Centre for Maintenance Optimization & Reliability Engineering

Director
Chi-Guhn Lee

Semi-annual report

December 5, 2019
Charbonnel Lounge, St. Michael's College

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Executive summary

Chi-Guhn Lee, C-MORE Director

Introduction

The following report summarizes work undertaken between C-MORE and collaborating companies and notes the major changes at C-MORE since the meeting in June 2019. I'd like to highlight just a few of our efforts.

I am particularly excited about the new course we will be offering, together with the School of Continuing Studies. Andrew Jardine's annual Physical Asset Management course has attracted industry professionals for years, and we adding to it with a course called PAM 2 - Machine Learning and other Emerging Technologies. We anticipate it will be first offered in May 2020.

We are keeping up with the C-MORE agenda of being a leader in machine learning in maintenance, reliability, and asset management. Our general research is going in this direction, and I am happy to say our efforts have been recognized outside C-MORE: in a recent example, Janet sat on the innovation panel at the MainTrain conference in Edmonton.

In another area of innovation, we have been working on a new website for our group (https://cmore.mie.utoronto.ca). News and new research will be posted there, and it will allow password protected areas for members and guests. This should enhance collaboration and permit more timely dissemination of news.

As director, I continued to lead C-MORE in research projects and industry partnerships throughout this term. I gave several talks on integrating machine learning technologies in the area of physical asset management and am working steadily on developing relationships with various organizations to increase C-MORE's presence in the area of asset management in the face of emerging technologies. In particular, I met with professors from Korea Advanced Institute of Science and Technology and University of the West Indies and attended workshops at the Korea Asset Management Forum.

Finally, this meeting marks the 25th anniversary of C-MORE. This is a milestone in the life of an excellent research facility. I am proud to play a part in its ongoing evolution.

The C-MORE team

Janet Lam, Assistant Director

Since June, Janet has continued to work on various projects with all member companies through direct research as well as student supervision. Aside from the various meetings with member companies and other industry partners, she spoke at Kinross' biannual asset management conference at Niagara on the Lake in September. This was an opportunity to meet with many members at Kinross, improving the buy-in of the individuals at Kinross to C-MORE's activities. In September, Janet also attended the MainTrain conference held by PEMAC in Edmonton, where she gave a talk titled "Applications of machine learning in the field of reliability and maintenance optimization" and was one of four members on the Innovation Panel on the final day of the conference.

Andrew K. S. Jardine, Professor Emeritus

Professor Jardine has continued to teach aspects of Engineering Asset Management at both the graduate and post-experience levels. He has also participated by invitation at several conferences during the past six months (Canada, USA, Switzerland) where his presentations focused on the general area of Evidence Based Asset Management. He was honoured to receive the 2019 Highly Commended Award from Emerald Publishing for paper titled "Maintenance Strategies: Decision Making Grid vs. Jack-Knife Diagram," published in *Journal of Quality in Maintenance Engineering*. The paper's co-authors were Turuna Seecharan (lead author and a former C-MORE post-doctoral fellow) and Ashraf Labib (University of Portsmouth, England).

Dragan Banjevic, C-MORE Consultant

In his work with C-MORE, Dragan has collaborated with Janet on projects with Consortium members, notably with TTC and DND and to some extent with MOD and Kinross Gold. He has also provided help in other projects with C-MORE students.

Sharareh Taghipour, Affiliate Professor, Ryerson University

Sharareh is currently supervising/co-supervising two postdoctoral fellows, seven PhD students, two Master's students, and two undergraduates. She is co-teaching a graduate course, Engineering Asset Management, at the University of Toronto with Andrew Jardine, and she is serving on a number of committees at Ryerson University, including the Department Hiring Committee (DHC), Strategic Research Plan (SRP) Steering Committee, and Faculty Awards Committee.

