineering and Mechanics at the University of California, Davis. Professor Azhari is interested in structural health monitoring (SHM) and prognosis of engineering systems. Her main areas of research are twofold: (I) sensor development and assessing the performance of novel sensing devices, and (II) developing decision-making frameworks that use probabilistic models to translate collected data into meaningful information and efficient remedial strategies for various infrastructure systems.

MIE490 - CAPSTONE DESIGN PROJECT WITH PRINCESS MARGARET HOSPITAL

The CAPSTONE design project with Princess Margaret Hospital (PMH) has been initialized in September 2017, with Prof. Chi-Guhn Lee as a supervisor and Prof. Daniel Letourneau, also from U of T, as a representative of PMH. The U of T students team includes Tonglin Jin, Yuheng Lin, Xuehan Wang, and Yuze Li.

Project Description

Radiation therapy uses high energy ionizing radiation (photon and electron beams) to treat patients with cancer. The goal of radiation therapy is to deliver a high dose of radiation to the tumor to eradicate it or control its growth while limiting the delivered dose to surrounding organs that might be sensitive to radiation dose. Medical linear accelerators are the treatment units used to delivery radiation therapy treatments. They are complex equipment that can deliver lethal dose of radiation to the patients if they are miss-calibrated. Performances of medical linear accelerators are assessed using a quality control (QC) program with daily, weekly, monthly and annual tests. Linear accelerators are computer-controlled devices and record machine parameters and machine states during operation. The objective of this project is to use QC test results and machine-recorded parameters to:

1- Help diagnostic the cause (which subsystem) of a change in machine performance and advice on the appropriate service intervention.
2- Predict timing for servicing intervention of the linear accelerator.

The Project Executive Summary is included in this report.

In addition to the Capstone project, another team of two students, Mozam S. Shahin and Daniel M. Duklas are conducting statistical analysis of PMH data as a part of their graduation thesis, in coordination and predating Capstone team. An abbreviated report of their work is included in this Report.

C-MORE EDUCATIONAL PROGRAMS

Andrew Jardine has continued to offer courses in asset management around the world. Since June 2017, he has been involved in the following:

AUGUST 20-24, 2017
Five-day course, “Certificate in Physical Asset Management,” Abu Dhabi, UAE.

NOVEMBER 6-15, 2017
Eight-day course, “Certificate in Physical Asset Management,” University of Toronto.

C-MORE GRADUATE STUDENTS

Mike Gimelfarb successfully defended his MASc in summer 2017 on "Thompson Sampling for the Control of a Queue with Demand Uncertainty." He is now in the PhD program under the co-supervision of Professor Scott Sanner and Chi-Guhn Lee on Bayesian reward shaping for reinforcement learning algorithms, an essential tool for maintenance optimization when the models are unknown; expected completion date 2022. He will be presenting his work at the Progress Meeting.

Ya-Tang Chuang is continuing his PhD research on "Failing to Learn: Information Boost in Maintenance Optimization." He has finished his literature review for the project, and he is now working on developing an approximation algorithm to solve the maintenance problem; expected completion date December 2018. Ya-Tang will make a presentation on his work at the Progress Meeting.

C-MORE NEWS

Dragan Banjevic, C-MORE Project Director: Dragan is retiring from his position at C-MORE, after 23 years of work, as the first staff member of the lab, called CBM Lab at that time. The Lab was established by Professor Andrew Jardine and inaugurated in December of 1994, with the support of six industrial partners. Dragan's input has been invaluable to all students and postdoctoral fellows associated with the program.

Neil Montgomery, Senior Research Associate: Left C-MORE in July 2017 for a leadership role at Canadian Bearings, Toronto. The extent of his contribution to C-MORE over the years cannot possibly be overestimated. We were sorry to lose him but congratulate Canadian Bearings on its acquisition.

OVERALL PROJECT DIRECTION

DRAGAN BANJEVIC, C-MORE PROJECT DIRECTOR

GOALS AND RETROSPECTIVES

This report gives an overview of the activities in C-MORE for the period June 2017 - December 2017. C-MORE director Mike Kim left University of Toronto in June for the University of British Columbia. Fortunately, Professor Ghi-Guhn Lee from MIE accepted the position of Director and is working hard to rejuvenate C-MORE, with help from Founding Director Andrew Jardine. The consortium members have expressed interest and support for continuation, so the transition has gone quite well. Neil Montgomery also left C-MORE in June, creating some delays in our activities, but collaboration with the consortium members has continued on the current projects, and we have discussed ideas for new ones. Research activity has continued with our two graduate students. More students will find their place at C-MORE, depending on budgetary opportunities.

ACTIVITIES

THEORETICAL WORK

This section on theoretical work is oriented towards students' and postdoctoral fellows' research topics and topics of interest for further development.

NAME	ACTIVITY
Ya-Tang Chuang, PhD Candidate	Ya-Tang continued his PhD research on Bayesian Dynamic Programming Approach to Preventive Maintenance Optimization: "Failing to (be able to) Learn: Information Boost in Maintenance Optimization." He is now working on developing the stochastic model. A more detailed review of his work is included in the report.
Michael Gimelfarb, PhD Candidate	Michael Gimelfarb successfully defended his Master's thesis and began his doctorate under the co-supervision of Professor Scott Sanner and Chi-Guhn Lee on Bayesian reward shaping for reinforcement learning algorithms, which will be an essential tool for maintenance optimization when the models are unknown. A more detailed review of his work is included in the report.

INDUSTRY COLLABORATIONS

This section gives details on progress in research conducted with consortium members.

NAME	ACTIVITY
MOD (UK)	A new project on dangerous flying incidents in Squirrel helicopters fleet has been started. Tim Jefferis sent historical data for 2011-2017 for preliminary analysis. Dragan has worked on a plausible mathematical model for testing incidence occurrences. The results will be presented at the meeting. Tim also sent data on Squirrel flying hours in November, for further analysis and comparison.
Teck	Justin Cvetko Lueger proposed a survey of online condition sensor technology. Teck will incorporate this technology to trigger certain engine maintenance interventions. The main contact will be Graeme Dillon, the author of Teck engine asset health reports. Jeff Sutherland sent a sample of Teck Greenhills oil transformer data for preliminary analysis to investigate a feasibility of a possible project. Dragan is working on the both projects. More details are included in the report.
Toronto Hydro	Chi-Guhn Lee and Andrew Jardine visited Toronto Hydro in October to explore options for projects.
TTC	Collaboration continued on the project on the optimal frequency and schedule of subway track inspections. An analysis of the BD line has been performed. The analysis of two other lines is ongoing. TTC is going to send NDT MOWIS results (non-destructing tests results) for the past three years for analysis and reporting.
Barrick	Andrew Jardine gave a presentation to Barrick engineers on EXAK and SMS. Barrick expressed keen interest in using C EXAK for condition-based maintenance, and SMS for slow-moving spares. Discussion on a possible project is under way.

LAB GOALS FOR WINTER 2018

The theoretical research and collaborations with companies will continue, depending on C-MORE staff availability. The software development options will be explored, for example, developing a prototype incidents process control chart, as initiated by MOD UK. This chart will be useful to other companies in similar settings.

C-MORE ACTIVITIES WITH COLLABORATING COMPANIES: AN OVERVIEW

DRAGAN BANJEVIC, C-MORE

Since June 2017, C-MORE has continued working on research and meeting with collaborating companies. C-MORE is currently involved in the following projects with industry partners:

- **MOD UK**: A new project on flying incidents in Squirrel helicopters fleet has been started after discussions at the June meeting. Tim Jefferis sent historical data for 2011-2017 for preliminary analysis. Dragan has worked on a plausible mathematical model for testing incidence occurrences. The key problem was uncertainty in collecting flying hours (FH) and possible under reporting of dangerous incidents. The current results will be presented on the meeting. Tim was able to find data on FH in November, which will be useful for validation of underlying assumptions and further analysis and comparison.

- **Teck**: Justin Cvetko Lueger proposed a survey of online condition sensor technology. Teck is interested in incorporation of this technology to improve certain engine maintenance interventions. Graeme Dillon, who is the author of Teck engine asset health reports, will be the main contact with C-MORE for this project. The initial findings will be presented.

  Jeff Sutherland sent a sample of Teck Greenhills oil transformer data for preliminary analysis to investigate a feasibility of a possible project with C-MORE. Preliminary findings are included in the report.

  Kevin Hatch is seeking feedback on his approach to the effective age of major mobile equipment components. At present there is a planned preventive removal at 25,000 hours. But perhaps the removal should be earlier due to events during the life of the component such as “fuel”, “glycol” etc. that would impact the useful life of the component. A conference call with Teck and C-MORE has been arranged in early December.

- **TTC:** Neil Montgomery had started the project on the optimal frequency and schedule of subway track inspections continued. An analysis of BD line has been performed. The analysis of two other lines, YUS and SHP, is ongoing. TTC is going to send NDT MOWIS results (non-destructing tests results) for the past three years to perform the analysis and reporting. An important question for the analysis is whether major repair and maintenance actions performed three years ago on TTC subway lines made positive differences. The main goal of the study is to optimize inspection frequency with respect to expected number of incidents and limited resources.

- **Toronto Hydro**: Chi-Guhn Lee and Andrew Jardine visited Toronto Hydro in October to explore options for projects. There was already a plan to expand and generalize previous work on asset hazard function estimation problems.

- **Barrick Gold**: Barrick renewed its interest in collaboration with C-MORE. Andrew Jardine presented C-MORE software EXAK and SMS to a distinguished group of Barrick engineers interested in reliability and maintenance. Discussions of possible projects are under way. A WebEx meeting has been planned on a case study: Veladero Pumping System.

TECHNICAL REPORTS: CONSORTIUM

DEVELOPING A NEW PROJECT WITH MOD, UK: A HISTORY

DRAGAN BANJEVIC, C-MORE,
TIM JEFFERIS, DSTL/MOD

Note: This piece of work is an overview of a process of initiating a project of interest to a supporting C-MORE partner, discussion about feasibility, data available and data required, underlining theoretical model, appropriate assumptions, questions and feedbacks. Details on the approach, data analysis, and solution are also included in this report. The original messages are slightly edited to remove unrelated material, and to fix typos, etc.

START

August 29, 2017, from Tim

Hi Dragan,

As we previously discussed with Neil I have a problem relating to management of serious safety incidents, which crop up in the general run of incident reporting.
We have a process for reporting incidents, hazards, observations (etc) relating to our aircraft operations. This generates a significant number of reports (about 250 per annum for the fleet we are interested in).

Each of these reports has to be individually examined, investigated, managed (etc) which takes considerable effort. There is also a requirement to detect and investigate any underlying common causes. This is not easy to do, as it isn't always clear when a cluster of incidents is just 'stuff that happens' and when a cluster is significant and so should be examined in more depth.

The initial data that I have contain all of the relevant reports for the Squirrel helicopter fleet and I have marked up those with risk of a mid-air collision (An AirProx), as we are pretty clear that we can identify everything that falls into this category with minimal uncertainty.

From the data, can we tell when a cluster of Airproxes is just a random cluster and when the cluster is of an unexpected size and so should be investigated to see if there is an underlying cause?

When we chatted with Neil about this he suggested that it might be possible to build some form of process control chart.

Please let me know what you think,

Regards, Tim

August 31, 2017, from Dragan

Hi Tim:

Thank you for sending the data and describing the problem. I just have moved from my house (we sold it, we downsized) to a condo, so it took me a couple of days to find time to think more about the problem.

Neil is right, we can do some analysis and, likely, create a tool for controlling stream of incidents/events. In essence, we assume that we have a Poisson Process (PP) of events in time with some intensity (estimated from the data) and then check the process to see whether we have deviation from PP. PP is a model for purely random occurrence of events in time, but can sometimes behave very strange, with clusters and gaps, which is often confused with irregularities (a plain example is sudden surge of car incidents, or crimes/murders, making panic in news). In your case, if I understand it properly, we have to consider # of events in cumulative flying time, or an appropriate similar operating time, not just calendar time.

This information is not provided in your data. Is this information available, i.e., operating time of the copter at the moment of an event? In this moment, don't send me anything, just tell me if it is available. I have looked at the data briefly and I will prepare soon a more detailed report and comments/questions to start discussion. For example, we may need to classify events and consider them separately, but we will see it. We did some similar work in the past, and even developed a "theory" for some kind of control chart, but I have to find it in our reports.

Regards, Dragan

WARMING UP

September 1, 2017, from Tim

Hi Dragan,

The cumulative flying time should be available, but isn't easy to access (otherwise I would have also sent it to you).

I have some comparable data where I do have the fleet flying hours and the total number of events. My assumption was that there will be less variation in the total events per 1000 FH, as there are many events, than in the safety related events, which are infrequent. We could certainly examine the variation in total number of events vs flying hours for this other data.

I had wondered whether we could use the total number of events in a period as a surrogate for the total activity level, and then use this to drive the PP which predicts the number of safety related events. [Dragan's italics]

Classifying the different events can be done, but is tricky as some of it is a matter of opinion. I have sent you all the AirProxes as these are all explicitly identified and also all of the events raised.

Let me know what you think, Tim

September 12, 2017, from Dragan

Hi Tim,

I did some (theoretical) work on your problem in relationship with missing operating time. Your idea how to approach it when you don't have (use) operating time is quite interesting and exciting.

Here is a short description: You have two Poisson processes, one you consider "stable" and which does not have changing characteristics (event/failure rate) over time, and the other you are interested in and suspect of having a changing event rate (say, sudden increase) (even more general/flexible interpretation can be given). If we count time in the number of occurrences of the of the first type of events, then the distribution of the number of the second events occurring in that time follows "negative" binomial distribution (NBD), with certain parameters, if all is OK. Deviations from NBD (described, e.g., with some confidence limits - in form of a chart) will warn us of changes in rate of the second process. I will provide a formal mathematical description for it.

I will try to do some calculation from the data. Give me a couple of days to ask you for more (complete?) data and other possible information. As I told you above, I found this as an excellent application of a probabilistic problem, I never thought about before (missing operating time).

Regards, Dragan

SOME PRELIMINARY DATA INALYSIS

September 21, 2017, from Dragan

Hi Tim,

Please give explanations to my questions and guesses. I was able to look for all of these airport bases, squadrons, history, etc., on internet to understand "RecordID" (so much for secrecy).

List of aircrafts records (ReportID).

Middle Wallop\670 Sqn\Squirrel: 11, 12, 13, 14, 15, 16, 17 (469)
Middle Wallop\7 Regt\Squirrel: 15, 16 (4)
Middle Wallop\Middle Wallop - FBH\Squirrel: 13, 17 (3)
Shawbury - RAF\60(R) Sqn\Squirrel: 13 (1)
Shawbury - RAF\660 Sqn AAC\Squirrel: 11, 12, 13, 14, 15, 16, 17 (390)

Shawbury - RAF\705 NAS\Squirrel: 11, 12, 13, 14, 15, 16, 17 (416)
Shawbury - RAF\CFS(H)\Squirrel: 11, 12, 13, 14, 15, 16, 17 (269)
Shawbury - RAF\Stn - RAF Shawbury\Squirrel: 12, 13, 14, 15, 16, 17 (29)
Total: 1581 records

Please explain the recordID format. Are all these different aircrafts for different bases, or 11, …, 17, are the only aircrafts? E.g., “11” records belong to the same aircraft, or it belongs to different aircrafts for different bases/squadrons? Why field “C”? Just copy of “Airprox?”?

In “incident type” we have records “Accident” (1), “Hazard/Observation” (363), “Hostile Action/Loss” (2), “Incident” (1214), and “e” (1), see the record “asor\Shawbury - RAF\660 Sqn AAC\Squirrel\12\13474, 20/04/2012”, likely a typo.

Last field is “Mk.” What is it? Records are “BLANK” (1) (missing?), “HT1” (992), “HT2” (586), “HT3” (2).

You said that incidents “with risk of a mid-air collision (An AirProx)” are of our interest. Do they involve two aircrafts? I see only one reported (if I understand the RecordID properly).

In brief, you are interested in occurrence of near mid-air collisions with respect to all (?) other events? Shall we exclude/ignore some of them, or look at all of them? We also may look at the whole fleet (of interest) and individual aircrafts.

These are my first observations, but, for now, I want to understand the data properly.

Regards, Dragan

FEDBACK

October 23, 2017, from Tim

Hi Dragan,

I have finally got around to looking at this, sorry about the delay…

I do have some observations:

Background

This data set is all about incidents. These can range from observations about the correct paperwork to authorise the flight not being in place through to accidents that result in the loss of an aircraft. There are three main categories of incident, Engineering, Administrative and Operational, each of which can have a huge range of causes. There is nothing to initially indicate that any particular category or cause dominates the others. I therefore expect that all of these competing factors would tend to produce a pretty good approximation to a Poisson Process, or something similar that has a constant expectation of x incidents per fleet flying hour.

When one pulls out one specific category and a particular cause within that, then I expect that more variation might be evident. It is known (for example) that Air Proxes will tend to occur more when particular parts of the flying training curriculum are being under taken and that there may be other, external causes that will also cause an increase in the rate.

As far as I can tell this blurb is probably the same as what you wrote, but I just like to add the ‘real-life’ context, to check that we are situating the mathematical analysis in the right context.

Statement of the Problem

The case of $X_t = 0$ is of interest. If we get suspiciously few occurrences reported, then this is also valuable. There is no direct way of measuring the actual number of occurrences; we can only see those that the Aircrew enter into the system. If some units underreport (say Airproxes) then we don’t get the full picture and hence cannot manage things appropriately.

Application

I envisage that this would be easiest to implement in a per calendar time form. Thus the safety manager would look at the number of Air Proxes every 3 months (say) and see whether the number that had occurred looked unusual. They would then check how many total events had occurred, just to check that there was no change in the overall rate that would significantly adjust the number of Air Proxes that they would expect to see. If the analysis indicated that some unexpected level of events had been observed, then they would dig in further.

Does this help?

Many thanks, Tim

Oct 23, 2017, from Dragan

Hi Tim,

Yes, it helps. So, in essence, for now, we can just look at all copters as a single group, and look at all incidents without classification, which would make simple calculation. Even non-reporting may be considered as a part of the problem, if it is kind of random, not systematic. If the number of Air Proxes increases, it is up to your people to analyze the cause. We can make a chart that makes, e.g., a 5% upper bound of Air Proxes in comparison with other incidents (5% probability to exceed the bound) which you can use at any moment of time, e.g., every 3 months. But, it can be constructed so that, whenever you look, you will get the answer. It means, you may look for the first period of 3 months, then 4 months, then 2 months, then 5 months, and so on. You also may look retroactively for one year results, to avoid problem of larger than expected number of Air Proxes over longer periods, which might not be seen in smaller periods separately.

I will work on it and will estimate frequency of incidents from the data, and send an example of it. Once we agree on technology, we may consider writing a small prototype program for it. I think I can make a simple function in Excel for calculation, that will be easy to use, for start.

The methodology can be applied also to any categorization and to selected types of incidents, which we may consider in the future.

Please send me your comments.

Regards, Dragan

MORE DATA, ANOTHER APPROACH POSSIBLE

November 11, 2017, from Tim

Hi Dragan,

I am waiting for the flying hour data on the Squirrel Fleet. I have contacted my customer and he has requested the data from the people who manage that.

I have an alternative source that I will also try, but I won't be able to do that until next week (i.e. about the 20th November).

I will let you know how this goes. *Also, will you be around on the Monday before the C-MORE meeting? I have a question about estimating MVBF and how rapidly our estimate would converge.* [Dragan: a new project option?]

Many thanks, Tim

November 12, 2017, from Dragan

Hi Tim,

Flying hours will help in the analysis, obviously, if you can trust them. So, we may have a direct approach to our problem, in addition to one I already have developed using your idea to use incidents of one type as a time variable. ... I will be glad to help with any question.

Regards, Dragan

November 22, 2017, from Tim

Hi Dragan,

Here are the monthly Squirrel fleet FH back to April 2012.

I hope that this will allow you to do the analysis to see how well the Total DASORs raised represent a homogeneous Poisson process.

Regards, Tim

A PROJECT PROGRESS REPORT

November 24, 2017, from Dragan

Hi Tim,

I finished the report on Squirell incidents data, with analysis, and I think it works well. I did not have time yet to analyze hourly data you sent me, but I will do it soon, just after the meeting (or maybe even before, if I find time). I am very busy with the December Meeting report, but luckily Elizabeth is here to help. My report on incidence data is attached*. I am looking forward for your comments.

Regards, Dragan

*Report included in this Meeting Report

APPENDIX

The list of all previous collaborations/projects with Tim since MOD joined the Consortium in 2003, as they appear in C-MORE Meeting reports, going backward.

1. December 2016: Neil Montgomery (NM) and Tim working on exploratory data analysis related to two vehicle fleets, Foxhound (since July 2016), and BATUS (before and after July 2016). Data sources are maintenance actions, failure reports, onboard sensor data, engine oil analysis data.
2. May 2016: UK MOD Clothing order data exploratory analysis. The question to be answered through this data analysis is: *are there patterns in clothing orders that can be used to assist in future clothing supply decisions?* Our answer is that it is unlikely that there are identifiable patterns in clothing delivery quantities that would assist in supply decisions. It appears that order patterns are a combination of random fluctuation punctuated by non-random operational decisions.
3. Dec 14-June 15: Warrior vehicle dataset. Warrior Vehicle Longitudinal Data Quality Assessment.
4. May 2013: NM completed the draft final report for the Gearbox CBM project
5. Dec 2012: Tentative collaboration related to evaluating the design and maintenance of capital equipment through real options related to the comparison of the Unmanned Combat Air System and Joint Strike Fighters.
6. June 2012: NM continued to compile data for the project health prediction modelling study, which is ongoing.
7. NM carefully reviewed the data on the gearbox CBM case study in light of his conclusion that there was no useful model to be gained. Tim provided additional data for the project health prediction modeling study, which is ongoing.

8. June 2011: NM completed a report on the gearbox CBM case study. Tim and Neil decided on the format of the data to be used for predicting the health of a long term project and have begun building histories.
9. Dec 2010: NM continued work on the gearbox CBM case study. Tim and Neil decided on the format of the data to be used for predicting the health of a long term project.
10. June 2010: NM continued work on the gearbox CBM case study, and began consideration of the problem of predicting the probability that a long term project will be cancelled. Waiting on comments to Nima's report on aircraft maintenance scheduling. Maliheh started incorporating reliability perspective into the aircraft maintenance scheduling.
11. Dec 2009: NM presented results on the spre parts problem for new fleet deployments. Working on gearbox CBM case study. Nima Safaei completing work on workforce-constrained maintenance scheduling for aircraft fleet.
12. June 2009: NM worked on the spare parts problem for new fleet deployments posted by Tim. Neil processed a large number of new histories for the gearbox CBM case study.
13. Oct 2008: NM and Tim wrote a paper that Neil presented at ICOMS 2008 in Perth, Australia in May, entitled "The Effect of Minor Maintenance on Condition-Based Maintenance Models. James Bell worked with Tim to compile more histories for the gearbox CBM project.
14. April 2008: James Bell is working with Tim at UK MOD to compile more histories for the gearbox dataset, which will be used for validation and further modeling. Neil is preparing a brief research note on the use of oil change and additional data in CBM models motivated by this case study. Dragan continues his work with Tim on utilization and interpretation of SOAP data from diesel engines. Some new challenges appeared, particularly related to on-board and off-board.
15. Oct 2007: The work on diesel engines (Dragan and Tim) is nearing conclusion. Tim continues to work on updating the gearbox dataset. NM has carefully examined the date for possible problems and has altered the layout of the data to incorporate oil additions into the model. Neil also assisted MEng student, now new PhD student Lorna Wong (starting January 2008). Lorna, Neil, and Tim are preparing a paper about her analysis of the armoured fighting vehicles dataset that comprised a substantial part of her MEng thesis. Neil, Tim, and Tim Dowd presented a paper for the MIMAR conference in September 2007 concerning repair histories of various classes of aircraft.
16. June 2007: The work on diesel engines is nearing conclusion. Tim has written the core of a publication that Dragan and Neil will complete for submission as a research publication. Tim has also worked on updating the gearbox dataset and provided a new diesel engine dataset.
17. Dec 2006: Tim works with Dragan on CBM for diesel engines on ships. Updating gearbox dataset.
18. June 2006: Working on diesel engines dataset. New project on helicopter gearboxes.
19. Dec 2005: Diesel engines dataset.
20. June 2005: Diesel engines dataset updates.
21. Dec 2004: Diesel engines dataset and modeling.
22. June 2004: Diesel engines dataset project started in September 2003. More data received. Dragan the main collaborator from C-MORE.
23. Dec 2003: Initial DE oil analysis date set on ships received in July.
24. June 2003: MOD joined in January 2003.

MOD PROJECT: TESTING THE FREQUENCY OF AN EVENT WITH RESPECT TO ANOTHER EVENT

DRAGAN BANJEVIC, C-MORE

BACKGROUND

Two (of more) types of events (accidents) are recorded in flying time of aircrafts (Squirrel helicopters). For the first type of events (type 1), we may expect relatively steady and random appearance in flying time, but for the second type (type 2) we may suspect some non-random variations, clustering, external causes, etc. Under "normal" conditions, type 2 events should also appear with random fluctuations, so we are interested in checking possible deviations from random appearance, preferably in a form of a process control chart. The data for actual testing were provided by Tim Jefferis from DSTL/MOD UK in August 2017.

STATEMENT OF THE PROBLEM AND METHODOLOGY

To solve the problem first theoretically, and then apply it to actual data, we will introduce certain assumptions. The key assumption is that events of both types occur at random in cumulative flying time *t* (that may deviate substantially from calendar time), and they occur independently. A common reasonable assumption for this situation is that these processes are homogeneous Poisson processes (HPP) with appropriate occurrence rates.

Let the number of events of type 1 in time *t* is X_t, with occurrence rate λ and of type 2, Y_t, with occurrence rate μ. If time *t* is available we can just check every, say, 100 hours whether Y_t, the number of events of type 2 in 100 hours is compatible with the assumed Poisson process with rate μ, or not. The actual methodology of testing will be discussed later. But, as emphasized by Tim, the operating time *t* is hard to obtain, or could be unreliable, so we cannot check Y_t directly. Tim's idea was to use (more common) events of type 1 *as a time variable*, that is, to compare occurrence of type 2 events with occurrence of type 1 events. In mathematical terms, it means if it is known at a certain moment in calendar time that $X_t = k$, what is the distribution of Y_t, or probability of $Y_t = i$, for *i*=0, 1, 2, …, *but without knowledge of t.*

Let us state the question in terms of probability. Let

$$T(k) = \min\{t : X_t = k\}, k \geq 1,$$

be the moment when type 1 event occurred *k*-th time, in operating time *t*. Then we are interested in finding distribution of $Z_k = Y_{T(k)}$, or of Y_t at the moment $t = T(k)$,

$$P(Z_k = i) = P(Y_{T(k)} = i), \ i = 0,1,2,...$$

The case $X_t = 0$ should be discussed separately (but it may not be interesting in practice). Also, it should be noticed that Z_k is considered in moments when type 1 events occurred, not in between, but if the occurrence rate of type 2 events is small in comparison with type 1 events ($\mu \prec\prec \lambda$), this problem can be ignored. Otherwise, it would require separate discussion.

DISTRIBUTION OF $Z_k = Y_{T(k)}$

By the above definition, $T(k), k \geq 1$, is the moment in (operating) time when the k-th type 1 event occurred. It is a continuous distribution of Erlang type (as a sum of interoccurnce times of type 1 events; interoccurence times follow exponential distribution, as equivalent to the assumption of HPP), with pdf (probability density function)

$$f_{T(k)}(s) = f_k(s) = \frac{(\lambda s)^{k-1} \lambda e^{-\lambda s}}{(k-1)!}, \ t > 0 .$$

As time *t* is unknown, we have to "integrate it out", that is, to apply the formula of total probability for continuous random variables. Then the following formula can be obtained (see Appendix).

If we denote by $p = \frac{\lambda}{\lambda+\mu}$ - the probability that, if an event occurred, it is of type 1, $q = 1 - p = \frac{\mu}{\lambda+\mu}$, probability it is of type 2, then in short,

$$P(Z_k = i) = \binom{i+k-1}{k-1} q^i p^k = \binom{i+k-1}{i} q^i p^k, i = 0,1,2, \ldots,$$

which is a *Negative Binomial* distribution type with parameters *k* and *p* (NB(*k*,*p*)). For example,

$$E(Z_k) = k\frac{q}{p} = k\frac{\mu}{\lambda},$$

which is intuitively appealing. Another important property of NB(*k*,*p*) is that when k is large and $\frac{\mu}{\lambda}$ is small such that $\theta = k\frac{\mu}{\lambda}$ is not very small or large (e.g., $1 \leq \theta \leq 8$), then NB(*k*,*p*) can be approximated by the Poisson distribution $P(\theta)$, or

$$P(Z_k = i) \approx \frac{\theta^i}{i!} e^{-\theta}, i = 0,1,2, .. ,$$

which can simplify calculation. In our application we can expect exactly this situation: rate of occurrence of type 2 events, μ, is much smaller than of type1, and we can choose *k* large enough to apply the approximation. Note that θ depends on k.

ESTIMATION OF PARAMETERS

To apply the above results, we need to estimate parameter p and/or θ. Let in the observation period type 1 event occurred n_1 times, and type 2 event n_2 times. It is obvious (we will not give formal arguments) that estimates are

$$\hat{p} = \frac{n_1}{n_1+n_2}, \hat{q} = \frac{n_2}{n_1+n_2}, \hat{\theta} = k\frac{n_2}{n_1},$$

where k is selected large enough so that $\hat{\theta} = k\frac{n_2}{n_1}$ represents the expected number of type 2 events in a convenient calendar time units, under "stable" conditions.

Example: The Squirrel data report 1581 incidents of both types, with 33 incidents of type 2, and 1548 incident of type 1, in calendar time span from 18/07/2011 to 31/07/2017, almost exactly 6 years. The average number of the incidents of type 2 per year is 33/6 = 5.5, a number good for Poisson approximation. If we take it as $\hat{\theta} = 5.5$, then we can use equation $\hat{\theta} = 5.5 = k\frac{33}{1548}$, or $k = 5.5\frac{1548}{33} = 258$. So, we may observe the number of type 2 events on every 258 events of type 1. We may adjust these numbers to more convenient, longer or shorter intervals. If we like to check type 2 events, e.g., roughly every 6 months, we may expect 2.8 events of type 2 on 130 events of type 1. This logic allows us to use two methods:

A: Fix (e.g.) k =130, and then on every 130 events of type 1 check the number of type 2 events. If all is "normal", we expect to get about 2.8 events of type 2.

B: Fix (e.g.) 6 months of calendar time. Check the number of type 1 events, which is *k* (say, k=115 in a given 6 months period). Calculate the expected number of type 2 events (under "normal" conditions) (here it is $115 \times \frac{33}{1548} = 2.45$) and compare it with the observed number of type 2 events.

Formal comparison is done by a suitable statistical method, using the derived Poisson distribution, or exact NBD; we will give details below.

Method **B** might be more convenient for practical purposes (fixed calendar time), but it assumes no big variation in cumulative flying times per time periods, and number of type 1 events. But, if in an interval of 6 months the number of type 1 events is small (as well as type 2 events) we may wait for another 6 month period, or 130 incidents of type 1, whichever comes first. Other variations of the method are possible, such as applying more accurate (no approximation) NB distribution regardless of the *k* value.

The theory can be also applied in the opposite way.

C: As the number of type 2 events is expected to be much smaller than of type 1, we may wait until (e.g.) 5 of them (type 2) occur, and then check the number of type 1 events. If the number of type 1 events is significantly smaller than expected, it indicates an "alarming" increase in the rate of events of type 2.

Fine-tuning of this method is possible, by checking type 2 events, e.g., every 3 months, 6 months, and in one year intervals, per single interval and cumulatively. This method would help to avoid being alarmed by random fluctuations that might look suspicious on short time span, but are actually OK on a longer time span.

TESTING METHODOLOGY

Consider primarily methodology B for testing, and using of NBD. At the given checking date, e.g., every 3 months (Tim's suggestion), the number of events of type 1, *k*, and type 2, *i*, is observed. Then the probability of exceeding the observed value *i* is calculated, given the observed value *k*, or

$$\boldsymbol{P(Z_k \geq i) = \sum_{j \geq i} \binom{j+k-1}{j} q^j p^k \, , i = 0, 1, 2,} \ldots$$

If the probability $\boldsymbol{P(Z_k \geq i)}$ is smaller than a selected critical value, e.g., 0.05, we raise the red flag and investigate type 2 incidents for possible unusual behaviour. This method is usually called, one-sided upper limit test. As Tim noticed, a small value of *i* could be also suspicious, e.g., due to unreporting, i.e., we can also use one-sided lower limit test, by calculating

$$\boldsymbol{P(Z_k \leq i) = \sum_{0 \leq j \leq i} \binom{j+k-1}{j} q^j p^k \, , i = 0, 1, 2,} \ldots$$

and comparing it with the critical value. We also can use a double-sided test, by checking whether $(\boldsymbol{Z_k \leq i}) \leq 0.025$, or $\boldsymbol{P(Z_k \geq i)} \leq 0.025$, for example.

The probabilities $\boldsymbol{P(Z_k \leq i)}$ can be easily calculated, as well as $(\boldsymbol{Z_k \geq i) = 1 - P(Z_k \leq i - 1})$; see Appendix.

APPLYING THE TESTING METHODOLOGY TO THE SQUIRREL DATA SET

From Squirrel data, we can calculate $= \frac{1548}{1581} = 0.979127$, $q = 1 - \boldsymbol{p} = \frac{33}{1581} = 0.020873$. Starting with the first record in the data, on 18/07/2011, and using checking points at every three months interval (approximately), in January, April, July, and October every year, and ending on 31/07/2017, the following results are obtained (see Table 1 on the next page).

The table shows the counts of events T1 and T2 in columns 2 and 3, and the appropriate probabilities of occurrence of T2 events, given the observed T1 events. The first column shows **Prob(count(T2)=0|count(T1))**, the second **Prob(count(T2)>=1|count(T1))**, and so on. E.g., between 01/10/2012 and 07/01/2013, 28 T1 and 3 T2 events were found in the records, with **Prob(count(T2)>=3|count(T1)=28)=0.0246**, which may raise a flag. The appropriate probabilities for every checking point are highlighted. If we look at all checking point, only the one on 03/10/11 comes close to small probability, less than 10%, except the first one mentioned. If we look at the "grand" scale, for all checking points, even the first one on 07/01/2013 may just show random fluctuations, because in 25 checking point, we should expect some of them to be suspicious (the expected number of “red flag” cases, if we use 0.05 critical limit is 1.5). Overall, in this data set we cannot find anything overly irregular.

Check date	Count T1 (k)	Count T2 (i)	Prob(=0)	Prob(>=1)	Prob(>=2)	Prob(>=3)	Prob(>=4)
03/10/2011	44	3	0.395294	0.604706	0.241666	0.071168	0.0166
04/01/2012	33	1	0.498528	0.501472	0.158083	0.036236	0.006564
05/04/2012	47	1	0.371054	0.628946	0.264933	0.082581	0.020413
02/07/2012	51	1	0.341031	0.658969	0.295937	0.098921	0.026271
01/10/2012	71	1	0.223653	0.776347	0.444899	0.195841	0.069343
07/01/2013	28	3	0.55398	0.44602	0.122251	0.02426	0.003807
03/04/2013	42	0	0.412327	0.587673	0.226203	0.063987	0.014327
02/07/2013	63	1	0.264766	0.735234	0.387069	0.154518	0.049349
01/10/2013	70	2	0.228421	0.771579	0.437833	0.190532	0.066646
07/01/2014	97	2	0.129238	0.870762	0.609097	0.341474	0.157134
01/04/2014	86	1	0.16299	0.83701	0.544432	0.27878	0.116129
02/07/2014	58	2	0.294216	0.705784	0.349597	0.130276	0.038718
01/10/2014	62	0	0.27041	0.72959	0.379647	0.149561	0.047107
05/01/2015	54	0	0.320118	0.679882	0.319065	0.111955	0.031259
01/04/2015	52	0	0.333912	0.666088	0.303663	0.103194	0.027876
02/07/2015	52	3	0.333912	0.666088	0.303663	0.103194	0.027876
06/10/2015	86	1	0.16299	0.83701	0.544432	0.27878	0.116129
07/01/2016	75	2	0.205557	0.794443	0.472652	0.217417	0.080678
01/04/2016	77	1	0.197065	0.802935	0.48621	0.228382	0.086667
01/07/2016	85	1	0.166465	0.833535	0.538194	0.273116	0.112661
03/10/2016	94	2	0.137681	0.862319	0.592182	0.324352	0.145459
04/01/2017	67	0	0.243343	0.756657	0.416346	0.174835	0.058892
03/04/2017	65	2	0.253829	0.746171	0.401793	0.164583	0.054006
03/07/2017	53	2	0.326943	0.673057	0.311373	0.10754	0.029539
31/07/2017	36	1	0.467958	0.532042	0.180407	0.044624	0.008724
Total	1548	33					

Table 1: Application of testing methodology to Squirrel data set

A method to present the data and the analysis in a process control chart format can be conveniently designed. We are looking forward to describe it.

RECENT DEVELOPMENT

Tim recently sent Squirrel Flying hours data, April 2012-October 2017; these data can be used for testing HPP assumptions for the processes of interest. They can be used for the process control chart, as well. An analysis of the data will be performed in the near future.

APPENDIX

Derivation of the probability distribution:

$$P(Z_k = i) = \int_0^\infty P\big(Y_{T(k)} = i | T(k) = s\big) f_k(s) ds = \int_0^\infty P(Y_s = i) f_k(s) ds$$

$$= \int_0^\infty \frac{(\mu s)^i}{i!} e^{-\mu s} \frac{(\lambda s)^{k-1} \lambda e^{-\lambda s}}{(k-1)!} ds = \frac{\mu^i}{i!} \frac{\lambda^k}{(k-1)!} \int_0^\infty s^{i+k-1} e^{-(\lambda+\mu)s} ds$$

$$= \frac{\mu^i}{i!} \frac{\lambda^k}{(k-1)!} \frac{\Gamma(i+k)}{(\lambda+\mu)^{i+k}} = \frac{\mu^i}{i!} \frac{\lambda^k}{(k-1)!} \frac{(i+k-1)!}{(\lambda+\mu)^{i+k}} = \binom{i+k-1}{k-1} \left(\frac{\mu}{\lambda+\mu}\right)^i \left(\frac{\lambda}{\lambda+\mu}\right)^k.$$

Calculation of $\boldsymbol{P(Z_k \leq i)}$ can be easily done (and also of $\boldsymbol{(Z_k \geq i) = 1 - P(Z_k \leq i-1)}$) by noticing that $\boldsymbol{p_k(j) = \binom{j+k-1}{j} q^j p^k = \frac{j+k-1}{j} q p_k(j-1)}$ **,** and $\boldsymbol{p_k(0) = p^k}$. Then $\boldsymbol{(Z_k \leq i) = \sum_{j=0}^{i} p_k(j)}$ **.**

TECK GREENHILLS OIL TRANSFORMER DATA PRELIMINARY ANALYSIS

DRAGAN BANJEVIC, C-MORE

BACKGROUND

Jeff Sutherland sent a sample of Teck Greenhills oil transformer data for preliminary analysis to investigate a feasibility of a possible project with C-MORE. Preliminary findings are included in the report.

The idea for the project was initiated after a visit to Teck at Sparwood, BC, by Chi-Guhn Lee and Andrew Jardine to explore whether “we have any mutual interests in the area of data analytics and machine learning as applied to maintenance practices.” The visit on September 18 was hosted by Mark Bernadet. After the visit, Chi-Guhn Lee sent a working paper on machine learning which could be applied in condition based maintenance of transformers. Jeff Sutherland has been assigned to the project, and he gave this feed-back:

> I had a quick read through the paper – if I’m reading it right, the data used was just the total dissolved gas from the 10 early failure transformers, and this was from hand samples taken every 6 months? Is this correct? Typically we take dissolved gas samples once a year on our transformers, except occasionally where a problem sample is found and the frequency may be increased. Would this once a year sampling period be enough to give decent feedback from your model?

Chi-Guhn responded: “Yes, you understand the sampling done from the state grid. I believe the same approach can be used when the sampling is done less frequently such as yearly.” On October 12 ,Jeff sent CM data on transformers to C-MORE, with a comment, “Here’s a sample of data, from one of our mines. It’s got the yearly transformer oil testing results since 2009. There’s quite a few transformers, but only 6 or 7 samples per unit. Have a look and let me know if it’s something you can use.”

Dragan glanced at the data; this was his first impression:

> … it appeared what I was suspecting. These are oil/gas CM data, and they don't include any lifetime information, such as manufacturing time, installation time, maintenance, failures, etc. … From my experience with transformers, the analysis may not be a simple task, due to, mostly, missing information. At least, some recommendation on data quality, data collection and usage can be produced. Also the data span is short for transformers (which are long lasting assets, in decades), only from 2009 to 2016.

On November 6, Dragan produced a more detailed report, given on the next page.

INITIAL COMMENTS ON TECK GREENHILLS OIL DATA

The data include records of DGA/oil analysis from 45 (power?) transformers from various Teck stations collected from 2009 to 2016, 305 records in total. The data show DGA analysis for several gases, oil properties, and some derived variables (such as total DG, ratios co2/co, o2/n2, etc), and comments (dga remarks, and oil quality remarks) important for interpretation of results. The initial goal for this analysis is to explore methodologies researched and developed in scientific community, and in particular at the University of Toronto, for data analysis, predictions and maintenance decisions of Teck transformers. These methodologies may include

A: Machine learning, and
B: Proportional hazards modeling (PHM).