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Scott has been involved in a range of applied projects covering network and power grid security, predictive modelling for residential HVAC, prediction of high resource health users with the Dalla Lana School of Public Health, uses of social media in financial applications, a new project for traffic signal control in large urban traffic networks, and a number of projects involving recommender systems for eCommerce applications. Scott also continues to engage in fundamental research on machine learning and data mining (journal article accepted by IEEE TKDE), with applications to HVAC (journal article accepted by *Building and Environment*) and biotechnology (journal article accepted by *Communications Biology*), as well as recommendation systems and deep learning (conference paper accepted for RecSys 2019).

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Fae's research group now consists of 4 doctoral students, 3 MASc students, and 1 undergraduate student. Her projects include: complex naval asset management using sensor data, optimizing the fabrication and performance of multifunctional cementitious composites, fibre optic sensors for vibration monitoring, sensing system for gait analysis, bridge scour monitoring, condition-based maintenance of bridges, and compression creep behaviour of lead-free solder alloys. Her students Niloofar, Fredric, and Raymond presented their work at IWSHM 2019 at Stanford. Fae has been meeting with various people in the industry regarding research opportunities. Her lab was recently relocated, and she is in the process of obtaining more equipment.

Jue Wang, Affiliate Professor, Queen's University
Jue is an Assistant Professor at Smith School of Business, Queen's University. His research field is maintenance optimization, with a particular focus on condition-based maintenance, and optimization of smart and connected products. He has collaborated with industrial partners in mining, power grid, and manufacturing. His research has appeared in top journals such as *Operations Research* and *Naval Research Logistics*. He received his PhD from University of Toronto

Somayeh Alizadeh, Visiting Professor
Somayeh is an Associate Professor in the Industrial Engineering faculty at Khaje Nasir Toosi University in Iran. She joined C-MORE as a visiting scholar in July. Since her arrival, Somayeh has been researching Association Rule Mining and Sequence Pattern Mining. More specifically, she is using Sequence Pattern Mining algorithms on CEA data produced through the maintenance of hydroelectric generating units.

Ali Zuashkiani, Director of Educational Programs
Ali has been active in providing consulting services to various industries such as oil and gas, power generation and distribution, mining, and petrochemical. He has been especially busy working with a major utility company (Marafiq) to improve their Operation and Maintenance business processes and procedures. Ali has also been working with Don Barry and Steve Sinkoff to develop CMORE's 5-day comprehensive spare parts management program.

C-MORE students and postdoctoral fellows

Li Yang, postdoctoral fellow
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Grid Canada to discuss the overall health management control system of smart grid network, and their smart manufacturing process. Li is currently working on two research topics: prognostics of remaining useful lifetime integrating statistical model and machine learning process, and prognostics technology via fusion of multiple sensor data. He has submitted two journal papers; they are under review and appear in the list of publications.

Aakash Iyer, MEng student
Aakash is a 2nd year graduate student pursuing his Master's of Engineering degree in Mechanical and Industrial Engineering with an emphasis on Data Analytics, and an MEng certification in Financial Engineering. His main research project under the supervision of Professor Chi-Guhn Lee and Dr. Li Yang deals with developing a hybrid approach to RUL estimation using Deep Learning algorithms and stochastic processes. Since September 2019, he has analysed data driven and model driven approaches to RUL estimation. He is also volunteering with Dr. Li Yang in the KPI analysis for Kinross Gold.

Kuilin Chen, PhD student
Kuilin continues his research in digital twin for reheat furnace. He is currently working on probabilistic sequence-to-sequence learning models. A more detailed review of this work is included later in the Report and will be presented at the consortium meeting. He is working toward his PhD qualifying exam in the near future.

Michael Gimelfarb, PhD student
Michael is working on Bayesian region identification and policy transfer in reinforcement learning (RL) with multiple source tasks to improve the sample efficiency of modern state-of-the-art RL methods. In this framework, a reinforcement learning agent is presented with multiple solved source tasks (both dynamics models and optimal policies) and uses transitions data collected in the new target task to reason about local task similarity for the source tasks in each state. Only dynamics differ between source and target tasks. This posterior distribution over source tasks is parameterized as a deep neural network, in order to allow efficient and scalable inference. This posterior is then used to sample actions from the source tasks to help guide the agent to promising regions of the state space and learn a good policy more efficiently. He is planning to submit this work to the International Conference on Machine Learning (ICML) in January 2020. A more detailed write-up is provided later in the Report.