We have the following comments and questions on the data:

1. There are 45 transformers (identified by equipnum/serialnum), classified as transformers (TRN), except one case classified as LTC (MAINTXLTC). Is it a transformer with LTC (load tap changer)? Does it mean the other transformers are not LTC (NLTC)? Does it make any difference for the analysis?
2. Are the listed TRNs just a sample of all TRNs, or all TRN of interest for analysis? It should be understood that we would analyze only the TRNS (e.g., power transformers) form the same class, at least for now.
3. The measurements are collected in yearly intervals, by default, and when recommended for additional analysis. The number of records for a single TRN varies between 1 and 9, typically 7-8. Are these records all available records for listed TRNs, or just a sample? For some TRNs, the records start in 2009, and for some only in 2015. Some TRNs don't have records for every year after the initial one. Measurements haven't been taken on those years? Why?
4. Do the previous measurements exist? Either, the oil and gas analysis program was not used at earlier times, or those TRNs in the sample had been installed at time prior to the recorded measurements?
5. In the case of the analysis, a detailed discussion about reported variables, their meaning, interpretation and importance will be substantial. In this moment, we will not discuss it in details.
6. The measurements results are used to evaluate TRNs health state, either from the DGA, or oil conditions, mainly in "dga_remarks", and "fq_remarks" from the Lab (is it a contracted sampling and analysis, or a Teck lab?). These remarks may be used to validate both the Lab's interpretation/diagnostic/prognostic methodology with one we will try to apply. What methodology/rules/manuals are used by the Lab for interpretation of measurements? Are they available? Do you have any comment on validity of these recommendations?

The following comments and questions are essential for our approach to the analysis.

1. The key object of the analysis of the state/health of a TRN is its history, which should include its type (model, etc., from nameplate) manufacturing date, its installation date, all

inspection records (in form of DGA/oil measurements, and other observations, with their dates), and all maintenance information since installation, such as minor/mayor repairs, preventive or reactive component replacements, oil replacements (or a policy of oil top ups), and failures with failure modes. Also, we need to know when the DGA/oil analysis was started for every TRN in the data set.

2. A complete data set would include all existing TRNs (currently in operations) and all that had been used in the past, but failed, and had not been repaired (being scrapped) and are not now in the inventory. Ignoring these TRNs would make the analysis biased, if the number of these cases is not insignificant.
3. For our analysis, diagnosis, and predictions of TRN's state, we want to correlate measurements with events histories. Please explain what events/maintenance information is available for the analysis.

We hope these comments/questions will help you to improve mutual understanding of the further steps we need to take in this project. This collaboration also can help you in data collection and interpretation methodology and to us in our collaborative research with industry.

Please provide your answers/comments either in another document, or, preferably, embedded in this document.

Thank you,

C-MORE

TECK: A REVIEW OF ONLINE CONDITION SENSOR TECHNOLOGIES

DRAGAN BANJEVIC, C-MORE

BACKGROUND

Chi-Guhn Lee and Andrew Jardine visited Teck in their offices at Sparwood, BC on September 17. Justin Cvetko Lueger proposed a survey of online condition sensor technology, among other projects of interest to Teck. Teck is interested in incorporation of the technology to improve engine maintenance interventions. Graeme Dillon, the author of Teck engine asset health reports, will assist C-MORE in surveying the relevant technology.

INITIAL STEPS

After a request from C-MORE to describe in some detail the goals of the survey, Justin sent the following list of initial questions:

In terms of surveying this technology, these are our starting questions that we'd like your help answering:

- What is the state of this technology?
- What can these sensors do, and what can't they do? Are some sensors better than others?
- Who are the current providers of these sensors? Any alliances with lubricant providers or engine OEM's?
- Who has tested/trialed them? If production systems are available, who is using them? Any users in mining?
- What types of assets have used these sensors? Transport trucks, generating sets, shipping/merchant fleets? Any high-horse-power truck engines?

As a warm-up for the survey, Dragan sent Teck a review article on Condition Monitoring (CM) written for *Encyclopedia for Quantitative Risk Analysis* (Wiley, 2008), by Dragan and Andrew Jardine (included as an appendix in this report). Online CM techniques are in wide use, particularly because of the fast development of IT technology, in both the hardware and software areas, and their decreasing costs. Some of the above questions are relatively easy to answer, and some are not, especially the effectiveness of the technology. The scholarly journals are often out-of-date, with more on the results of actual applications, and less on theory. There are hundreds (even thousands!) of articles published on manufacturers' web-sites, in professional magazines, and as part of consultants recommendations. They are mostly written in a "grandiose" style, with big words, but have very little useful information for the survey we are interested in. There are many manufacturers of CM technology competing on an expanding market, and marketing their equipment, so it is not easy to make real comparisons of their products.

In this report we will give some initial findings, as a base for more detailed results. As the information for this survey is mostly found by searching the Internet, more time is needed to answer all Teck's questions. Luckily, as the mining industry uses big and expensive equipment such as large mining trucks, the information on using online CM in mining can be found without much trouble. Whether it is true is a different matter.

INTRODUCTION TO CONDITION MONITORING

The following is a short introduction to CM methodology, following the above mentioned article by Dragan and Andrew (full citation appears at the end of this section of the Report).

Condition monitoring (CM) is a set of various techniques and procedures that people use in industry to measure the indicators/parameters of the state/health of equipment, or to observe conditions under which the equipment is operating. The user's main interest is in equipment's proper functioning (i.e., to operate as designed). CM is mainly applied for early detection of signs of malfunctioning and faults, and then for faults diagnosis and timely corrective or predictive maintenance. CM is also applied for operation/process control (e.g., to signal a jam on an assembly line and/or to stop the process), or safety control (checking machine's safety door closure), with a primary goal to prevent or reduce consequences of failures.

Two common examples of CM are vibration analysis of rotating machines (e.g., centrifugal pumps, or electrical motors) and oil analysis of combustion engines (analysis of metal particles and contaminants in the lubrication oil), transmissions and hydraulic systems. The whole combination of CM data acquisition, processing, interpretation, fault detection and maintenance strategy is often called **CM system/program** (alternatively, **Condition-based Maintenance** (CBM)). An ideal situation would be to monitor conditions of all elements/parts of the machine, or, at least ones most likely to develop significant problems.

Complete monitoring is usually not possible technically, or is expensive, and thus is important to (a) select parts/elements of the system to monitor, (b) select a method of monitoring. Common criteria for selection are based on experience and past information about failure modes and their frequencies, consequences of failures, such as downtime and cost, lost production, low quality of products, and so on, and availability of appropriate techniques.

CM is either an "off-line" procedure, when measurements/samples are taken and analyzed at predetermined moments of time (or when convenient), or an "online" procedure, when measurements are taken (and often analyzed) continuously or at short intervals by sensors permanently mounted on the equipment [*as of interest to Teck*]. CM is often a combination of off-line and online procedures. A typical example of an off-line procedure is oil analysis and an online procedure is vibration analysis. Vibration monitoring is still commonly used as an "off-line" technique, if the equipment deteriorates gradually. Now, with advanced technology, oil analysis can in some cases be applied online (e.g., using wear debris light detectors).

QUICK ANSWERS TO TECK QUESTIONS

Question: *What is the state of this technology?*
Answer:

Instruments and software. Instruments/sensors for CM data collection/acquisition could be portable or mounted. Some instruments originated a long time ago, such as temperature sensors, stroboscope (1830s) and piezoelectric accelerometer (1920s). Some are more recent, such as fiber-optic laser-diode-based displacement sensors (late 1970s), laser counters combined with image analysis technology, or on-line transducers for wear particle analysis (1991). A lot of new instruments now in use have implemented software for data processing, analysis, display, or wireless storage into a database.

The most common CM techniques/methods are vibration analysis, tribology (oil/debris analysis), visual inspections, current monitoring, conductivity testing, performance (process parameters) monitoring, thermal monitoring, corrosion monitoring, acoustic (sound/noise) monitoring.

The methods of data/equipment condition assessment can be simple, such as measurement value checking, trending against time, or comparison with templates. They can be more advanced, such as mathematical models of deterioration and risk of failure, and artificial intelligence (AI) methods, such as neural networks, machine learning systems, and expert systems.

Question: *What can these sensors do, and what can't they do? Are some sensors better than others?*
Answer:

Monitored parameters/features can be direct, such as thickness (e.g., for brakes), amount of wear, corrosion, or cracks; or indirect, such as pressure, temperature, efficiency, vibration, infrared and ultrasound images; or others, such as operating age. The parameters could be also operational (pressure, temperature, flow rate etc.), or diagnostic (vibration, amount and/or shape of metal particles in oil, water content in oil). Note that parameters/features are aggregated CM indicators calculated from collected raw CM data. The sensors either indicate external working environment conditions that are outside of specified limits, or internal indicators of the equipment health that might show deterioration or sudden problems. They use condition assessments (see above) to trigger alarms, suggest timely maintenance, or predict incipient failures. Their predictions depend on the methods of data interpretation, and cannot be 100% accurate. The sensors are as good as is the correlation between monitored parameters and system conditions. For example, vibration monitoring (and sensors) are typically more reliable for assessing state and problems of rotating equipment that the oil analysis for engines.

Question: *Who are the current providers of these sensors? Any alliances with lubricant providers or engine OEM's?*
Answer:

There are many. Some of them are (not in any specific order) Scanimetrics, PRUFTECHNIK, Honeywell, Matrikon, Wenco**,** General Electric, National Instruments, Crystal Instruments, PARKER, DMT-group, VALMET, Siemens, Schenck Process, Dresser Rand, TUCK, and PerkinElmer (see more below).

As for OEM alliances, they are likely, but we have to search it.

Question: *Who has tested/trialed them? If production systems are available, who is using them? Any users in mining?*
Answer:
Mining is a big user of these systems (see examples below).

Question: *What types of assets have used these sensors? Transport trucks, generating sets, shipping/merchant fleets? Any high-horse-power truck engines?*
Answer:
In mining high-horse-power truck engines are ones of regular users, with oil and vibration analysis. Oil analysis for engines and wheel motors. *See the abstract of a paper on wheel motor application from C-MORE at the end of this review*.

INDUSTRIAL WEBSITE: A USEFUL EXAMPLE

The website **Direct Industry**, styled as **The Online Industrial Exhibition**, provides useful information on condition monitoring systems (http://www.directindustry.com/industrial-manufacturer/condition-monitoring-system-80028.html). It lists type, applications, other characteristics, and manufacturer search categories. This is the list, as it appears on the website.

Type

- condition (81)
  - condition for machines (26)
  - condition with diagnostics (8)
- vibrating (4)
- pressure (3)
- temperature (3)
- flow (2)
- position (1)
- level (1)
- current (1)
- concentration (1)
- climatic (1)
- humidity (1)

Applications

- for machines (27)
- measurement (13)
- for wind turbines (5)
- process (4)
- turbine (4)
- for pumps (4)
- alarm (4)
- device (4)
- chemical (3)
- air (3)
- construction (3)
- for water (2)
- environmental (2)
- for electrical cabinets (2)
- for temperature sensors (2)
- server (2)
- for bearings (2)
- gas (1)

- charging station (1)
- movement (1)
- for indoor air quality (1)
- for panels (1)
- for compressors (1)
- for medical applications (1)
- for combustion chambers (1)
- for PV installations (1)
- battery (1)
- vehicle (1)
- water (1)
- brake (1)
- for solar power plants (1)
- for chain (1)
- for clean rooms (1)
- secured area (1)
- industrial (16)
- control system (2)
- GPRS (2)
- RS485 (2)
- automatic (1)
- cloud-based hazard (1)
- digital I/O (1)
- analog I/O (1)
- with visualization system (1)
- robust (1)
- tire pressure (1)
- ultrasound (1)
- with PCT touch screen (1)
- infrared (1)
- RS232 (1)
- multi-channel (1)
- not specified (40)

Other characteristics

- continuous (14)
- portable (13)
- wireless (8)
- online (8)
- real-time (6)
- data acquisition (5)
- modular (4)
- remote (4)
- mobile (3)
- measuring system (3)
- Ethernet (2)
- multi-point (2)
- digital (2)

Manufacturers

- 4B Braime Components (1)
- ACOEM (1)
- BossPac Engineering and Technology (2)
- Brüel & Kjær Vibro (1)
- CEC Vibration Products (1)
- Condition Monitoring and Protection (9)
- CSI Technologies (1)
- Dresser-Rand (2)
- Electro-Sensors (2)
- Flowserve SIHI Pumps (1)
- GERSTEL (1)
- GRUNDFOS (1)

- Hangzhou Zetian Technology CO., Ltd (1)
- Hauni (2)
- ifm electronic (1)
- InfraTec GmbH Infrarotsensorik und Messtechnik (1)
- iwis antriebssysteme GmbH & Co. KG (1)
- KittiwakeHolroyd (1)
- mageba (1)
- MANVIA (1)
- MC-monitoring (1)
- montronix (1)
- NRG Systems (1)
- Opto 22 (3)
- OTT-JAKOB Spanntechnik GmbH (1)
- OutBack Power Systems (1)
- PCE Instruments (1)
- PerkinElmer (1)
- Pintsch Bubenzer (1)
- Power Electronics (1)
- PRÜFTECHNIK Condition Monitoring GmbH (8)
- RENISHAW (2)
- RONDS (2)
- ROTRONIC AG (1)
- Schaeffler Technologies AG & Co. KG (3)
- Schenck Process (1)
- SDT International (1)
- SKF Condition Monitoring - Fort Collins (7)
- SPM Instrument (4)
- SPP (1)
- The IMC Group Ltd (1)
- Trimble Navigation - Construction Division (1)
- Trutzschler (1)
- UE SYSTEMS (1)
- UWT GmbH Level Control (1)
- Webtec (1)
- YSI Life Science (1)

REFERENCE

Jardine, A K S; Banjevic, D; Wiseman, M; Buck, S; Joseph, T. 2001. “Optimizing a mine haul truck wheel motors' condition monitoring program: Use of proportional hazards modeling,” *Journal of Quality in Maintenance Engineering,* Vol. 7(4): 286-302.

ABSTRACT

Discusses work completed at Cardinal River Coals in Canada to improve the existing oil analysis condition monitoring program being undertaken for wheel motors. Oil analysis results from a fleet of 55 haul truck wheel motors were analyzed along with their respective failures and repairs over a nine-year period. Detailed data cleaning procedures were applied to prepare data for modeling. In addition, definitions of failure and suspension were clarified depending on equipment condition at replacement. Using the proportional hazards model approach, the key condition variables relating to failures were found from among the 19 elements monitored, plus sediment and viscosity. Those key variables were then incorporated into a decision model that provided an unambiguous and optimal recommendation on whether to continue operating a wheel motor or to remove it for overhaul on the basis of data obtained from an oil sample. Wheel motor failure implied extensive planetary gear or sun gear damage necessitating the replacement of one or more major internal components in a general overhaul. The decision model, when triggered by incoming data, provided both a recommendation based on an optimal decision policy as well as an estimate of the unit's remaining useful life. By optimizing the times of repair as a function both of age and condition data a 20-30 percent potential savings in overhaul costs over existing practice was identified.

TTC TRACK INSPECTION CASE STUDY: AN APPROACH TO INSPECTION SCHEDULE OPTIMIZATION

DRAGAN BANJEVIC, C-MORE

BACKGROUND

Early in 2017, TTC initiated the Track Inspection Case Study of its subway system. A large amount of historical data was sent to C-MORE. Neil Montgomery reported initial findings on the Bloor-Danforth (BD) line at the June meeting, 2017. In this report, we consider an approach to optimizing inspection schedule under limited TTC resources, and depending on results of faults frequency analysis.

PROBLEM STATEMENT (as reported at June meeting)

The TTC performs visual inspections to monitor rail health of its subway system. The entire system is covered every 7 days. Additionally, non-destructive testing (NDT) is performed system-wise with a much smaller team. The entire system is covered every year. Incipient faults are re-inspected by the NDT team, and it is difficult for them to keep up with demand for inspections. Total rail failures (cracked) that actually occur in practice tend to arise between annual inspections, while the re-inspected incipient faults tend not to progress.

We have been asked to determine if the inspection schedule(s) can be modified to prioritize areas of track by history, track type, or track geometry, while maintaining or improving reliability. The key constraint is that the optimal solution should be found under the constraint of limited total time of man working hours for NDT team. That is, the time of inspecting different sections of the system should be redistributed without the total increased.

INITIAL ASSUMPTIONS

We will propose a basic methodology of optimizing inspection schedule based on certain simple assumptions about the subway railway system and its faults. The approach can be expanded and improved if more elements of the systems state and operation are considered. A practical solution can be obtained after completion of statistical analysis, with appropriate defects frequencies calculated.

1. The entire subway rail system (SRS) is divided into non-overlapping segments (e.g., between subway stations).
2. For every segment, its length is known (in fixed units).
3. When inspected, the whole segment is inspected in one visit (e.g., not just a part of the segment).
4. Frequency of defects per year (defect rate) is known for every segment. In more advanced study, different types of defects and their rates may be considered. Here we look at all defects (of interest) as one category, for simplicity, e.g., in all HP (high priority) defects.

5. Defect rate is assumed constant, for a given section, under given conditions (such as track type, track geometry, usage and age), and may change when conditions changed (e.g., age).
6. "Cost" of visiting a segment is proportional to its length, and is given in men hours. Or, inspecting one unit of length costs a fixed amount of men hours, regardless of the segment (this assumption can be easily generalized).
7. Total amount of men hours available for all inspection over one year is fixed. Or, the total "cost" of inspecting SRS in men hours over one year is fixed.

FURTHER ASSUMPTIONS AND OPTIMIZATION CRITERIA

Here we will consider more technical assumptions and introduce some notation to be able to formulate and solve problem mathematically. We need to assume that SRS is in some kind of steady state (see A 5. above), and that inspections don't affect the rate, unless the conditions are changed (e.g., a significant part of the truck has been replaced).

1. Defects come randomly in time and cannot be predicted (at least, cracks, see the problem statement above, or their first occurrence; this assumption can be better formulated).
2. Inspection frequency does not affect defect rate, but decreases time between onset of the defect and its discovery (meaning, accuracy and validity of this condition can be discussed). We call this time the "unsupervised defect time", or dormant time (DT).
3. The current inspection schedule of inspecting entire SRS once a year makes 6 months of DT for every defect, on average (1/2 of inspection time unit). If a section of SRS is inspected *k* times a year, DT for its defects is 1/(2*k*) of one year, on average. E.g., if a segment is inspected 2 times in one year, DT of every defect will be 3 months, on average.
4. Let the total length of SRS (subject to inspections) is *L*, and the total "cost" in men hours is *C* (see A 7. Above), then the cost of inspecting one unit of segment length is *a* = *C*/*L* (see A 6. above).
5. SRS has *N* segments, with lengths L_i and defects rates $\lambda_i \ , i=1,2,...,N$. Then $\sum_{i=1}^{N} L_i = L$.

   Here the defect rate is defined as #defects/length unit/year. We could equally look at "unstandardized" rate = #defects/year = $\lambda_i L_i$, but this is not convenient for comparison of different segments.
6. With one inspection of the system once a year, the total DT (unsupervised defect time!) is $\frac{1}{2}\sum_{i=1}^{N}\lambda_i L_i$ (the total number of defects of the system x 0.5years). $\lambda_i L_i$ is, clearly, the number of defects for segment *i* (see B 3. above).
7. Assume now that we inspect different segments with, possibly, different frequencies. Let the segment *i* be inspected $k_i, k_i > 0,$ times a year, $i=1,2,...,N$. If $k_i > 1$, the segment is inspected more than once a year, e.g., twice if $k_i = 2$. If $k_i < 1$, the segment is inspected lest than once a year; e.g., for $k_i = 0.5$, the segment is inspected *once in two years*. For $k_i = 0.666.. = 2/3$, the segment is inspected 2 times in 3 years, or on every 18 months.

8. From 7. and 4., the "cost" of inspecting segment I in one year will be $k_i L_i a$, or of inspecting the entire SRS, will be $\sum_{i=1}^{N} k_i L_i a = \sum_{i=1}^{N} k_i L_i \frac{C}{L}$, with a constraint $\sum_{i=1}^{N} k_i L_i \frac{C}{L} \le C$, or just $\sum_{i=1}^{N} k_i L_i \le L$,. If we use all available man hour resources, we have the constraint on inspection frequencies $\sum_{i=1}^{N} k_i L_i = L$. The fact that the constraint does not depend on actual C, is the consequence of the assumption on equal unit costs, A 6. , and B 4. This assumption can be easily replaced by one with variable section inspection costs.
9. The key amount for our inspection optimization is the total DT time for the system, for given schedule of inspection frequencies, $k_1, k_2, ..., k_N$, which is

$$DT_{SYS} = \sum_{i=1}^{N} \frac{\lambda_i L_i}{2k_i} = \frac{1}{2} \sum_{i=1}^{N} \frac{\lambda_i L_i}{k_i} ,$$

following 3 above. Our goal is to find $\min_{k_1,...,k_N} DT_{SYS}$, under the constraint $\sum_{i=1}^{N} k_i L_i = L$, and optimal schedule $k_1^*, k_2^* ..., k_N^*$.

OPTIMIZING INSPECTION SCHEDULE

Using the objective function of total dormant time, or total unsupervised defect time, DT_{SYS}, described in B 9 above, we get the (surprising?) result:

1. The optimal inspection frequencies k_i^* for different segments are proportional to the square roots of defect rates λ_i, or

$$k_i^* = L \frac{\sqrt{\lambda_i}}{\sum_{i=1}^{N} \sqrt{\lambda_i} L_i} = \frac{\sqrt{\lambda_i}}{\sum_{i=1}^{N} \sqrt{\lambda_i} W_i}, i = 1,2,...N \ .$$

The minimal total dormant time is (from B9.)

$$DT_{SRS}^* = \frac{1}{2} \sum_{i=1}^{N} \frac{\lambda_i L_i}{k_i^*} = \frac{1}{2L} \left(\sum_{i=1}^{N} \sqrt{\lambda_i} L_i \right)^2 = \frac{L}{2} \left(\sum_{i=1}^{N} \sqrt{\lambda_i} W_i \right)^2 ,$$

where $W_i = \frac{L_i}{L}$ is the "relative" size of segment *i*, and $\sum_{i=1}^{N} W_i = 1$. The result can be easily obtained using optimization under constraints for multidimensional functions (see Appendix). The "proportionality" of k_i^* means simply that $k_i^* / k_j^* = \sqrt{\lambda_i} / \sqrt{\lambda_j} = \sqrt{\lambda_i / \lambda_j}$.

2. It may appear surprising at first glance that the optimal scheduling does not depend on the total men hours, but it is misleading, because we have assumed that this total is just enough for one inspection per year per length unit (see B 4., and B 8.). If we assume the cost of inspecting one unit of length is fixed to *a*, and the total man hours'

budget for one year is *C*, then the total length of lines that can be inspected in one year is *C*/*a*. Then the optimal inspection schedule will still be calculated as proportional to the square root of defect rate, but with a different constant of proportionality

$$k_i^* = \frac{C}{a} \times \frac{\sqrt{\lambda_i}}{\sum_{i=1}^{N} \sqrt{\lambda_i} L_i} = \frac{C}{aL} \times \frac{\sqrt{\lambda_i}}{\sum_{i=1}^{N} \sqrt{\lambda_i} W_i}, i = 1,2,...N .$$

The minimal total dormant time is then

$$DT_{SRS}^* = \frac{a}{2C}\left(\sum_{i=1}^{N} \sqrt{\lambda_i} L_i\right)^2 = \frac{aL^2}{2C}\left(\sum_{i=1}^{N} \sqrt{\lambda_i} W_i\right)^2 .$$

3. For the “uniform” inspection schedule, $k_i = k = \frac{C}{aL}$, and the total DT is

$$DT_{SYS} = \frac{1}{2k}\sum_{i=1}^{N} \lambda_i L_i = \frac{aL}{2C}\sum_{i=1}^{N} \lambda_i L_i = \frac{aL^2}{2C}\sum_{i=1}^{N} \lambda_i W_i .$$

   The ratio $DT_{SRS}^* / DT_{SYS} = \left(\sum_{i=1}^{N} \sqrt{\lambda_i} W_i\right)^2 / \sum_{i=1}^{N} \lambda_i W_i$ is smaller than 1 (except if all λ_i are equal; this is a well-known fact in probability theory), as it should be. It is important to notice that the ratio (the “saving”) depends only on defect rates and segments relative “weights” in the system, but not on inspection costs.

NUMERICAL EXAMPLE

To make the solution of the optimal scheduling easier to understand, we provide a simple numerical example, not an analysis of a real line. Let we have *N* = 3 segments in our SRS, with lengths $L_1 = 5, L_2 = 8$, and $L_3 = 12$ (e.g., in kilometers), with total length *L* = 25. Let the defects rates are $\lambda_1 = 4, \lambda_2 = 2$, and $\lambda_3 = 1.5$, per year, per kilometer. Let the cost of inspecting one kilometer of line is 2 men hours (you may put your more realistic value), and let the total budget for inspections is 75 men hours a year. It clearly means that the line can be inspected more than once a year, because 75/(2x25) = 1.5. What is the optimal schedule per segment? From C 2.,

$$k_i^* = \frac{75}{2} \times \frac{\sqrt{\lambda_i}}{\sqrt{4} \times 5 + \sqrt{2} \times 8 + \sqrt{1.5} \times 12} = 1.04136\sqrt{\lambda_i}, i = 1,2,3,$$

or $k_1^* = 1.04136\sqrt{4} = 2.083, k_2^* = 1.04136\sqrt{2} = 1.473, k_3^* = 1.04136\sqrt{1.5} = 1.275$.

In plain language, it means inspecting segment 1 in every 365/2.083 = 175 days, segment 2 in every 365/1.473 = 248 days, and segment 3 in 365/1.275 = 286 days. If we inspect all segments equally, 1.5 times a year, as the budget allows (every inspection of the whole line costs 2x25 = 50 men hours), the inspection frequency would be 365/1.5 = 243 days. Look now on the effect of these two schedules on total dormant time:

“Uniform” inspection schedule: $DT_{SYS} = \frac{1}{2\times 1.5}(4\times 5 + 2\times 8 + 1.5\times 12) = 18$ years,

Optimal inspection schedule: $DT^*_{SRS} = \frac{2}{2\times 75}\left(\sqrt{4}\times 5 + \sqrt{2}\times 8 + \sqrt{1.5}\times 12\right)^2 = 17.29$,

Saving in DT time: $1 - DT^*_{SRS} / DT_{SYS} = 1 - 17.29/18 = 1 - 0.9606 = 0.0394$.

The saving does not look great, only about 4% of DT, due to not very big differences between segments, e.g., in total numbers of yearly defects, 20, 16, and 18, for segment 1, 2, and 3, respectively. But even this saving may be important, if a defect, if unsupervised, may develop into a catastrophic event. It all depends on the risk associated with unsupervised defects. This example and the result show that an analysis of usefulness of the optimal scheduling over the logistically simpler “uniform” scheduling is of interest. We leave it for the next step in this project.

CONCLUSION

An optimal inspection schedule of a subway railway system can be devised depending on clearly defined objective function and observed defects rates. In this study we have used the system total dormant (“unsupervised”) defect time as an optimization criterion. Using the total DT may be justified by reducing time in which unsupervised defects may develop into catastrophic ones, if not detected early enough. For this criterion, it appeared that an optimal inspection schedule characterized by the inspection frequency of different sections of the line is proportional to the square roots of the segments defects rates (per segment length per year).

APPENDIX

Mathematical derivation of the optimal inspection schedule, case C 2. This can be easily done using “Lagrangian multipliers” for constrained optimization of multidimensional functions. In our case, we want to minimize the function $DT_{SYS} = G(k_1, k_2, ..., k_N) = \sum_{i=1}^{N} \frac{\lambda_i L_i}{2k_i} = \frac{1}{2}\sum_{i=1}^{N} \frac{\lambda_i L_i}{k_i}$, with a constraint $\sum_{i=1}^{N} k_i L_i a = C$, or $\sum_{i=1}^{N} k_i L_i = C/a = C'$, where also $k_1, k_2, ..., k_N > 0$. With one constraint (one equation), we introduce one dummy variable α, and then minimize the extended function $F(k_1, k_2, ..., k_N, \alpha) = \frac{1}{2}\sum_{i=1}^{N} \frac{\lambda_i L_i}{k_i} + \alpha(\sum_{i=1}^{N} k_i L_i - C')$, without constraints. Using partial derivatives $\frac{\partial}{\partial k_i} F(k_1, k_2, ..., k_N, \alpha) = \frac{1}{2}\left(-\frac{\lambda_i L_i}{k_i^2} + \alpha L_i\right) = 0$, we come to the solutions $k_i^* = \frac{\sqrt{\lambda_i}}{\sqrt{\alpha}}, i = 1, 2, ... N$, depending on dummy variable $\sqrt{\alpha}$. After replacing k_i^* into the equation $\sum_{i=1}^{N} k_i^* L_i = C'$, we get $\sqrt{\alpha} = \frac{1}{C'}\sum_{i=1}^{N} \sqrt{\lambda_i} L_i$, hence the final solution for k_i^*. An argument The minimal cost is easily obtained by replacing k_i^* into function $G(k_1, k_2, ..., k_N)$.

TECHNICAL REPORTS: PRINCESS MARGARET HOSPITAL

MIE 490 CAPSTONE DESIGN: PROJECT REQUIREMENTS & PROJECT MANAGEMENT PLAN (PR/PMP)

TONGLIN JIN, YUHENG LIN, XUEHAN WANG, YUZE LI,
CHI-GUHN LEE

Note: An abbreviated version of the Project Report from October 20 is presented here.

EXECUTIVE SUMMARY

Treatment for cancer plays a vital role in modern world because of the increasing number of cancer patients. Radiation therapy is one of the most useful cancer treatments. To ensure the safety of the patients, the maintenance of the gun machine using for the radiation therapy is extremely important. However, the current procedure of the maintenance in PMH is considered inefficient and has discrepancies. Therefore, the need is to improve the current procedure, thereby increasing its efficiency.

The team decided to focus on two types of the designs, virtual design and physical design. The function of both designs is to correlate data thereby improving the current system. To achieve the primary function, the design should be able to collect monitoring data from the gun units and store the data, etc.

For the purpose of differentiating and choosing the best alternative designs, the team also set several objectives for the design. For instance, the design should be cost efficient and should provide the maintenance estimations at least seven days prior to servicing intervention with accuracy. For the physical design, the size of the design product should be small and the weight of the product should be light.

There are also constraints that are needed to be addressed. For the virtual design alternative, one of the constraints is that the design must be compatible with the current platforms for the LINAC system as required by the client. Moreover, the design must not require any prior knowledge of any programming. Finally, the design must indicate all the gun units which caused the change in operational performance. For the physical design alternative, first, the design must endure radiation exposure up to 25 MeV. Second, the design must use in-room power supply. Third, the design must provide an external interface.

There are numerous users and stakeholders associated with the project. The Equipment Maintenance team, as the primary user, is mainly responsible for monitoring and maintenance. The Specialist Physician, as the secondary user, is charged with checking the safety of the scheduled system. Patients, as the Tertiary users, can get benefit from the design because of the improved reliability. Hospitals, government and manufacturing are the main stakeholders for the design. They have influence on the functions, objectives and constraints of our design according to their own interests.

Given the above information, the team will brainstorm and come up with various design ideas that meet the expectations in the next step. The team will apply multiple decision making methods to devise the best possible solution out of the alternative designs.

PROBLEM STATEMENT

Radiation therapy uses high-energy radiation to reduce tumor size and kill cancer cells for cancer treatment [1]. The radiation is either delivered by a machine outside the body which is called the external-beam radiation or by radioactive material placed in body near cancer cells which is called the internal radiation therapy [1]. The principle of radiation therapy is to damage the DNA of cancerous cells. Although radiation therapy is an effective treatment for cancer, it can also harm normal cells if inappropriate dosage is delivered to surrounding organs. Therefore, the dosage accuracy and performance of the device used for radiation therapy is vital.

Cancer patients are commonly treated with External Beam Radiation Treatments (EBT) [2], for which a linear accelerator (LINAC) is used. In the event of effective treatment, a tumor is targeted and destroyed by highly focused beams of high-energy x-rays. The radiation flatness level must be controlled within the designated critical limits (radiation flatness limitations). The performance of the intensity control is determined by the working state of the gun unit . Currently, the maintenance team conducts daily maintenance check in the beginning of the day. There are three main disadvantages for the current procedure. First, the procedure is conducted daily and it is highly maintenance-intensive. Second, the daily maintenance procedure does not provide preventative measures for mitigating the consequences when a failure is detected. Third, the current procedure does not account for situations in which the guns experience failure during the day.

The previous periodical monitoring quality control (QC) data provided by the client include radiation flatness data collected from the LINAC machine gun units, symmetry data and other critical parameters such as monitoring timing, historical configurations and observed hump error data. Based on the identified problems in the current maintenance approach, the design team were asked to utilize the quality control test results and machine-recorded parameters to aid the maintenance procedure of the linear accelerators in order to eliminate inefficiency and discrepancy. The design should also propose servicing intervention recommendations for all gun units by analyzing periodically assessed radiation flatness scorings. The gap between the current system performance and client expectations is illustrated in the following diagram (figure 1).

As shown in the diagram, by using the given QC parameters, such design must correlate the radiation flatness with significant machine parameters in order to help diagnose the cause of a change in machine performance (indication of faulty system units by gun number), advice on the appropriate service intervention and predict timing for servicing intervention of the linear accelerator based on the recorded machine parameters. Furthermore, the design should also be compatible with the AQUA system implemented by Princess Margaret Hospital.

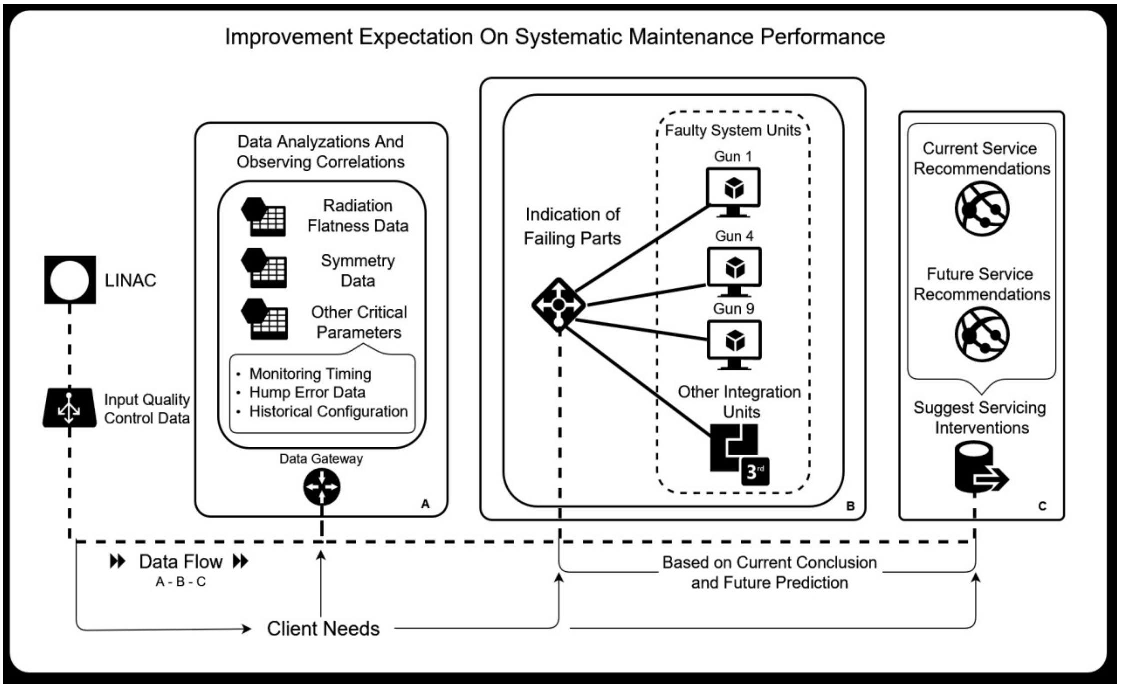

Figure 1. Project Scope Diagram

CONCLUSION

The main problem of the design is to increase the efficiency of the current approach for maintenance and improve the performance of the current system of linear accelerator. After identifying the function of the design, the team decides to focus on mainly two types of designs, physical design and virtual design. Based on the research and information provided by the client, the team outlines the objective, constraints and service environment for two different types of designs.

In the next step, based on these outlined functions, objectives and constraints, the team will brainstorm ways to solve the problem and come up with multiple feasible design ideas to satisfy the constraints and achieve most of the objectives. The team will compare the ideas using a weighted decision matrix to determine the proposed conceptual design, which will be delivered in the form of a Conceptual Design Specification document.

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PREDICTING THE RELIABILITY OF LINEAR ACCELERATORS BY ANALYZING TRENDS AND CORRELATIONS OF FLATNESS OVER TIME: PMH

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U of T UNDERGRADUATE STUDENTS

Note: The following is a digest of the Progress report submitted in conformity with the requirements for the degree of BASc, Department of Applied Science and Engineering, University of Toronto.

EXECUTIVE SUMMARY

The purpose of this thesis is to ensure that patients receive the optimal amount of dosage by linear accelerators (LINACs). This will be accomplished by creating a prediction model which will indicate when it is optimal to maintain or replace the components.

To meet the goal we analyzed data for 11 linear accelerators in Princess Margaret Cancer Care Center, in Princess Margaret Hospital (PMH). They are tested daily on the following two photon energies: 6MV and 18MV. We focused on 6MV and omitted the 18MV because only the 6MV data was complete. The hospital is also collecting flatness data, maintenance logs, as well as data about input and set parameters for the devices.

Initially, we plotted the time series plots for the flatness of the machines: flatness vs time. We found that while typically in the time series plot there was an upwards trend, there were some instances in the machines' flatness data where it trended downwards.

We then created histograms for flatness to determine the underlying distribution of the machines' flatness. The histogram containing all the machines' flatness data shows that the data is normally distributed, with a slight tail towards the right. The maximum and minimum points were removed to ensure that the outliers would not have an impact. The individual machines also follow a similar normal distribution.

Second, we analyzed the maintenance logs. That there are five (5) locations, that when adjusted impacts the flatness. The locations are: KV Imaging, MLC/ Collimator, Electron Gun and the Modulator/ Klystron affect the flatness. Usually, KV imaging has the most effect on flatness, and it starts in the beginning when the device starts operating, while the effects of MLC/ Collimator, and Electron Gun are realized after 2 years of operation of the device.

Third, we investigated the electron gun parameters and other parameters to find, if any, were related to flatness. If the flatness value changed when the parameter value changed, it would indicate that the parameter impacted the flatness. For the 6MV, the following parameters had changes throughout the period of analysis and they can influence the flatness value: Gun_aim__I_Set_value, Electron_Dose_level_Set_value, Chargerate_Set_value. The remaining parameters did not change throughout the period of analysis or were unrelated to flatness. Such a claim will be verified through the maintenance logs.

From our data analysis we derived four hypotheses:

- All machines follow a linear upward trend for the first 5 months.
- Gun V mean, Gun I mean, and Gun V Standby are correlated with flatness. Most of the time correlation is positive.
- The other parameters have no correlation with flatness.
- The flatness increase is caused by three factors on the machine: Initially it is caused by KV imaging (usually ongoing). After 2 years, the issues are also a result of problems with MLC / Collimator and after 3 years there are additional issues caused by the electron gun. Maintaining, adjusting, or replacing components in these three locations decrease flatness.

Going forward, we will start to focus on rigorously proving the conjectures that were found. We will accomplish this through statistical analysis. Once the conjectures are proved, we will create a prediction model based on the results. If disproved, we will look for other conjectures to create an adequate prediction model.

ACKNOWLEDGEMENTS

We would like to thank our research supervisor Professor Chi-Guhn Lee, for his assistance and insight throughout this process, and to Dragan Banjevic, from C-MORE for help in statistical analysis. We are especially thankful to Professor Daniel Létourneau, Associate Head of Medical Physics at Princess Margaret Cancer Centre in University Health Network and the Professor of Radiation Oncology at the University of Toronto, because without him none of this work would have been possible. He provided us with the essential data and resources to investigate and analyze LINAC machines.

PROGRESS REPORT

Introduction

Linear accelerators are a main source of cancer treatment. It is estimated that nearly 50 percent of all cancer patients receive some form of radiation therapy via a linear accelerator[1]. Linear accelerators (LINAC) emit electrons that, when aimed at the cancerous tissue, kill the cancer cells and, potentially, surrounding tissue.

The emission of radiation of a LINAC is done through an electron gun, which is a specific device which emits the beam of radiation. This treatment by the electron gun is referred to as external beam radiation[2].The electron gun is pointed towards the patient's cancer cells, which then proceed to kill the cancer cells.

The correct dose (amount of energy) is determined by a radiation oncologist with the potential help of a radiation dosimetrist and a medical physicist. Once the correct dose is determined, the patient is treated using the LINAC with the specific dose [3].

Over time the components of the machine start to deteriorate which may result in the optimal dosage not being delivered correctly. This can be caused by several factors. One of the factors is the performance of the electron gun. To prevent non optimal dosage from being delivered, LINACs undergo daily quality assurance tests.

One of the tests performed on the LINACs is the test for flatness. The flatness test measures the uniformity of the electron beam [4]. This is important because uniform dosage is vital to killing all the cancer cells equally. Non-uniform dosage might either kill healthy tissue, or not kill cancerous tissue, or both.

Purpose of the Thesis

The purpose of this thesis is to help to ensure that patients receive the optimal amount of dosage by the linear accelerator. This will be accomplished by analyzing and predicting the flatness. Specifically we are focusing on determining the correlation between input parameters with respect to dose uniformity and predicting when it is optimal to replace the components. To meet the goal we will analyze 11 linear accelerators in use in Princess Margaret Hospital.

Flatness of Linear Accelerators

To calibrate the optimal flatness of the LINAC initially, the machines' undergo a water test, where the electron gun radiates electrons in a water tank (chosen to simulate the human body), and the amount of radiation and its flatness is measured.