Scott Koshman, PhD student
Scott Koshman is on an academic leave of absence to enjoy being a full time parent to his newborn daughter. He will be returning to academic research in fall 2020.

Saravanan Kumar, MEng student
Saravanan is currently working on his MEng project with the Toronto Transit Commission (TTC) to help optimize the re-inspection schedule for TTC's rail defects. He has pre-processed inspection data from TTC's Non-Destructive Testing (NDT) team from years 2015-18 to develop statistics that can be used to build a re-inspection optimization model. Further, he will use the defect priority transition data to optimize

the re-inspection schedule with the objective of maintaining current track reliability. His study will provide for future scope to include defect modes, geometry of track and location of defects for sensitizing the re-inspection schedule.

Arun Shanmugam, MEng student
Arun is an MEng student in Mechanical and Industrial Engineering. He is working on a reliability study of Propulsion Diesel Engines in Halifax Class frigates for the Department of National Defence (Navy).

Avi Sokol, PhD student
As a flex-time PhD student and a full-time employee, Avi continues to research integration of Reinforcement Learning and Inventory Control to reduce waste in supply chains. In the past 6 months, Avi did a literature review of inventory control theory and practice, along with the emerging trends in reinforcement learning. As a proof of concept, he developed 2 reinforcement learning inventory models applying deep Q-learning and policy gradient methods. Both achieved near-optimal solutions.

Bin Yang, visiting PhD student
Bin is a visiting PhD student from Xi'an Jiaotong University. His research focuses on applying transfer learning to automatically recognize the health states of machines such as locomotive bearings and wind turbine gearboxes. His paper "An intelligent fault diagnosis approach based on transfer learning from laboratory bearings to locomotive bearings" was published in *Mechanical Systems and Signal Processing*. His paper "A polynomial kernel induced distance metric to improve deep transfer learning for fault diagnosis of machines" was published in *IEEE Transactions on Industrial Electronics*. More details on the papers appear in "Overall project direction."

Zihan Zhang, MASc student
Zihan began her MASc program in September 2019. In addition to completing three courses (Linear Programming and Networks, Stochastic Processes, Engineering Asset Management), she has made progress as follows: finished a project proposal for TITAN with Li; processed vibration signals and analysed them in both time and frequency domain; gave a rough research proposal for her thesis with Li's help; continued studying GNN and other AI techniques and tried to define the system graph network.

C-MORE activities with consortium members

Defence Science and Technology Laboratory (DSTL)
C-MORE and DSTL continued progress on the long-term procurement project; we looked at the effect of a probabilistic distribution among the parameters and computed the equivalent project values and durations, in other words, the required relative yield of a shorter project to have equal value to a longer project. Tim Jefferis also proposed a project inspecting different types of maintenance projects that require different levels of investment at the management level. Both projects will be presented at the meeting.

Department of National Defence
The DND team and C-MORE have been working diligently on the propulsion diesel engine health analysis project. Defining a failure that can be identified in the data was a challenge that the team overcame together. As detailed information is not easy to extract, we have worked on alternative methods that can act as a proxy to clear definitions.

Kinross
Kinross invited C-MORE to speak at its bi-annual asset management conference at Niagara on the Lake. Janet spoke to the group about applications of C-MORE's work in the mining industry. Li, Aakash, and Jiayue are working on the new KPI project – determining the KPI factors that affect equipment availability. This project will be presented at the meeting.

Teck Resources
Graeme Dillon proposed a project on determining the late-life of engines in haul trucks. The question is to decide whether an asset should be retired or refit at about 60% of the expected life, based on its previous performance. Two engines that are the same age may have a different result, if one has performed well in its youth, while another has caused a lot of headaches and has clocked in many hours in the shop.