Once the machines are calibrated, they are tested every morning by a sensor strip. In an ideal world a water tank would be used. However, it is not feasible to do that because the water tank test usually takes long time to complete. To compensate for that, sensor strips are used which measures the max and min intensity emitted by the electron beam. Figure 1 shows the diagram of

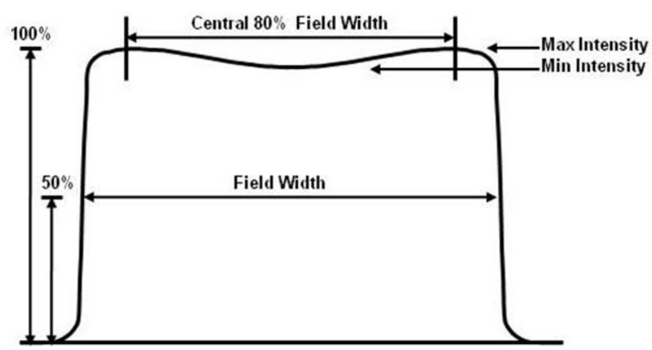

Figure 1 Flatness Measurement [5]

the measurement of the sensor strip.

The field flatness is then calculated using the following equation:

$$Flatness = \frac{D_{\max} - D_{\min}}{D_{\max} + D_{\min}} \times 100\%$$

Equation to calculate field flatness [6]

"D_{max} and D_{min} are the maximum and minimum dose along the profile within the core 80% of the field size."[6]

Each machine in Princess Margaret has a different optimal flatness that is calibrated by the water tank.

Characteristics of Machines and Testing Protocol

Princess Margaret has 16 different machines and in this thesis we analyze 11 of them. Five machines have been omitted because they are of a different make and model. The analyzed machines are installed between 2008 and 2016.

Most LINACs are used 5 days a week with the exceptions of two units which are used on-call.

The machines are tested daily on two photon energies: 6MV and 18MV. The flatness that is measured is then compared to the control. The control number is based on the water test performed when the machine is initially calibrated. The control values are 4 (for 7 machines), 4.4 (one machine), and 4.5 (three machines). Specifically for PMH, the result of the test is a warning if any of the measurements are off control values by ±2% and it is considered a failure if the data points are off by more than ±4%.

Range tests are performed with the following possible outcomes: 'Pass', 'Warning', and 'Fail'. 'Pass' indicates that the test value is within the 'Warning' limit. A test receiving a result of 'Warning' means that the value is more than the 'Warning' limit but less than the fail limit. Finally, 'Fail' indicates that the value is greater than the 'Fail' limit. If any of the tests resulted in a 'Fail', then the overall test failed. If none of test failed but any of the tests received a 'Warning' then the overall test result is warning. If none of the tests failed or received a 'Warning', then the overall test get 'Pass'.

Statistical Analysis: Time Series Plots of the Flatness

We initially plotted the time series plots (TSP) of the flatness vs time for all machines. The TSP starts from installation of the machine until October 31, 2017 (the last day data is available for each machine). We found that while typically there is an upwards trend of flatness in TSP with constant variation, there are often instances when flatness data trended downwards or upwards with an increase in variation.

The following is the TSP of flatness of machine NA09. The inward (yellow) lines indicate the warning limits and the outward (red) lines indicate the failure control limits:

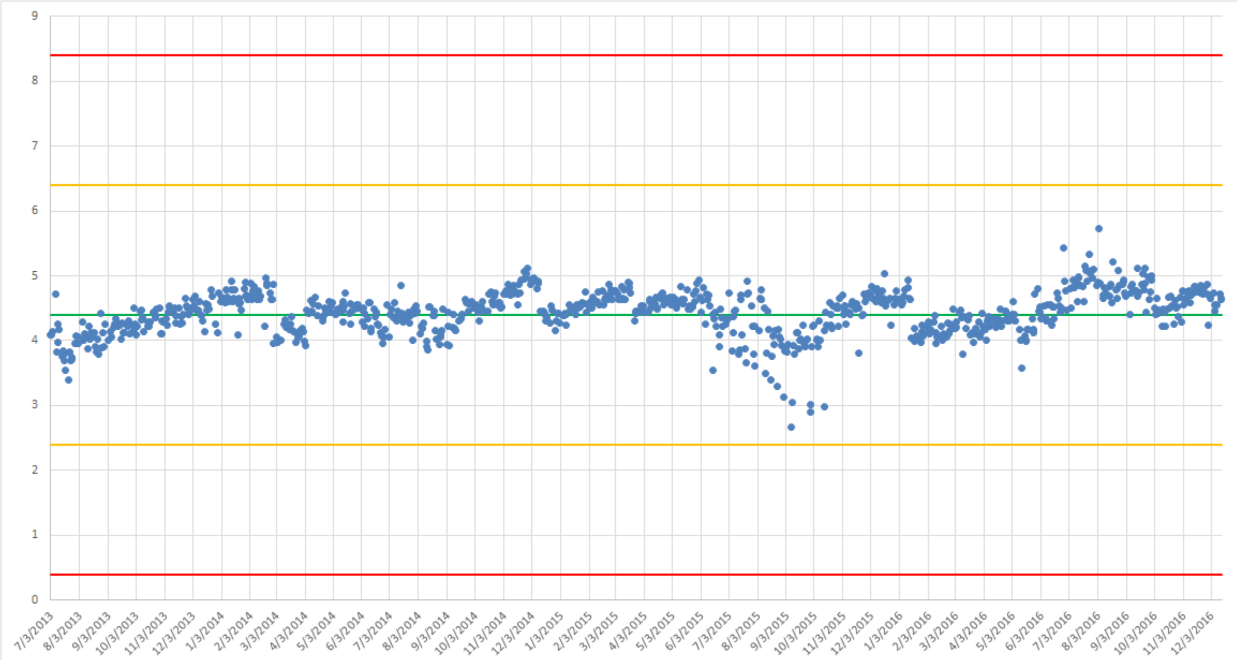

Figure 2: Time series plot for LINAC NA09

Three major trend types can be visually identified.

1) Linear Increase with constant variation

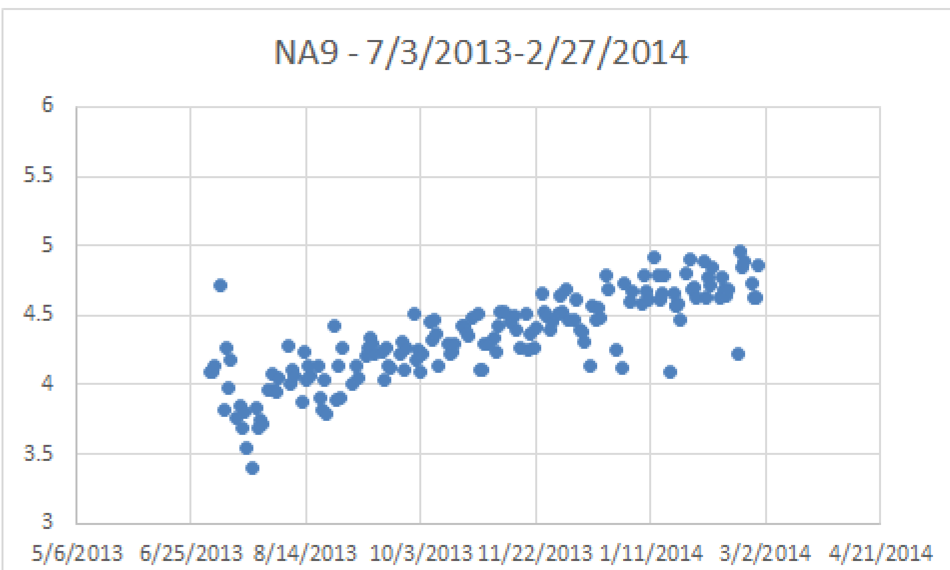

Figure 3: Time series plot for LINAC NA09 from date 7/3/2013 to 2/27/2014

This is the most common trend type as the LINAC ages. As time increases, so does the flatness [6]. The statistical regression analysis provides clear evidence of a flatness linear increasing trend in this specific interval. Once the operators recognize that there is a clear linear increase trend, they inform the mechanics who should adjust the flatness back to the target. The process of adjustment is vast and could be from a simple readjust of the gun, to an entire replacement of the component. The "Jumps in Data" section shows the result of the adjustment.

2) Linear Decrease with constant variation

An example of "Linear Decrease" for NA09 is show below. The regression analysis also shows clear decreasing trend; the variation is still constant, even not small.

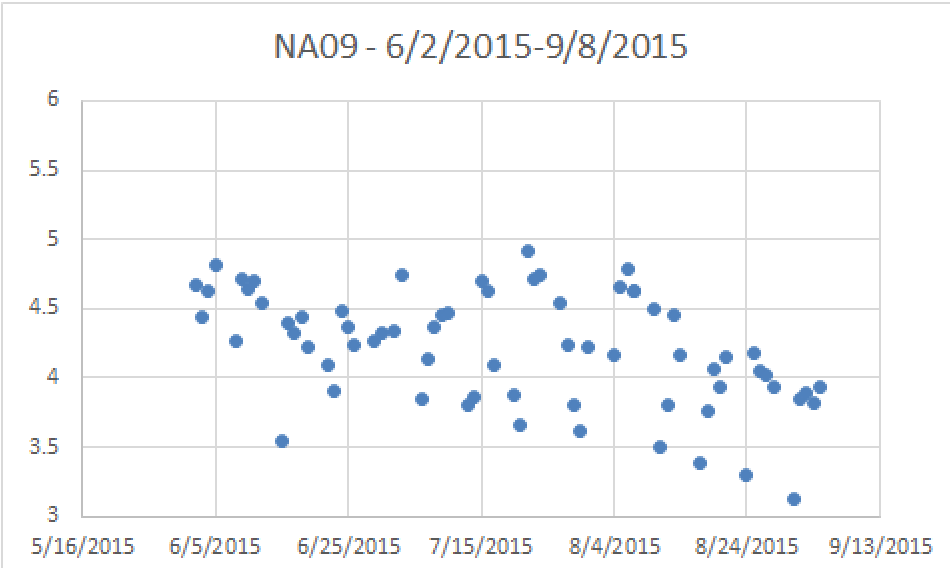

Figure 4: Time series plot for LINAC NA09 from date 6/2/2015 to 9/8/2015

3) Increase in variance over time (upwards/downwards trend)

An example of variance increase with upward trend for NA09 is show below.

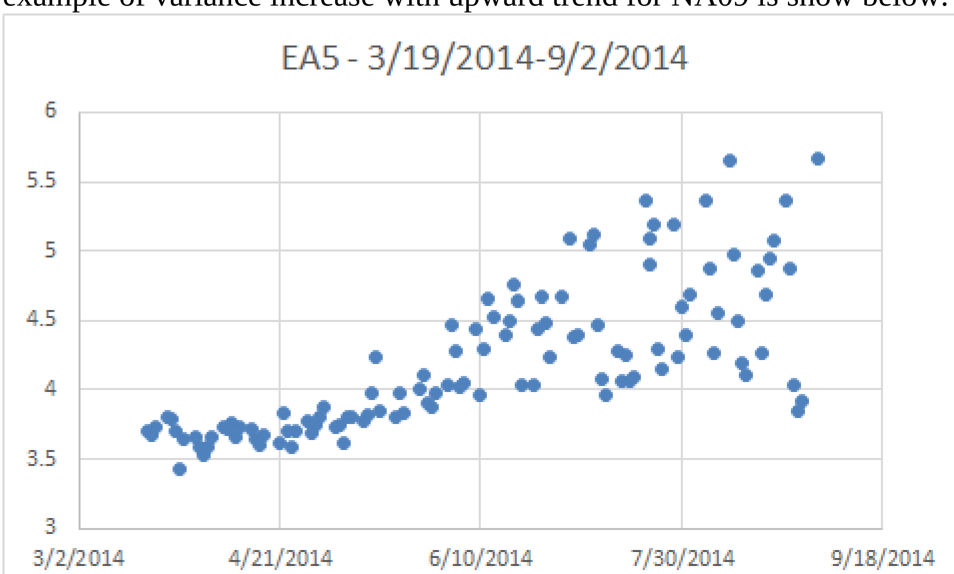

Figure 5: The time series plot for LINAC EA5 from date 3/19/2014 to 9/2/2014

“Jumps” in Data

Generally, after the data show a linear increase, the mechanic realigns the machines back to near the target. This can be seen through the data, as there are “jumps.” It was later attested with maintenance records. The following figure highlights the jumps (backwards) in the data:

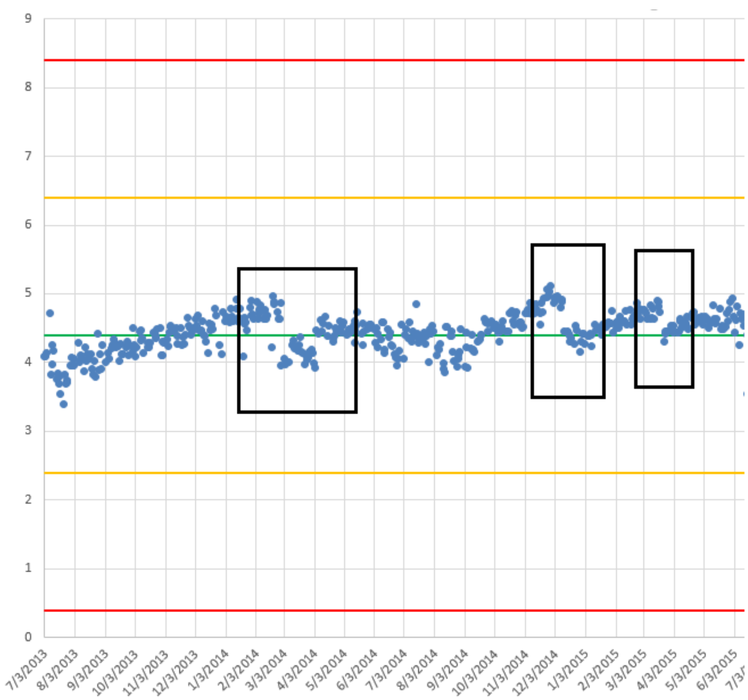

Figure 6: Jumps in Data for LINAC NA09

Distribution of Flatness

The following section considers the distribution of flatness data for all machines combined, and for individual machines, using flatness histograms.

The histogram for all the combined data was used to get understanding of the underlying distribution of the flatness since all machines are from the same manufacturer and of the same model. The data for each LINAC was scaled between 0 and 1, to account for the fact that the controls for all the LINACs are not the same. The following is the histogram for the combined flatness for LINACs:

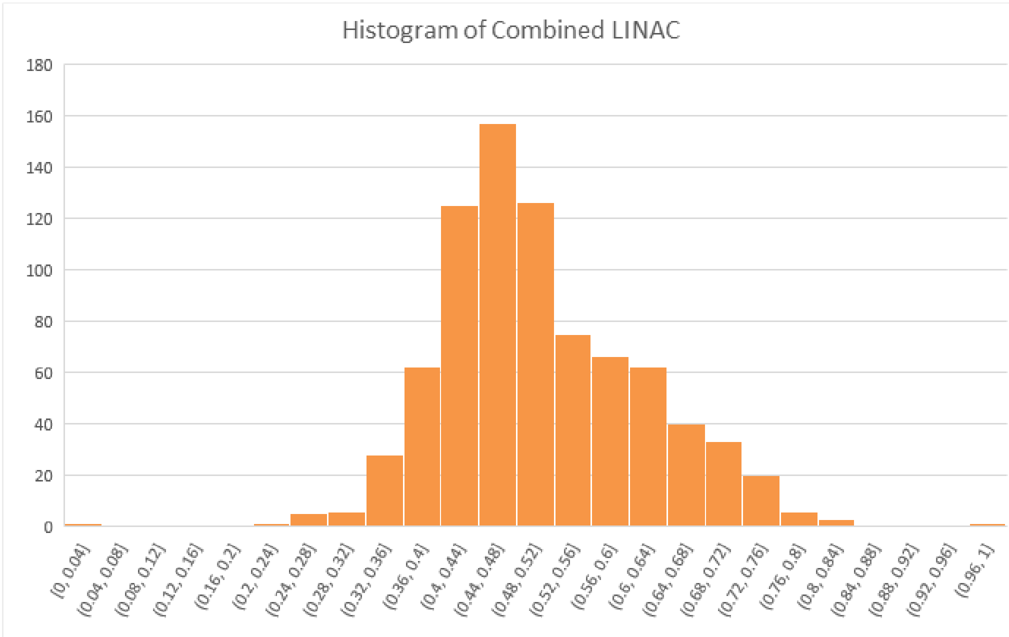

Figure 7: Scaled combined histogram of all the LINACs

The graph and the analysis show that the data follows distribution close to normal, with a slight longer tail towards the right. The maximum and minimum points were removed to ensure that the outliers would not have heavy impact on the analysis. The following is the probability plot with the maximum and the minimum removed:

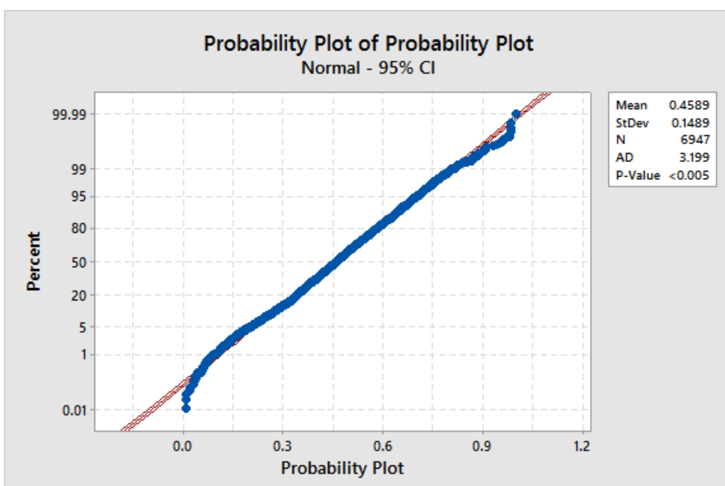

Figure 8: Scaled probability plot of all the LINACs

The individual machines also follow a similar normal distribution, with some variations, sometimes with the tail towards left.

Maintenance Intervals for the Machines

Maintenance is performed continuously on the LINAC machines. There are about 12 different locations on the machine, for which the maintenance interventions has been performed either at the same or different times. The maintenance data is available, but not convenient to show for all of them on a single graph (an example displayed in the presentation).

When displaying the maintenance near the "jumps of flatness" five (5) locations emerge where the LINAC was adjusted. The following is the table and the figure of servicing interventions:

Type/Location	Date	Fault description
KV Imaging	2/26/2014	kv/mv panel collision.
KV Imaging	12/12/2014	fault 33
KV Imaging	12/12/2014	Fault 33
Couch	3/23/2015	Hexa-pod error cannot find reference frame
MLC / Collimator	1/13/2016	mlc calibrated
Electron Gun	1/14/2016	cal factor adjusted
MLC / Collimator	9/27/2016	Leaf Y1-40 will only move in one direction
Modulator / Klystron	3/23/2017	no output both energies

Table 1: Points of servicing interventions near the jumps in flatness for LINAC NA09

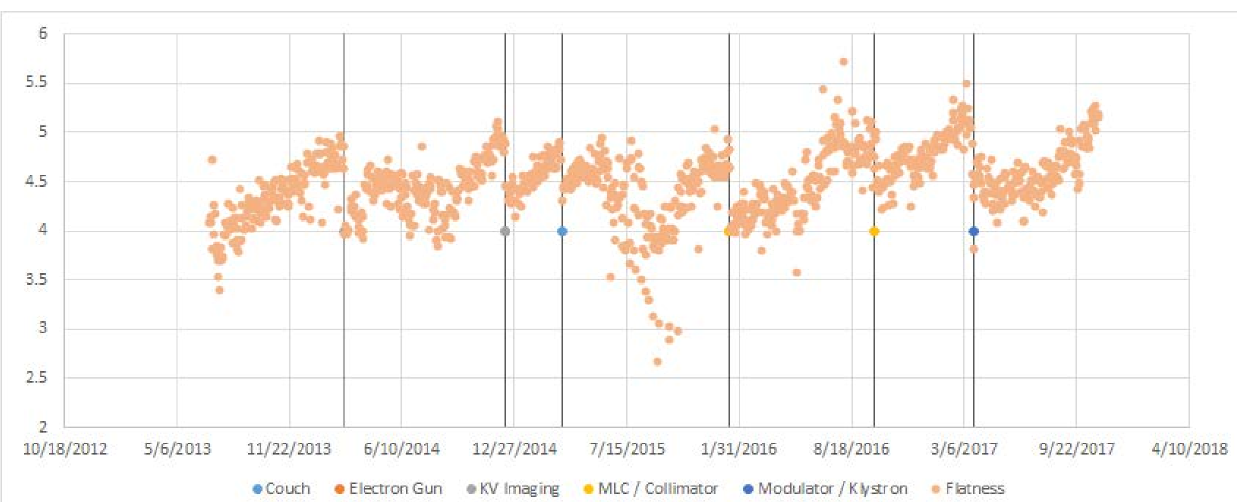

Figure 9: Servicing interventions near the jumps in flatness.