Toronto Transit Commission
Since the last meeting, C-MORE and TTC have continued progress on the re-inspection project. In October, there was an important discovery that when defects change status from a low-priority to a high-priority defect, they are re-entered into the system as a new defect. These pairs of entries had to be linked and identified as one defect to allow proper analysis. This project will be presented at the meeting.

C-MORE educational programs

Andrew Jardine gave his annual course on Physical Asset Management in November 2019, in conjunction with the School of Continuing Studies (SCS) and co-taught by Don Barry. Ali Zuashkiani, Don Barry, and Steve Sinkoff are developing a new course to be offered by C-MORE and SCS. This 5-day comprehensive course, PAM 2 – Machine Learning and Other Emerging Technologies, should be offered in May 2020. It will complement Andrew Jardine's ongoing and extremely popular PAM course.

Concluding remarks

This has been an extremely busy six months at C-MORE. As always, I want to thank the C-MORE staff and students and all collaborating Consortium members for their hard work. This is indeed a collaborative effort!

Chi-Guhn Lee
December 2019

C-MORE – 25th anniversary
Elizabeth Thompson

December 2019 marks the 25th anniversary of the Centre for Maintenance Optimization and Reliability Engineering (C-MORE) at the University of Toronto. This is a milestone in the life of an outstanding research facility.

C-MORE was founded in 1994 at the University of Toronto by Professor Andrew K.S. Jardine, with the help of the Manufacturing Research Corporation of Ontario (MRCO). Its goal was to advance Professor Jardine's ground-breaking theoretical work on condition-based maintenance (CBM) optimization. His vision included a dedicated research centre involving industry, faculty, researchers, and graduate students. The driving idea behind the initial Consortium, which evolved into the Centre for Maintenance Optimization and Reliability Engineering (C-MORE) in 2007, was the need to develop a mathematical model to arrive at equipment replacement decision indicators that were more accurate than relying either on the age of equipment or its current condition. Professor Jardine approached MRCO, working with Joe Brennan to get the financial support of NSERC and find industry partners. The idea immediately took off; MRCO and NSERC came on board, along with a number of industry partners.

The inaugural meeting was December 1, 1994. The lab's first members were Alcoa, Molson Breweries, Dofasco Inc., Oliver Interactive Inc., and Wear Check Canada Inc. The CBM lab opened for business with 3 researchers working under Professor Jardine: Dragan Banjevic, Marguerite Ennis, and Dusan Braticevic. Professor Viliam Makis was another team member; there were 7 graduate students and an administrator. By 1998, the lab had produced its EXAKT software, now commercially available; the software indicates the optimal time to renew, repair, or replace equipment subject to condition monitoring.

Possibly the biggest change in 25 years has been the retirement of Andrew Jardine, but with Director Chi-Guhn Lee at the helm (July 2017), C-MORE is obviously in good hands. Professor Lee is working hard to move maintenance optimization and asset management up to speed with the new technology in machine learning (ML) and artificial intelligence (AI). He wants to honour the work done in the past but boost it using ML to streamline CBM processes and access previously unavailable information.

For 25 years, C-MORE has expanded and evolved, using its combined industry and

NSERC funding to perform valuable research in asset management in condition based maintenance, spares management, maintenance and repair contracts, and failure-finding intervals for protective devices. Simply stated, C-MORE's goal in working with some of the world's leading asset-intensive industries such as utilities, mining, and the military is to take advantage of their existing data to make good evidence-based management decisions. This has not changed.

Current Consortium members who fund the Centre and profit from its research are Defence Science and Technology Laboratory, Department of National Defence, Kinross Gold, Teck Resources, and Toronto Transit Corporation. Together with C-MORE staff, they are working on the following projects: CBM for a frigate propulsion diesel engine (DND), a track re-inspection policy (TTC), a comparison of procurement duration periods (DSTL), data analytics using key performance indicators (Kinross), and equipment life extension decision support (Teck).