There seems to be a pattern that the KV Imaging, MLC/ Collimator, Electron Gun and the Modulator/ Klystron affect the flatness. On the other hand, we cannot find a reason for correlation between the couch and the flatness (see the table above); but it was the only maintenance mentioned in the records for that case. However, it is likely that on that specific day another intervention was performed as well, but only the couch was entered into the database.

The following graph shows the combined servicing interventions for LINAC NA09 for each of the locations mentioned above:

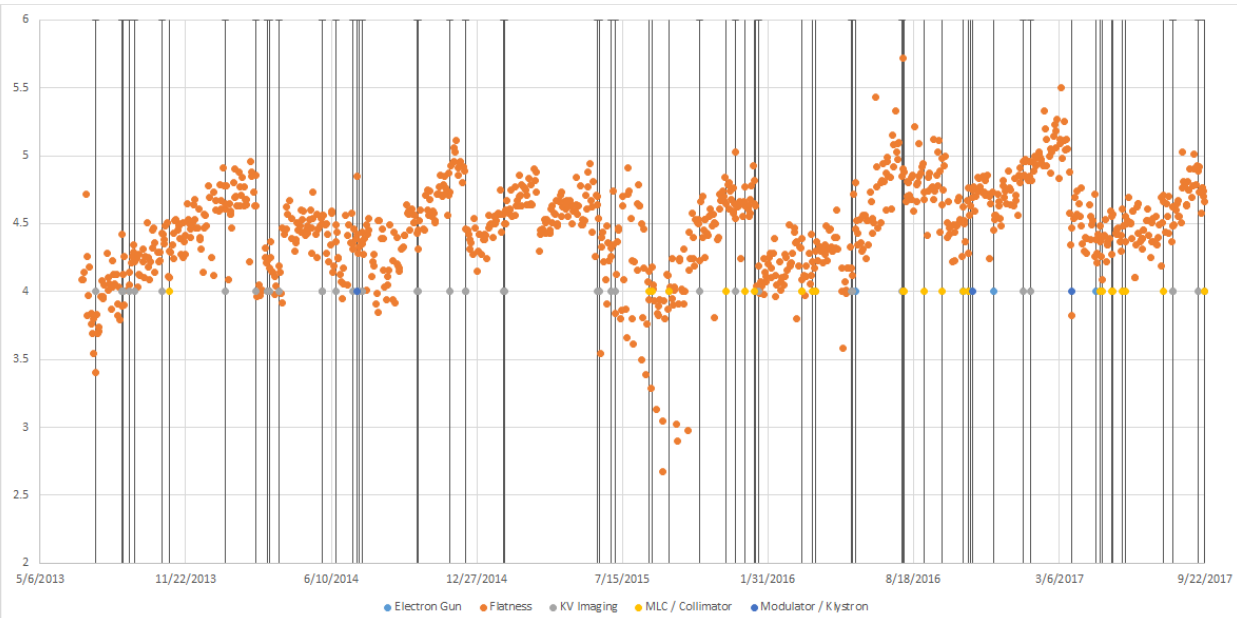

Figure 10: Servicing interventions near the jumps in flatness

From the data, a clear pattern can be seen; the KV Imaging maintenance is performed regularly while the other maintenance is performed more frequently once the machine ages.

Correlation between Electron Gun Parameters and Flatness

The electron gun parameters were investigated to determine which parameters, if any, were related to flatness. If the electron gun parameters were related to the flatness, it could serve as a leading indicator of when maintenance would be required. Not only it would enable more accurate predictions of when the LINAC would require maintenance, it also would narrow down the cause to the electron gun.

Most of the parameters have almost constant value over time. An example of TSP of the gun nonconstant parameter alongside the flatness for LINAC NA09 is given below.

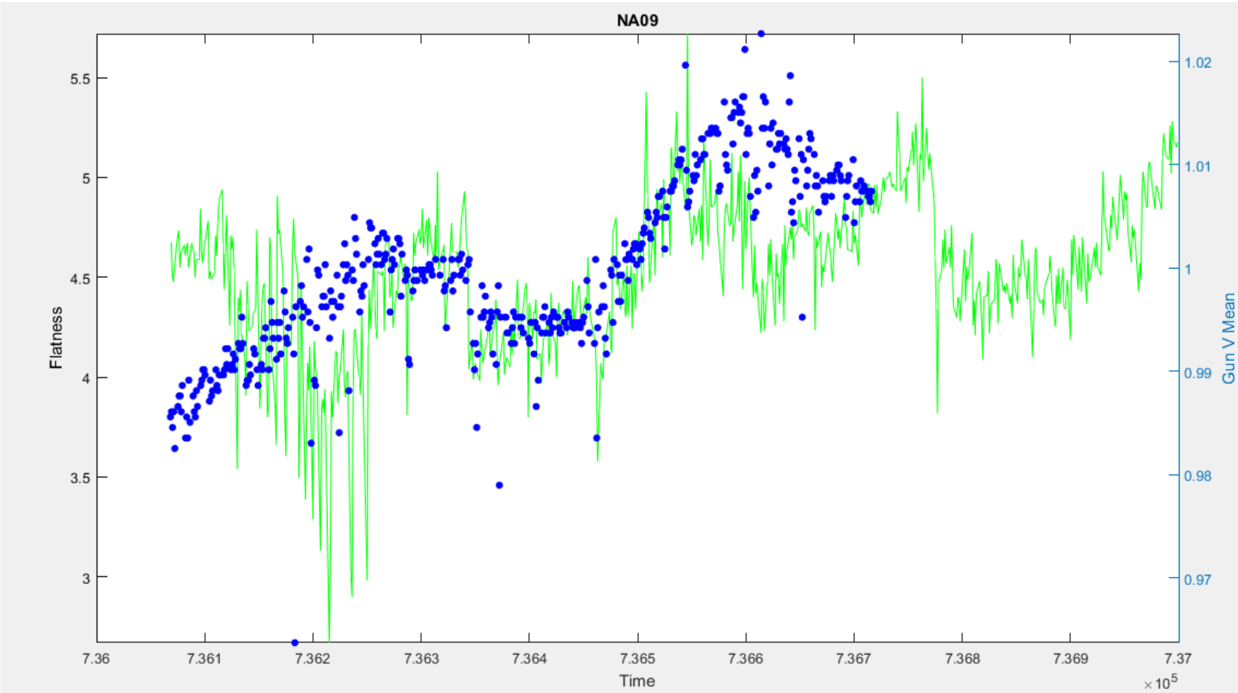

Figure 11: Plot comparing Gun V Mean (dark, in blue) and Flatness (light, in green)

Correlations between Other Parameters and Flatness

In order to determine the impact of those parameter changes, the parameters were plotted alongside the flatness. If the parameter value changed and the flatness value changed, it would indicate that the parameter impacted the flatness. Such a claim would be verified through the maintenance logs.

Conjectures/Hypothesis on Flatness Trend and Correlation with Parameters

The following four major conjectures were created based on the data gathered; these require more detailed statistical and expert analysis:

1) All machines follow a linear upward trend for the first 5 months.

2) Gun V mean, Gun I mean, Gun V Standby are all correlated to flatness. Most of the time there is a positive correlation.

3) Other parameters have no correlation with flatness.

4) Flatness almost always increases with time:
   - Initially it is caused by KV imaging (usually ongoing).
   - After 2 years the issues are also a result of problems with MLC / Collimator and after 3 years issues are additionally caused by the electron gun.
   - Adjusting/replacing components in these three locations, if they are malfunctioning, will decrease flatness.

Next Steps

The team will try to prove or disprove the hypothesis with data. This will be accomplished by first, further analyzing the maintenance logs of other machines. Second, gathering data from the maintenance personnel and finally statistically proving and disproving the conjectures.

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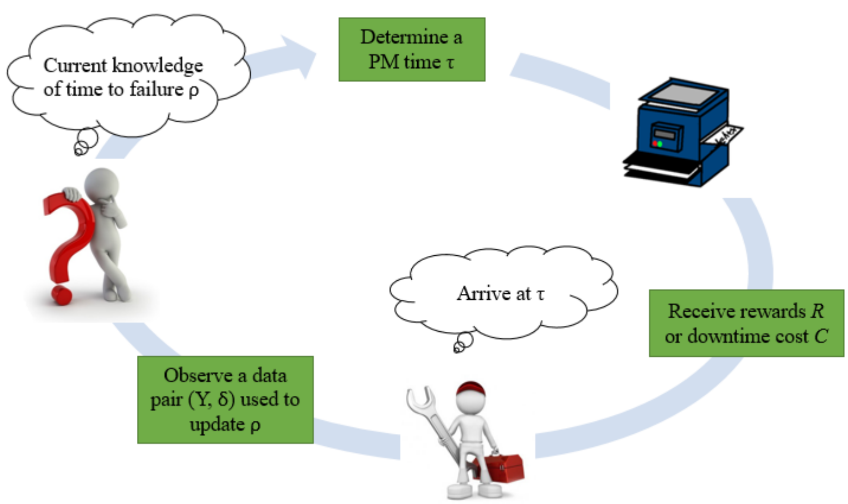
A BAYESIAN DYNAMIC PROGRAMMING APPROACH TO PREVENTIVE MAINTENANCE OPTIMIZATION

YA-TANG CHUANG, C-MORE PHD CANDIDATE

INTRODUCTION

The preventive maintenance literature is primarily concerned with determining the optimal time to replace or repair an operational system so as to avoid costly failures. One of the earliest papers contributing to this stream of the research is Barlow and Hunter (1960). They proposed preventive replacement policy while failure events are uncertain. Several papers consider the failure time is uncertain but follows a certain probability distribution (see e.g. Dogramaci and Fraiman (2004), Kurt and Kharoufeh (2010)). However, the estimate of the lifetime distribution of the system may be not accurate (see de Jonge et. al., 2015). Therefore, we investigate a class of sequential maintenance optimization problems where parameters of the lifetime distribution are not known a priori, but need to be learned using right-censored failure data. At the beginning of each experiment, the decision maker fixes a preventive maintenance (PM) time based on his/her current knowledge of time to failure. After that a technical system is run until either it fails at a random time or reaches the planned PM time, whichever occurs first. Then the decision maker observes the data pair and updates the knowledge of time to failure; see the figure below for the procedure of the experiment



METHODOLOGY

In this stream of research, we propose a Bayesian dynamic optimization framework to investigate this Bayesian maintenance optimization problem. In particular, we assume the failure distribution of the system depends on unknown parameters that we want to learn about over time. The decision maker endows the unknown parameters with an initial prior distribution, and refines this distribution over time (to a posterior distribution) via Bayes' Theorem as new data become available. In this setting, observable data takes the form of either failure times or planned replacement times. It can be shown that failure time data is far more informative than preventive replacement data in the sense that it leads to a larger reduction in the standard deviation of the posterior distribution (i.e., it leads to a better estimate of the unknown parameters). Therefore, the dynamic optimization problem seeks to optimally balance between avoiding costly failures (by replacing systems early) and allowing failures to occur to gain statistical benefits (by replacing system late).

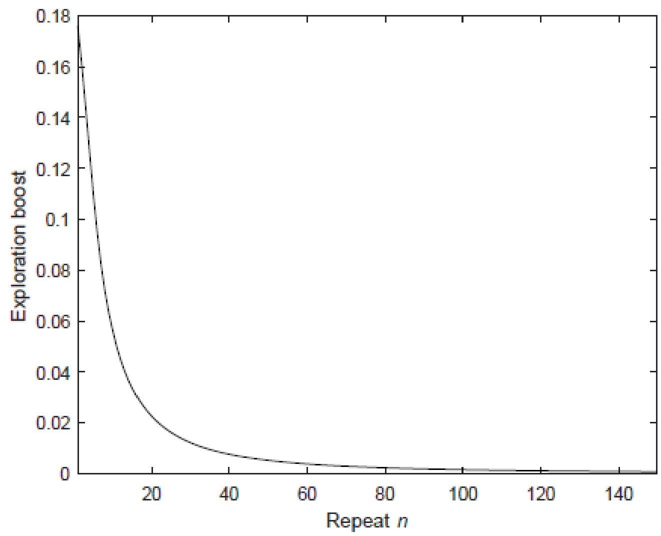
MAIN RESULTS

An analysis of the Bayesian dynamic programming (BDP) equations shows the main result of this project, that the structure of the optimal PM time is characterized by

$$Optimal\ PM\ time = \ myopic\ optimal\ decision\ +\ variance\ of\ mean\ time\ to\ failure.$$

This main result establishes that under the Bayesian dynamic programming framework, the optimal decision is greater than the myopic decision. Here myopic decision means the decision maker ignores the benefit from obtaining more informative data and maximizes the current reward only. This result can be explained by the intuition that decision maker will delay the maintenance time a little bit in order to have higher chance to observe the failure data (informative data) which will be beneficial in the future.

Moreover, the key insight we obtain from the above representation is that this structure clearly articulates the manner in which the failing to learn trade-off is achieved when the posterior variance is large (i.e., there is a high degree of parameter uncertainty); then the preventive maintenance decisions are delayed to induce a higher chance of failure so as to more quickly resolve statistical uncertainty. Over time, as the parameter uncertainty disappears, i.e. variance tends to zero, failures are induced less frequently. In this regard, the second (non-negative) term on the right-hand side of the main equation may be interpreted as an “exploration boost” that is added to the myopic-optimal PM decision to account for the current level of uncertainty in the unknown lifetime distribution. See the figure below for the illustration of the exploration boost.



CONCLUDING REMARKS

In this paper, we consider combined statistical learning and optimization for a class of sequential maintenance optimization problems where parameters of the lifetime distribution are not known a priori, but need to be learned over time using right-censored failure data. Our main result showes that BDP-optimal PM times can be expressed as the sum of a myopic-optimal PM time plus an "exploration boost" which is proportional to the posterior variance of the mean time to failure (MTTF). This structure explains in clear terms the manner in which the learning and maintenance are jointly optimized: when there is a high degree of parameter uncertainty (encoded as a large posterior variance), PM decisions are delayed to induce a higher chance of failure so as to more quickly resolve statistical uncertainty, and as parameter uncertainty resolves, the decision maker induces failures less frequently.

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LEARNING THE POTENTIAL FUNCTION IN POTENTIAL-BASED REWARD SHAPING FOR MACHINE LEARNING APPLICATIONS

MICHAEL GIMELFARB, PHD PRE-CANDIDATE

BASIC FRAMEWORK

In many reinforcement learning applications, we are often interested in finding an optimal plan or policy to take over a future time horizon, when there is inherent randomness in the underlying state variables. Such stochastic processes are best modelled as **Markov decision processes (MDP)**. Formally, we define an MDP in the discounted framework as a collection $M = (S, A, P, \gamma, R)$ where:

- S is the state space
- A is the action space
- $P = \{P_a : a \in A\}$ is a collection of transition probabilities, where P_a is the matrix of whose element at s, s' is denoted $p(s' | s, a)$
- γ is a discount factor in [0,1]
- $R: S \times S \times A \to \mathbb{R}$ is the reward function, in which $r(s, a, s')$ describes reward obtained when in state s, action a is chosen, and then a transition occurs to state s'.

We define a **policy** μ as a sequence of functions $\mu_0, \mu_1 \ldots$ from states to actions. Given an arbitrary MDP (S, A, P, γ, R) and policy μ, we can compute the discounted total infinite-horizon reward as

$$V^{\mu}(s) = E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \mid s_0 = s\right]$$

where s_t is the state at time t evolving according to M and a_t is the action taken in state s_t, e.g. $\mu_t(s_t)$. More importantly, we are interested in finding a policy with the largest expected reward over all states, e.g.

$$V^*(s) = \sup_{\mu} V^{\mu}(s).$$

In this case, $V^{\mu^*} = V^*$ where μ^* is called the **optimal policy**.

There are many algorithms for solving MDPs directly, including value and policy iteration (see, e.g. [Be95]). However, these algorithms all suffer from the curse of dimensionality and are no longer practical for large-scale MDPs, as illustrated below.

Example 1. Consider an MDP with n states, and where for each state in S, there are two possible actions. Then the number of possible policies is 2^n. It can be shown that the worst-case running time of policy iteration to solve the problem exactly is $O\left(\frac{2^n}{n}\right)$, which is close to exponential in the number of states (see, e.g. [MS99]).

In order to address the curse of dimensionality, we instead maintain a table of values for each state-action pair $Q(s,a)$, which is defined as

$$Q(s,a) = E\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \mid s_0 = s, a_0 = a\right].$$

Typically, the Q-values are computed in an online (iterative) framework

$$Q(s,a) = Q(s,a) + \alpha[R_t - Q(s,a)] \qquad (1)$$

where α is a learning rate parameter and the second term $R_t - Q(s,a)$ is an error term which is the difference between our estimate of the future reward R_t and the reward estimate from the Q-table. There are many ways in which we can estimate R_t. The well-known **SARSA** (state-action-reward-state-action) update uses the one-step bootstrap returns

$$R_t = R_t^{(1)} = r(s_t, a_t, s_{t+1}) + \gamma Q(s_{t+1}, a_{t+1}),$$

where s_{t+1} is sampled according to P_{a_t} and a_{t+1} is chosen according to some exploration policy.

One such policy is **epsilon-greedy** in which we select $a \in \operatorname{argmax}_a Q(s,a)$ with high probability or a random action with low probability. A more sophisticated estimation procedure, called **TD-lambda**, defines the rewards recursively as

$$R_t^{\lambda} = r(s_t, a_t, s_{t+1}) + \gamma\left[(1-\lambda)Q(s_{t+1}, a_{t+1}) + \lambda R_{t+1}^{\lambda}\right] \qquad (2)$$

where λ is a positive tuning parameter (see, e.g. [SB98]) After a fixed number of episodes, we can obtain the best policy by choosing the entry in $\{Q(s,a), a \in A\}$ with the highest value.

THEORY OF REWARD SHAPING

While (1) and (2) are often useful in practice, training can take a long time if the rewards are relatively sparse. In other words, if $r(s,a,s') = 0$ for a large number of elements, then the errors $[R_t - Q(s,a)]$ will often be relatively small and the Q-values will be updated relatively infrequently. In order to help speed up the learning process, it is often useful to “shape” the original reward function R into another function R' defined by

$$r'(s,a,s') = r(s,a,s') + F(s,a,s')$$

by introducing a shaping function F. If F has many non-zero elements, then so too will R' and learning can be accelerated.

However, it is necessary to exercise caution in defining the shaping function, because it is possible to alter the reward structure in such a way that the optimal policies for the original MDP are no longer optimal for the new MDP. Fortunately, it has been shown that the only class of shaping functions which preserves policy invariance is the **potential-based shaping function**.

Theorem 1 [NDS99]. *Let $M = (S, A, P, \gamma, R)$ be an MDP and let $M' = (S, A, P, \gamma, R + F)$ be the MDP after reward shaping. Then any policy which is optimal for M is also optimal for M' (and vice-versa) if and only if F is potential based, that is,*

$$F(s, a, s') = \gamma \Phi(s') - \Phi(s)$$

for some function $\Phi: S \to \mathbb{R}$.

Furthermore, and crucially in our analysis, the policy invariance property has been extended for **dynamic reward shaping** where

$$F(s, t, s', t') = \gamma \Phi(s', t') - \Phi(s, t)$$

and the potential is allowed to depend on time [DK12].

PRELIMINARY ANALYSIS FOR LEARNING AN UNKNOWN POTENTIAL FUNCTION

Much of the current theory on potential-based reward shaping assumes that the potential function is known or can be directly specified. For many complicated domains, however, it is not easy to assign rewards to states without prior knowledge in such a way that learning can be accelerated substantially. In fact, most of the current literature assumes that there is some expert that can provide knowledge, which can in turn be used to construct the potential function. However, expert knowledge is not always available and is not always reliable. The question that I would like to address over the course of my PhD studies is this: *can a computational method be designed which, while working concurrently with a reinforcement learning algorithm (such as TD-lambda) in a Bayesian framework, can provably accelerate the convergence of the RL algorithm*?

Bayesian methods offer a structured approach to learning from data. To see how this can be done, we assume that the unknown potential function Φ takes the form

$$\Phi_{\mathrm{t}}(s) = \sum_{i=1}^{n} \mathrm{w_i} \Phi_t^i(s),$$

where Φ^i are a set of proposal shaping functions, and w_i are a set of weights. Due to policy invariance holding in the time-dependent case, we can allow the potential function to depend on time. The goal is to learn the unknown weights online using the feedback from TD-lambda. To do this, we assume that the Q-values over each state-action pair are Gaussian, e.g.

$$q_{s,a} | \Phi^i \sim \mathcal{N}\left(\mu_{s,a}^i, \left(\sigma_{s,a}^i\right)^2 \right)$$

where the model means are obtained by applying Theorem 1 to (2)

$$\mu_{s,a}^{i} = r_{t+1} + \gamma\phi_{t+1} - \Phi_t^{i}(s) + \gamma\big[(1-\lambda)Q(s_{t+1}, a_{t+1}) + \lambda R_{t+1}^{\lambda}\big] \qquad (3)$$

and where $s = s_t, a = a_t, \phi_{t+1} = \Phi_{t+1}(s_{t+1})$. Following the analysis and assumptions in [DS09] we can obtain a computationally efficient weight update

$$w_i = P\big(\Phi^i \big| D_{s,a}\big) = \frac{\mathcal{N}\big(\mu_{s,a}^{i}; \mu_{s,a}, \sigma_{s,a}^2\big)^{N_{s,a}}}{\sum_{j=1}^{n} \mathcal{N}\big(\mu_{s,a}^{j}; \mu_{s,a}, \sigma_{s,a}^2\big)^{N_{s,a}}} \qquad (4)$$

where $D_{s,a}$ is the data consisting of all rewards R_t^{λ} for state action pairs *(s,a)*, $N_{s,a} = |D_{s,a}|$, $\mu_{s,a}$ and $\sigma_{s,a}^2$ are the mean and variance of $D_{s,a}$, and $\mathcal{N}\big(\mu_{s,a}^{j}; \mu_{s,a}, \sigma_{s,a}^2\big)$ is the Gaussian($\mu_{s,a}, \sigma_{s,a}^2$) density evaluated at $\mu_{s,a}^{j}$. This gives us an efficient way to update the weights in the online framework of (3).

The future directions for this project include:

1. extending the potential function representation to a more general form which does not require specification of basis functions a priori; this will require function approximation or non-parametric Bayesian methods
2. extending the idea of reward shaping to transition shaping, in which we can also perturb the transition probabilities *P*
3. considering additional assumptions for the reward function, such as monotonicity or convexity, which can be used to reduce the complexity of the function representation.
4. conducting a thorough numerical analysis to verify that the proposed methods work at least as well as the current state-of-the-art algorithms.

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APPENDICES

APPENDIX 1: C-MORE PROJECT CHARTER

C-MORE

Collaborative Project
C-MORE, University of Toronto
Collaborating Company: XXX
V 1.0
DD-MMM-YYYY

Project Title:			
Brief Project Description:			
Consortium:			
Charter Date / Revision:		***Author:***	**[xxx], C-MORE** [xxx], [Consortium]

Project Background

Provide information about the history of the project – how it came about, who was involved from C-MORE and collaborating company, - be chronological. Assume that someone is reading this for the first time and knows nothing about the project and how it came about.

Project Milestones

Identify project milestones, deliverables and entities responsible from all schedules related to the project. List associated deliverables and Due Date including the year. Make any notes needed specific to the milestone.

MILESTONES	DELIVERABLES	Responsible	DATE
		[C-MORE, or coll. company]	

Resource Requirements

Provide high level estimate of required resources such as staff hours based on the criteria listed below. If not known, use TBD. List any constraints that may impact the project.

(i) C-MORE

Estimated Overall Requirements	
Available Resources in the next planning period *(such as in the following 6 months, or one year; it is understood, the costs will be made with respect to C-MORE resources that can be allocated to work with the collaborating company and to accomplish as much as possible of the scope of work required)*	(i) working hours (ii) $ amount (if applicable)
Requirement Estimate (C-MORE)	(i) working hours (ii) $ amount (if applicable)
Constraints:	

(ii) [collaborating company]

Estimated Overall Requirements	
Available Budget *(it is understood, all costs will be made whole to* [collaborating company] *to accomplish the scope of work required)*	
Project Cost Estimate	
Funding Variance	
Financial Coding	
Constraints:	

Project Governance

How will the project be managed? Who will be involved?
Outline any policies, regulations, functions, processes, procedures, and responsibilities that will govern the project and how they will help manage the project.
Graphics can be used to show the hierarchies if needed.
Provide the information in the table below of persons listed in your Organizational Chart.

(i) C-MORE

ROLE	NAME	ASSIGNED LEVEL OF AUTHORITY

(ii) [collaborating company]

ROLE	NAME	ASSIGNED LEVEL OF AUTHORITY

Communications

How would communications work throughout the project team? Consider if there are different departments involved, external and/or internal parties? Who is the single point of contact? What form of communication will be used? If there are phases of the project, would the communication channels change? Why is communication important for this project?

(i) C-MORE and [*collaborating company*]

(ii) [*collaborating company*]

Approvals

(i) C-MORE

NAME	SIGNATURE	DATE
Project Sponsor:		
Project Manager:		
Manager:		
Lead		

(ii) [*collaborating company*]

NAME	SIGNATURE	DATE
Project Sponsor:		
Project Manager:		
Manager: ***Department***		
Manager: ***Department***		
Manager: ***Department***		
Lead		

END OF DOCUMENT

APPENDIX 2: USEFUL EXAMPLES OF CM EQUIPMENT ADS FROM VARIOUS COMPANIES

DRAGAN BANJEVIC, C-MORE

NOTE: Here we give a snap-shot of companies and their web-sites related to CM products and services. In some cases (related to mining industry) more details are given. They are not in any specific order.

SCANIMETRICS at **https://scanimetrics.com**

Scanimetrics delivers a complete condition monitoring solution for heavy equipment — hardware, software, and expert support.

Equipment maintenance and repair is time-consuming and costly.
You want a safer operation, lower costs, and less frustration. We make it easier. Scanimetrics delivers a complete condition monitoring solution for heavy equipment that includes hardware, software, and expert support. We give you the data and the analysis you need to accurately monitor your equipment health and to schedule maintenance based on equipment condition. Our approach (predictive and condition-based maintenance) helps you reduce costs by cutting down on unnecessary preventive maintenance, and reduce risk by anticipating and preventing costly failures. The result: a safer operation, lower costs, and reduced downtime. Here's how we do it.

1. We make rugged wireless sensor devices.
These small wireless devices (called Motes) can be attached to any sensor including strain, vibration, temperature, and crack propagation gauges. The Motes collect, store, and transmit condition data from your equipment reliably — even in the harshest environments. They've spent a Canadian winter monitoring cracks in the H-frames of giant mining trucks that were hauling 400-ton loads across the oil sands. They've been used to measure bolt tension on a shaker screen exciter where vibrations generate more force than a space shuttle launch. They've been used to monitor weld creep in a steam pipe in a super critical coal-fired power generator where temperatures reach 460°C. In each of these situations, not only have the motes survived, they've worked — collecting and transmitting accurate sensor data reliably to our host servers and reducing the costs and manual effort of data collection for our customers.

2. We provide easy-to-use software to collect, view, and analyze sensor data.
But having reliable sensor data isn't the end of the story. We've developed easy-to-use online software to help you turn sensor data into information you can use to make better equipment maintenance decisions. Powerful analysis features help you determine the predicted time to failure and the remaining useful life of your equipment. Alert features notify you when there's a significant change in condition, such as when a structural crack begins to grow. And our reporting features help you detect trends and patterns, diagnose failures, and monitor and improve operator performance. We offer a complete solution for equipment condition monitoring... so you can lower operational costs and increase equipment uptime.

3. We supply installation, consulting, and support.

The Scanimetrics team works with your organization to design and implement your equipment condition monitoring solution. This includes consulting services to develop a solution that addresses your unique needs and challenges. It also includes installation and configuration of the physical sensors, the Motes, and Scanimetrics software. We also provide ongoing support to ensure the implemented solution continues to work as intended, and we look after any issues experienced by sensor equipment in the field. Other companies sell sensors... we provide a complete solution for equipment condition monitoring.

Is your mining equipment costing you more to maintain than it should?

You're spending four times your capital investment operating and maintaining your mining equipment. Your goal: reduce maintenance costs, downtime, and risk of catastrophic failure. What's holding you back? You don't have the tools to gather accurate data on the condition of your equipment. And you don't have the time to translate the data into information that helps you make better maintenance decisions.

Scanimetrics can help

Scanimetrics delivers a complete condition monitoring solution for mining equipment: hardware, software, and expert support. We can give you the data and the analysis you need to schedule maintenance based on the condition of your equipment. This helps you reduce costs by cutting down on unnecessary preventive maintenance and the labour required for manual inspections, and reduce risk by anticipating and preventing catastrophic failures. The result: lower maintenance costs, improved safety, and higher machine availability.

Applications

- Heap leaching.
- Haul trucks, shovels, dozers, drills.
- Operator training and performance.
- Mills, crushers, screens, apron feeders, conveyors.
- Environmental monitoring.
- Safety and compliance.

THE CHALLENGES OF MONITORING MOBILE MINING EQUIPMENT


Mine shovel

Vibration measurement has come of age in the last 20 years. While the practice of continuous on-line monitoring of critical machines in the oil, gas, and petrochemical industries has been common place for several decades, it is only recently that companies who had been using intermittent data collection techniques are now embracing continuous monitoring.
The new “horizon” is mobile equipment ... draglines, shovels, bucket-wheel excavators, stacker claimers, heavy haul trucks, are all equally important to production and just as “critical” as a gas compressor.

However, unlike stationary machinery, monitoring mobile equipment brings substantial challenges that must be addressed to ensure accurate, repeatable, and reliable data acquisition. Rapid speed and load variations are just one element of the application. The logistics of sensor mounting, cabling, network communications, and general serviceability, bring unique complications to the task of monitoring these machines.

We will discuss these obstacles and present new solutions that have the potential to bring significant reliability improvements to large mobile equipment.

A USEFUL ARTICLE FROM PRUFTECHNIK

The Challenges of Monitoring Mobile Mining Equipment

August 3, 2016
Author: Ron Newman, PRUFTECHNIK

Abstract:

Vibration measurement has come of age in the last 20 years. While the practice of continuous on-line monitoring of critical machines in the oil, gas, and petrochemical industries has been commonplace for several decades, it is only recently that companies who had been using intermittent data collection techniques are now embracing continuous monitoring. This session will discuss that the new horizon for continuous monitoring is mobile equipment; draglines, shovels, bucket-wheel excavators, stacker-reclaimers, heavy haul trucks, are all equally important to production and just as critical as a gas compressor. Participants will learn that, unlike stationary machinery, monitoring mobile equipment brings substantial challenges that must be addressed to ensure accurate, repeatable, and reliable data acquisition. Rapid speed and load variations are just one element of the application. The logistics of sensor mounting, cabling, network communications, and general serviceability bring unique complications to the task of monitoring these machines. Ron will discuss these obstacles and present new solutions that have the potential to bring significant reliability improvements to large mobile equipment.

The monitoring of mobile equipment brings substantial challenges that must be addressed to ensure accurate, repeatable, and reliable data acquisition. Vibration measurement has come of age in the last 20 years. While the practice of continuous online monitoring of critical machines in the oil, gas, and petrochemical industries has been commonplace for several decades, it is only recently that companies who had been using intermittent data collection techniques are now embracing continuous monitoring. The benefits are substantial! The new horizon is mobile equipment draglines, shovels, bucket-wheel excavators, stacker-reclaimers, heavy haul trucks; all are equally important to production and just as critical as a gas compressor. However, unlike stationary machinery, monitoring mobile equipment brings substantial challenges that must be addressed to ensure accurate, repeatable, and reliable data acquisition. Rapid speed and load variations are just one element of the application. The logistics of sensor mounting, cabling, network communications, and general serviceability, bring unique complications to the task of monitoring these machines. There are now new solutions available that have the potential to bring significant reliability improvements to large mobile equipment.

Speed and Load Variations

Reliable and repeatable vibration measurement has historically been dependant upon steady-state conditions, which are constant RPM and constant load. Repeatability, often regarded as the cornerstone of good vibration data collection, is essential for the accurate assessment of machine condition, and more so for intermittent monitoring strategies. The data must be representative of machinery health and reflect real changes due to incipient fault conditions and not to changes due to variations in operating conditions. As an example, when speed varies over the duration of a typical measurement cycle, adverse effects result:

- Affecting the reliability of the data and more importantly

• Compromising repeatability

One solution has been to perform the vibration measurement task on the machine in a quasi steady -state condition. Consider a typical mine shovel as illustrated on the next page. During routine PM inspections the shovel is stationary at level ground and the 2000HP electric motors are run at constant speed under no-load. Vibration measurements at each of the motor bearings (NDE & DE) are reliable, repeatable and do not suffer from the variations due to operation of the bucket, crowd, swing, or crawl.

$$T = \frac{LOR}{Fmax} = \frac{1}{\Delta f}$$

where:

T - FFT record length in seconds
LOR - Lines of resolution
Fmax - Maximum frequency range
Δf - FFT line spacing (bandwidth)

The limitation of testing in this manner is that fault conditions may only be evident while the equipment is under load, and so the data may be of limited use. Some would say it's better than nothing! But perhaps there is a better way through selective triggering, based on RPM. Defining a repeatable condition of operation or machine state which can be identified through the measurement of certain parameters, such as RPM, direction of rotation, and load, will help ensure that vibration data acquired during this machine state will be reliable and repeatable. In Figure 2 the variation with time of both the RPM and the corresponding vibration level would pose serious problems for meaningful trend data. The establishment of a machine state based on measured parameters, in this case RPM and direction of rotation, will ensure a measure of repeatability and give confidence to trended vibration levels.

Order Tracking and Analysis

In some cases the machinery RPM varies continuously, without even a short interval when the speed is in a pseudo-constant range, making the establishment of a machine state difficult. Normal FFT analysis would result in smeared spectral components due to the fast changing RPM over the period of one FFT record length. The smearing of the frequency components arises due to the fixed sampling rate of the FFT process, the rapid change in RPM, the fixed FFT record length, and the corresponding variation in level and frequency of the vibration. Order tracking is a process whereby a specific frequency component as an example, the 1X, is extracted from a composite of frequency spectra versus RPM. The method is particularly useful for run-up or coast-down measurements where the speed changes occur over a short span, typically 1800RPM to 300RPM, and at a relatively moderate slew rate. The raw data when presented in an X, Y, Z, display is known as a waterfall plot, while the extracted components are referred to as slices (along the Z-axis). The technique of order tracking is used most often as a diagnostic tool, as opposed to a continuous online monitoring method, and is principally employed to identify machinery resonances within the operating speed range. The extracted slices versus RPM (Z-axis) provide the analyst with a clear picture of how the amplitude of the individual frequency components such as the 1X may be exciting certain natural frequencies in the machine structure. Again, the measurement must be carefully configured to avoid smearing, taking into account the FFT record length (T*), RPM interval, and slew rate.

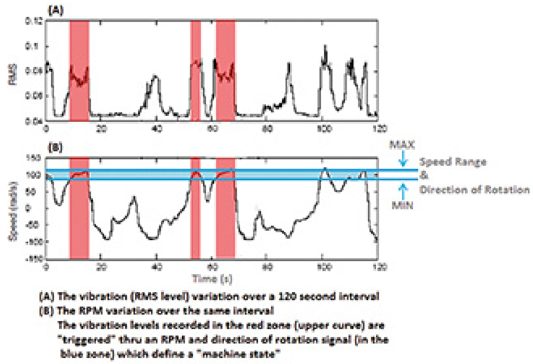

Figure 2: Machine states.

Order analysis on the other hand synchronizes the FFT sample rate with the machine RPM. In the past this procedure was performed in real-time using a tracking frequency multiplier whereby the sampling frequency was derived as an integer multiple (order) of the RPM. In modern digital signal analysis, the time signal and RPM signal are recorded, and the order analysis is performed as a post-processing function whereby interpolation of the RPM signal yields a re-sampling rate applied to the time signal and the subsequent FFT creates the order spectrum.

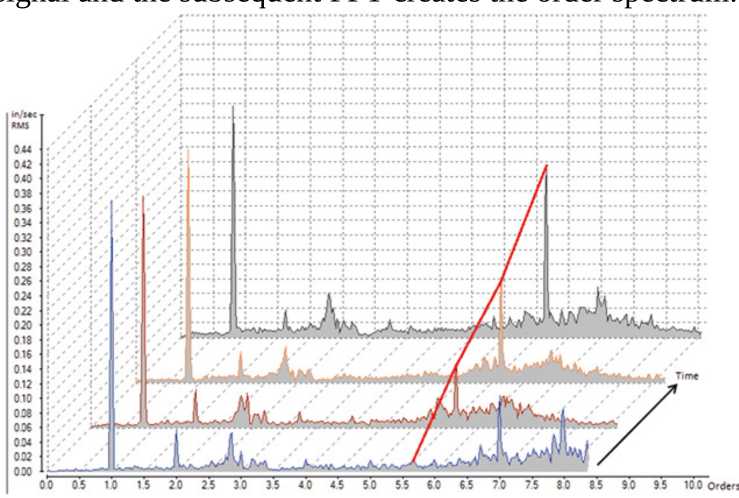

Figure 3: Order spectra versus time.

State-of-the-art online continuous vibration monitoring systems using order analysis provide operators with a reliable and repeatable method of comparing order spectra versus time to visualize trends that arise due to machine condition and not RPM, see Figure 3.

Hardware Installation and Logistics
The selection of machines and corresponding measurement points follows criteria similar to the monitoring of stationary equipment. Those are typically criticality ranking, maintenance history, accessibility and safety considerations. However, there are a few points peculiar to mobile mine equipment requiring additional scrutiny:

- Sensor connectivity and accessibility
- Equipment location within the mine site

• Network communication and PC software configuration

Sensors such as accelerometers are built to withstand harsh industrial conditions, but where cable runs in stationary installations are in a relatively static environment, mobile equipment sensor cables require additional protection against chafing. Small diameter hydraulic hose has been used successfully in these installations. Drilling and tapping for transducer mounting may not be permitted particularly during warranty periods since many OEM's are unfamiliar with the principal behind vibration monitoring and/or may simply object to the attachment of non-approved apparatus by third parties. Some major manufacturers do make provision for accelerometer mounting, but this is often an afterthought and is usually not the ideal measurement point. Current monitoring systems employ TCP/IP network communications and can be equipped with a wireless modem for communication with the in-house Wi-Fi network. Some manufacturers of online vibration monitoring solutions offer hosting of the application and data via cloud servers. This option is becoming increasingly popular and offers many solutions to the questions of in-house network security or outside vendor access. The networking element of the installation requires careful planning, disclosure, and a full understanding of ownership of the data. The IT department are the key players in the installation of the software, configuration of the network, and granting access to the vendor via the cloud, TeamViewer™, or remote desktop applications. Lastly, mine equipment that is completely mobile such as heavy-haul trucks may be required to stop at a data waypoint due to Wi-Fi coverage to upload measurements to the network. Figure 4 provides a generalized view of a typical mine shovel monitoring application.

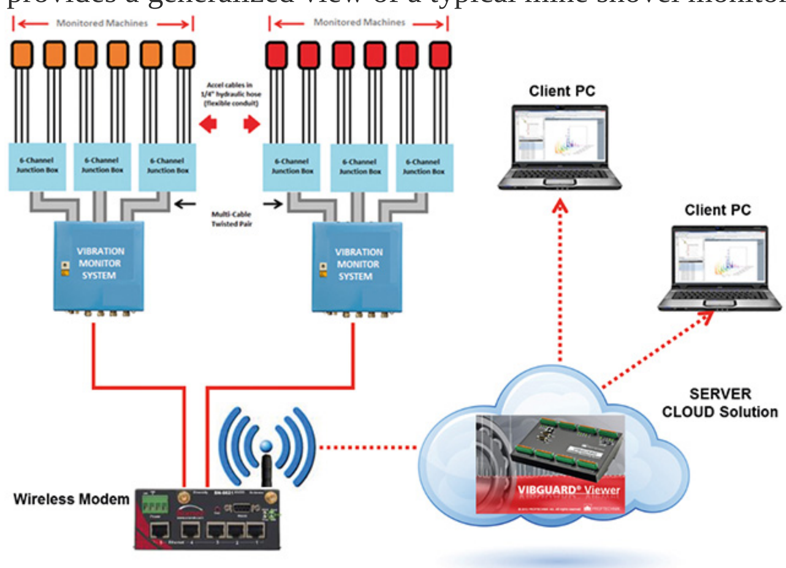

Figure 4: Vibration monitoring overview.

Mine managers, operators, planners, and maintenance personnel are not vibration analysts. They need timely, actionable information about equipment health via a quick and simplified user interface, without waiting days for VA reports. Mobile mine equipment represents huge capital costs – it is expensive to operate, expensive to maintain, and critically important to mine productivity. Vibration monitoring has provided significant savings for many years in the maintenance and operation of stationary plant equipment. Today, with advances in signal processing, transducer design, and networking options, mobile machinery operators can now begin to take advantage of the benefits derived from vibration monitoring – reduced downtime, lower operating and maintenance costs, decreased spare parts inventories, optimized PM schedule, improved equipment availability. The path to reliability-centred maintenance is becoming clearer. Remember – when you want something you have never had, you need to do something you have never done.

///article ends

CONDITION MONITORING SYSTEMS FROM PRUFTECHNIK

- Portable systems for Condition Monitoring
- Sensors and accessories for Condition Monitoring
- Online Condition Monitoring systems
- Condition Monitoring Software
- Machine protection systems
- Continuous wear monitoring system

Vibration monitoring and analysis

Vibration measurements are instrumental in the condition-based maintenance of machines and systems. Conditions can be documented and compared with the state of the art and, in the event of changes in the vibration behavior, the causes can be determined early on. Root cause analysis and fault analysis in the case of unusual vibration behavior is our specialty. We offer vibration-based machine monitoring and condition diagnosis as part of our on-site and remote services.