C-MORE has 2 PhD students, 1 MASc student, 1 visiting PhD student (soon to grow to 3 or 4), and 2 postdoctoral fellows. There are 2 staff members, Janet Lam and Dragan Banjevic, and 4 collaborating researchers, Scott Sanner, Fae Azhari, Sharareh Taghipour, and Jue Wang. Andrew Jardine continues to work with C-MORE as well, consulting or teaching courses to both graduate students and post-experience students.

In addition to EXAKT, C-MORE has commercialized its Spares Management Software (SMS) and introduced software to determine when to inspect protective devices for hidden failures. The work of C-MORE's researchers and students has been published in books and journals, taught to industry professionals at certificate-granting courses, and disseminated at conferences. C-MORE is an internationally recognized, world-class research facility with strong roots in addressing challenging real-world industry asset management decision problems.

Visits and interactions with consortium members and others

June 2019—December 2019

June 14, 2019
Murray Wiseman and Janet met to discuss potential models for expanding the C-MORE professional education program to Tecsup in Peru.

June 15-19, 2019
Chi-Guhn attended the Canada Korea Conference, Banff and gave a presentation on transfer learning from multiple experts.

June 16-18, 2019
Chi-Guhn attended the 2nd Canada-Korea joint committee meeting in Banff.

June 17-18, 2019
Scott Sanner was invited to speak at a Google Workshop on New Frontiers in Recommendation Systems at the Mountain View campus.

June 20, 2019 **GE Grid**
C-MORE joined the full-day meeting with GE Grid to explore different collaborative and research options.

June 25, 2019 **DND**
DND and Janet had a conference call to discuss progress on the PDE engine health analysis project. We determined that the cost of purchase orders being greater than 35,000 might be considered as failures.

June 27, 2019 **Kinross**
Emilio and Brian had a conference call with Janet to discuss the completion of the haul truck engine health analysis project. It was decided that a meeting with the staff at Round Mountain would be made to communicate the results of the project.

July 3, 2019
Janet had a phone call with Matthew Revie from University of Strathclyde to discuss how expert judgement might be used in maintenance and asset management.

July 4, 2019 **PLC Group**
Chi-Guhn and Janet visited the PLC Group office in Mississauga to discuss their existing tools and how C-MORE's research could be used to augment their systems.

July 8, 2019 **Brightorder**
Chi-Guhn and Janet visited the Brightorder office in Mississauga to discuss EXAKT and how its algorithms operate. Brightorder expressed interest in developing an expansion of EXAKT.

July 10-15, 2019
Scott Sanner attended the ICAPS conference in Berkeley California to present a tutorial on traffic signal control.

July 10, 2019 **Challenger**
Chi-Guhn and Janet had a conference call with Zahi Mitri of Challenger logistics to discuss potential areas of collaboration.

July 11, 2019 **Kinross**
Chi-Guhn and Janet had a conference call/in-person meeting with Emilio and Brian of Kinross to discuss next projects. We discussed a project that leverages reported KPI values in order to make predictions about equipment availability.

July 16, 2019
The C-MORE team had a conference call Tecsup and Murray Wiseman to discuss potential models to bring the PAM courses to Peru. Several potential models were proposed, to be considered by each party independently.

July 21-25, 2019
Scott Sanner attended the SIGIR conference in Paris France to present two papers.

July 24, 2019 **Challenger**
Chi-Guhn and Janet met with Zahi Mitri and Jim Peeples of Challenger logistics at the University of Toronto campus during their half-day meeting with various researchers at U of T. They are interested in developing models for fuel consumption reduction using maintenance techniques.

July 25, 2019 **GE Grid**
Li and Janet visited the GE Grid Markham office with FASE professors Zeb Tate and Ali Hooshyar to find out GE's main business focusses, and to discuss how maintenance may affect their operations.