Mobile on-site vibration analysis:

- Measurements for vibration diagnosis
- Troubleshooting measurements
- Structure-borne sound, vibration severity, shaft vibration (orbit), natural vibration
- Time waveform, frequency and order analysis
- Analysis of vibrations in buildings and pipelines.

Temporary telediagnosis:

- Startup inspection of new or modified machines
- Condition analysis over a period of several weeks
- Special troubleshooting measurements
- Identification, characterization and assessment of temporary disturbing vibrations
- Rental of pre-configured online CMS with analysis service
- This service is available worldwide.
- Condition Monitoring Partner Concept - CPC
- Life cycle monitoring
- Telediagnosis

HONEYWELL at https://www.honeywellprocess.com/en-US/explore/products/advanced-applications/software-operations-excellence/asset-management/Pages/mobile-equipment-monitor.aspx

MATRIKON at http://www.matrikonopc.com/data-connectivity-devices/industrial/industrial-data-logger.aspx

WENCO INTERNATIONAL MINING SYSTEMS at https://www.wencomine.com/maintenance/

Use your machine's OEM data to the fullest extent with ReadyLine, Wenco's real-time and historic asset health management module. ReadyLine provides mines with the ability to minimize the cost of ownership of assets over their lifespan while providing increased availability. This is accomplished using feedback from machine instrumentation combined with user-defined parameters. Drill down through real-time information quickly in the dashboard to analyze trends in machine health or even check on individual parameters. Historical data allows you to identify when equipment exceeded normal operating levels so you can build predictive maintenance routines. Track equipment hours not just by engine-on time but also by activity. Measure shovel bucket movements per hour, hauler bed dumps, or virtually any movement or action that is monitored to plan condition-based maintenance.

Maintenance Monitor

Record details of ongoing repairs to keep all staff in the loop. Stay up-to-date on down equipment with Maintenance Monitor. Our software lets you track all maintenance activities at the mine, keeping everyone in the loop from the first alert to the final status check. The moment any equipment enters a down status, Maintenance Monitor creates a new event on its real-time down display. Then, crew members edit the details to keep themselves, supervisors, and management aware of any repair progress. See the current status, failure cause, affected components, expected duration, and more for each unit undergoing maintenance. Set filters and permissions to show only the information most useful to each user. Follow all equipment, events, and actions currently underway in one easy-to-use program. Plus, Maintenance Monitor includes an inventory system to keep track of machine parts as they move out of storage bays and into commission. When equipment goes down, millions of dollars are on the line. Maintenance Monitor lets everyone know what's happening, when it's happening. It tells maintenance crew which tasks they need to complete. It shows shift supervisors what time equipment will be ready for new assignments. It lets mine managers know the biggest maintenance issues affecting the bottom line. Customizable for your operation's needs, Maintenance Monitor keeps teams working together until down equipment is back in order. Maintenance Monitor gives mines the tool they need to make tracking repairs and upkeep as easy and effective as turning a wrench.

GENERAL ELECTRIC at https://www.gemeasurement.com/condition-monitoring-and-protection?page=2

PARKER HANNIFIN CORP at http://solutions.parker.com/conditionmonitoring

VALMET at http://www.valmet.com/automation-solutions/condition-monitoring/

Condition Monitoring

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Keywords: equipment monitoring, condition-based maintenance, data acquisition, signal processing, decision support, diagnostics, prognostics, hazard function, risk of failure, artificial intelligence

ABSTRACT

Condition monitoring (CM) is a set of various techniques and procedures used in industry to measure the “parameters” of the state/health of equipment, or to observe conditions under which the equipment is operating. People apply CM for early detection of signs of malfunctioning and faults, and then for fault diagnosis and timely corrective or predictive maintenance. The whole combination of CM data acquisition, processing, interpretation, fault detection and maintenance strategy is called the CM system/program (alternatively, Condition-based Maintenance (CBM)). The most common CM techniques are vibration analysis, tribology (oil/debris analysis), visual inspections, current monitoring, conductivity testing, performance (process parameters) monitoring, thermal monitoring, corrosion monitoring, and acoustic (sound/noise) monitoring. The three major steps in a CM system are data acquisition, data processing, and data assessment for decisions (maintenance decision making, fault diagnostics and prediction). This article describes the key points of all three major steps, including CBM, gives a short of history of CM, discusses the implementation, advantages and disadvantages of CM, comments on the future development of CM, and recommends further reading. An example of CM implementation is also included.

INTRODUCTION TO CONDITION MONITORING

Condition monitoring (CM) is a set of various techniques and procedures that people use in industry to measure the “parameters” (also called “features”, or “indicators”) of the state/health of equipment, or to observe conditions under which the equipment is operating. The user’s main interest is in equipment’s proper functioning (i.e., to operate as designed). The British Standards Institution Glossary gives a nice and concise definition of CM: “The continuous or periodic measurement and interpretation of data to indicate the condition of an item to determine the need for maintenance” (BS 3811: 1993). CM is mainly applied for early detection of signs of malfunctioning and faults, and then for faults diagnosis and timely corrective or predictive maintenance. CM is also applied for operation/process control (e.g., to signal a jam on an assembly line and/or to stop the process), or safety control (checking machine’s safety door closure), with a primary goal to prevent or reduce consequences of failures. Two common examples of CM are vibration analysis of rotating machines (e.g., centrifugal pumps, or electrical motors) and oil analysis of combustion engines (analysis of metal particles and contaminants in the lubrication oil), transmissions and hydraulic systems. The whole combination of CM data acquisition, processing, interpretation, fault detection and maintenance strategy is often called **CM system/program** (alternatively, **Condition-based Maintenance** (CBM)).

The British Standards Institution Glossary's definition of CBM is "Maintenance carried out according to need as indicated by condition monitoring". An ideal situation would be to monitor conditions of all elements/parts of the machine, or, at least ones most likely to develop significant problems. Complete monitoring is usually not possible technically, or is expensive, and thus is important to (a) select parts/elements of the system to monitor, (b) select a method of monitoring. Common criteria for selection are based on experience and past information about failure modes and their frequencies, consequences of failures, such as downtime and cost, lost production, low quality of products, and so on, and availability of appropriate techniques. The main purposes of implementing a CM system are to be cost-effective by optimizing the maintenance program, and/or to avoid the consequences of inadequate functioning and failures. CM is either an "off-line" procedure, when measurements/samples are taken and analyzed at predetermined moments of time (or when convenient), or an "on-line" procedure when the measurements are taken (and often analyzed) continuously or at short intervals, by the sensors permanently mounted on the equipment. Often, CM is a combination of various off-line and on-line procedures. A typical example of an off-line procedure is oil analysis, and of an on-line procedure is vibration analysis. Vibration monitoring is still commonly used as an "off-line" technique, if the equipment deteriorates gradually. Now, due to advanced technology, oil analysis can for some cases be applied on-line (e.g., using wear debris light detectors).

The most common CM techniques/methods are vibration analysis, tribology (oil/debris analysis), visual inspections, current monitoring, conductivity testing, performance (process parameters) monitoring, thermal monitoring, corrosion monitoring, acoustic (sound/noise) monitoring.

Monitored parameters/features can be direct, such as thickness (e.g., for brakes), amount of wear, corrosion, or cracks; or indirect, such as pressure, temperature, efficiency, vibration, infrared and ultrasound images; or others, such as operating age. The parameters could be also operational (pressure, temperature, flow rate etc.), or diagnostic (vibration, amount and/or shape of metal particles in oil, water content in oil). Note that parameters/features are aggregated CM indicators calculated from collected raw CM data.

The methods of data/equipment condition assessment can be simple, such as measurement value checking, trending against time, or comparison with templates. They can be more advanced, such as mathematical models of deterioration and risk of failure, and artificial intelligence (AI) methods, such as neural networks and expert systems.

Instruments and software. Instruments/sensors for CM data collection/acquisition could be portable or mounted. Some instruments originated long time ago, such as temperature sensors, stroboscope (1830s) and piezoelectric accelerometer (1920s). Some instruments are more recent, such as fiber-optic laser-diode-based displacement sensors (late 1970s), laser counters combined with image analysis technology, or on-line transducers for wear particle analysis (1991). A lot of new instruments now in use have implemented software for data processing, analysis, display, or wireless storage into a database.

SHORT HISTORY OF CONDITION MONITORING

The development of CM technology was closely connected with development of electronic instruments, transducers, microprocessor technology, software, mathematical modeling, and maintenance strategies. Following [1], the history of CM, after its initial steps, may be briefly separated into four stages: (a) From the 1960s to the mid 1970s, simple methods were used, combining practical experience and elementary instrumentation. (b) In the 1970s the development of analog instrumentation was combined with the development of mainframe computers. At that time clumsy vibrometers came into practice to measure and record vibration. Tape recorders were used to transfer data to computers, where the data was analyzed and interpreted. (c) From the late 1970s to the early 1980s, rapid development of microprocessors made possible development of much more convenient digital instrumentation which was able to collect the data, analyze it, and store the results. (d) In the mid 1980s, instruments became much smaller, faster, and the data was routinely stored on PCs for long term use and development of maintenance strategies. Using CM was still a choice of advanced companies. Now, every more sophisticated piece of equipment arrives with built-in sensors/monitoring devices, and capability for data analysis, problem diagnosis, warning, and even maintenance recommendation. An everyday example is a new model of the private automobile.

Combination of emerging CM techniques, development of mathematical reliability methods and new approaches to maintenance resulted into development of new CM strategies. Initially, people predominantly used failure (breakdown/corrective) based maintenance. Then people started using preventive (time- based) maintenance, and then, with introduction of CM methods, predictive maintenance (or condition-based maintenance). This now resulted in many sophisticated and effective (but sometimes expensive) CM systems.

IMPLEMENTATION OF CONDITION MONITORING

People usually apply CM to systems where faults and problems develop gradually, so they are able to make timely maintenance decisions, such as: (i) to stop the operation immediately (due to an imminent failure with significant consequences), (ii) to stop at the closest convenient time (at the next planned shutdown), (iii) to continue normal operation up to the next planned monitoring, without any particular action. People use collected CM data, also for: (i) prediction of CM parameters/features and estimation of remaining operating life, (ii) long-term planning of further maintenance activities and need for spare parts, (iii) fault detection and diagnostics. The obvious advantages of using CM are in much better control of operation, timely prediction of problems, reduction in downtime, reduction in maintenance costs, planning of activities, etc. Problems related to CM could be in difficulty to select an appropriate CM technique, in possible high initial capital investment in instrumentation, implementation and education of personnel, in necessity of standardized data collection, storage, analysis, and application of results, etc. Often, CM methods cannot provide very reliable results, and then engineers prefer to use their own judgment, in combination with CM. CM may have only marginal benefits, particularly if applied to non-critical equipment, or applied with an inappropriate technique.

Basic steps in implementation and use of CM systems

The basic steps in CM implementation are (1) identification of critical equipment or systems, (2) selection of an appropriate technique/combination of techniques, (3) implementation of the technique (installation of instrumentation, setting baselines/alerts and diagnostics), (4) data acquisition and processing, conditions assessment, and if necessary fault diagnostics and equipment repair, and (5) after certain time the CM system review and adjustment. Selection of a CM system depends on several criteria, such as on the level of known relationship between the parameters and the conditions of the equipment, the ability of the system to provide timely warning of problems or deterioration, the availability of historical data and predefined and absolute standards for the assessment of equipment condition and fault diagnostics, and on the benefit of CM over an existing strategy.

An example of a CM implementation to the oil pump supplying a gas turbine (following [1]):

- **Main failure modes**: Bearing, coupling or impeller wear, oil seal failures (possibly due misalignment), out of balance, cavitation, overload, lack of lubrication or supply restriction.
- **Warning signs**: Changes in vibration, temperature, current and performance (measured as pressures or flows), visible signs of leak.
- **Most critical failures**: Bearing failure; damage could be significant.
- **Least critical failures**: Oil leak and cavitation; no immediate risk.
- **CM techniques**: Vibration analysis (prediction of failures caused by imbalance, misalignment, cavitation, wear and lack of lubrication), general inspection (looking for leaks, noise and changes in pump performance).
- **Setting up CM**: Select and mark the measurement locations on the pump. Take vibration readings monthly on all motor and pump bearings, and on casing. In case of first warning signs, take readings more often. Set alarm and warning levels.
- **Reviewing**: Review alarm and warning levels to optimize balance between failure consequences and excessive maintenance. Review regular measurement interval to decrease it, or to increase it. After a certain period of time, review usefulness of the whole CM system by checking reduction in failure frequency, pump performance, increase/decrease in maintenance efforts, cost benefits.

MORE DETAILS ON KEY STEPS IN CM SYSTEMS/PROGRAMS

The three major steps in a CM system are data acquisition, data processing, and data assessment in combination with decision making.

Data acquisition (data information collecting)

Data can be obtained from various sources, either by monitoring direct (thickness), or indirect (pressure, efficiency, vibration, cumulative stress parameters) state parameters, and by using various CM techniques and instrumentation/sensors. Methods of data acquisition are local inspections, local instrumentation, process computers, portable monitoring equipment, and built-in monitoring equipment/sensors.

The most common CM techniques are

- **Vibration analysis** (the most used and most convenient for on-line CM in industry today; intends to predict imbalance, eccentricity, looseness, misalignment, wear/damage, and so on),
- **Temperature analysis** (monitoring of operational/surface temperature emission - that is, infrared energy sources, using optical pyrometers, thermocouples, thermography, resistance thermometers),
- **Tribology** (oil/wear debris analysis of the lubricating and hydraulic oil)
- **Performance/process parameters monitoring** (measuring operating efficiency; possibly the most serious limiting factor in production),
- **Visual/aural inspections** (visual signs of problems by trained eye, such as overheating, leaks, noise, smell, decay; video surveillance of operation, utilization of visual instruments; these methods are usually cheap and easy to implement)
- **Other techniques**, such as current monitoring, conductivity testing, corrosion monitoring, and acoustic (sound/noise) monitoring.

Data processing

In the data processing step the acquired raw CM data is validated, and then transformed in a convenient form. After validation, the data may be either used in a raw form, such as from temperature, pressure, number and form of metal particles in oil, or in a transformed form (from vibration data, thermal images, acoustic data). The data can be collected as a direct value (*value type*) of the measured parameter (oil data, temperature, performance parameter), a time series (*waveform type*), where one measurement consists of information from a (usually short) time interval (vibration, acoustic data), and space-specific (*multi-dimension type*), where one measurement collects information over an area or volume (visual images, infrared thermographs, X-ray images, ultra-sound images). The **value type data** is either used directly, or some simple transformations is applied to it, such as rates of change, cumulative values, ratios between different variables, and various performance measures and health indicators. The raw waveform and multi-dimension data type is always transformed (a procedure called ‘signal processing’, or ‘feature/parameter extraction’) into a form convenient for diagnostic and prognostic purpose. The **multi-dimension type data** is most often transformed into plain images (infrared photo), or into some overall features of the image, such as density of points. The **waveform type data** is processed in time domain, frequency domain, or combined time-frequency domain. Some overall characteristics of the raw signal (e.g. vibration) are calculated in time domain, such as the mean, peak, peak-to-pick, standard deviation, crest factor, skewness, and kurtosis. In frequency domain, the contribution of different waves to the whole signal is analyzed (characterized by their frequencies and “weights” - amplitudes). A typical method of signal processing is to use frequency analysis (called spectral analysis or vibration signature analysis), by applying the Fast Fourier Transform (FFT) to the signal to calculate power spectrum. Then the overall measures of the spectrum are used (overall root-mean-square - RMS), as well as the measures of different frequency bands. Different frequency bands are indicative of different failure modes, or problems with different component of the system. This feature of the vibration signal is one which makes the vibration analysis the most popular of all CM techniques. The analysis must be adjusted to the operating conditions, notably to RPM (revolution per minute) for rotating machinery. For example, the changes of amplitudes in the frequency band of $1\times$ RPM may be indicative of motor imbalance, and in $2\times$RPM of mechanical looseness. In combined time-frequency domain, time and frequency characteristics of the signal are analyzed simultaneously, using joint time-frequency distributions, or more advanced methods, such as wavelet transforms.

Data management and interpretation and use in decision support

The final step in a CM system is the analysis and interpretation of the extracted parameters. The parameters can be used for **online decisions**, as described in the implementation section above, for **fault diagnostics** (detection, isolation, and identifications of faults when they occur), and for **prognostics** (prediction of time and type of potential faults).

Fault diagnostics

For fault diagnostics people use various statistical methods (statistical process control, pattern recognition, cluster analysis), system parameters, and artificial intelligence methods. The most common method for on-line fault detection is to use **signal levels** for monitored parameters, that is, predetermined control values (such as in oil analysis and vibration). This method falls into category of statistical process control (SPC), originating in statistical quality control. Typical signal levels are selected to show normal state, warning state, and alarming state of operation. Different parameters should be indicative of different problems, e.g., in oil analysis depending on metallurgy of components, or in vibration analysis depending on vibration frequencies of different parts. The signal levels are established either by manufacturer's recommendations, or from theory, or found by experience and experimentation. The other possibility is to use **pattern recognition**, when a suitable parameter is recorded over time and compared with templates for normal operation and different faults, often using some methods of automatic recognition. The **system parameters** method is used when the system can be described by a mathematical model with system parameters directly related to system conditions. The template (or *norma*l) parameters of the system are estimated from the past data of healthy systems. Changes in current parameter values indicate changes in system conditions and/or development of certain faults. **Artificial intelligence** (AI) methods are used for fault diagnostics, particularly with larger and more complicated systems. These include Artificial Neural Networks (ANNs), Fuzzy Logic Systems (FLS), Expert Systems (ES), Case-based Reasoning (CBR), and other emerging techniques. The application of AI in fault diagnostics and other areas of CM plays a leading role in the development of Intelligent Manufacturing Systems (IMS), which are now in increasing use. Practical applications of AI methods are still not widespread, due to the need for large amounts of past data (measurement and faults histories) and qualified judgments from experts, required for system training.

Prognostics

Prognostics use past and current CM data to predict the future behavior of the equipment by forecasting parameters/features, or estimating remaining useful life (RUL - expected useful life). Also, estimation of the probability of failure before the next inspection is of great interest, particularly when safety issues are important (e.g., in the nuclear industry). The main methods for prognostics are, as for fault diagnostics, statistical, model-based, and AI based. Of the statistical methods, **trending** is the most popular and simplest. The users extrapolate current and past measurements of parameters (e.g., using linear, or exponential trends) to predict when the parameters will cross warning (or alarm limits), to be able to prepare remedial actions. This method works well when measurements show clear, monotonic trend, but is less useful when measurements show large variations (for example, from the authors' experience, in oil analysis). Mathematical models of risk in the form of **hazard function** or **risk of failure** are a useful tool for risk prediction. Hazard function is particularly useful for short-term risk predictions when it includes operating time and measurements (in this area often called 'covariates'), e.g. in a form of Proportional-Hazards Model – PHM (***see risk0469**). It is also useful for long term predictions of probability of failure and RUL, when combined with a dynamic probabilistic model for parameters. The current hazard value can also be successfully used as a decision variable, by comparison with warning/alarming hazard levels. **Model-based** methods use a mathematical model for the equipment's operation in time, based on its structure, physical properties, and measurements (e.g. Kalman filter for wear prediction, or prediction of fatigue crack dynamics). The risk-based and model-based methods are often combined with economic consequences for optimization of maintenance activities.

FINAL COMMENTS AND RECOMMENDED READINGS

The rapid development and widespread use of CM can be easily observed from the internet. A search for **condition monitor** (industry) in product category results, revealed 50 categories of products, with about 7000 companies and products. For example, the category *Machine and Process Monitors and CM Systems* listed 214 companies, *CM and Machine Maintenance Services* 148, *Non-destructive testing (NDT)* 706, and *Oil Sensors/Analyzers 34*. Following [2], the **next generation of CM systems** will likely focus on continuous monitoring and automatic diagnostic and prognostics, and thus on the design of intelligent devices (e.g., micro-electro-mechanical systems technology) which will be able to monitor their own health using on-line data acquisition, signal processing and diagnostics tools.

Suggested reading for a quick introduction to CM and CBM are [1], [3] and [4]. For more information, see [5], [6], [7] (mostly on vibration), and [8]. Practical guides and overviews of CM techniques and instrumentation (though some of the instrumentation information is out-of date) are [9] and [10]. A good introduction to multiple sensor data fusion is [11]. For a more advanced introduction to model-based fault diagnostics see [12]. Various practical implementations of CM can be found in the previous references, and also in [13]. For an overview of AI methods, with some applications, see [14]. A good introductory **review article** of CM, with application to machine tools, is [15]. For a detailed overview of CM data processing, diagnostics and prognostic, see [2], and for applications of PHM in CM, see [16]. For an overview of the **history** of CM (with emphasis on vibration analysis), see [17].

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