August 6, 2019 **Challenger**
Janet hosted a web-conference to demonstrate EXAKT to the team at Challenger in order to illustrate how it could be leveraged for their fuel consumption problem.

August 6, 2019
Chi-Guhn hosted a workshop on ML and Advanced Manufacturing with Korea Advanced Institute of Science and Technology (KAIST).

August 7, 2019
Chi-Guhn had a meeting with Erwin Ekwue (Dean of Engineering at University of the West Indies) to discuss a possible collaboration on education.

August 9, 2019
Chi-Guhn had a meeting with Kishore Jhagroo (Professor from University of the West Indies) to discuss collaborative master program on maintenance and reliability optimization.

August 7, 2019
Chi-Guhn had a meeting with Erwin Ekwue (Dean of Engineering at University of the West Indies) to discuss a possible collaboration on education.

August 19-23, 2019
Chi-Guhn and Andrew attended a bootcamp on Machine Learning hosted by the U of T Faculty of Applied Science and Engineering.

August 26, 2019 **Challenger**
Chi-Guhn and Janet participated in a conference call with Challenger to discuss potential models of collaboration.

August 27, 2019 **Teck**
Janet and Graeme Dillon had a call to discuss a project with Teck. The project pertained to decision support in the late-life extension or retirement of a truck engine.

September 5, 2019 **DND**
Janet and Arun had a conference call with DND to discuss progress on the PDE health analysis project.

September 12 – November 28, 2019
Andrew taught a graduate course: Engineering Asset Management at U of T.

September 13, 2019 **Exxon Mobil**
Chi-Guhn and Janet had a conference call with many members of Exxon Mobil to discuss different areas of collaboration and our research portfolio.

September 16-18, 2019
Scott Sanner attended the RecSys Conference in Copenhagen Denmark to present a paper.

September 16-19, 2019
Janet attended the MainTrain conference by PEMAC in Edmonton. She presented a talk on applications of machine learning in maintenance and reliability. She sat as a panelist in the innovation talk on the final day.

September 17, 2019
Chi-Guhn and Somayeh attended the Canadian Electricity Association Consultative Committee on Outage Statistics in Ottawa to give a workshop in machine learning technologies for physical asset management.

September 18, 2019
Chi-Guhn visited the National Research Council (NRC) to discuss a possible collaboration.

September 24, 2019 **DND**
Janet and Arun had a conference call with DND on the progress of the PDE health analysis project. We had some unexpected results in the probability distribution of failure times.

September 25, 2019 **Kinross**
Janet visited Kinross's Biannual Asset Management conference at Niagara on the Lake. She presented on mining-related projects that C-MORE has completed over the years to inspire ideas in the Kinross team.

September 27, 2019 **Safety Power**
Janet and Li visited Safety Power's Mississauga office and Chi-Guhn joined by conference call to discuss control systems and how C-MORE's work in data analytics may be integrated to Safety Power's systems.

October 2, 2019 **Iris R&D**
Chi-Guhn and Janet had a conference call with David Keaney and Emil Ramos of Iris group to discuss research in managing municipal mobile assets.

October 21, 2019 **TTC**
TTC's Daniel Morneau, Krunal Mistry and Kevin Mak visited C-MORE to discuss potential projects with train and streetcar reliability. In particular, we discussed the systems that are used to open and close the train doors.

October 22, 2019 **TTC**
Janet and Kumar visited Jennifer, Hossein and Tauqeer at their Dundas West office to discuss the NDT reinspection project. It was discovered that when defects transition from low-priority to high-priority, they are re-entered as new defects.

October 23, 2019 **PEMAC**
Andrew became a member of the Planet Engineering and Maintenance Association of Canada (PEMAC) awards committee.

October 24, 2019
Andrew gave a keynote presentation titled "University/Industry Collaboration: Use of Analytics for Evidence Based Physical Asset Management" at the 4^{th} North American Conference on Industrial Engineering & Operations Management, Toronto, Canada October 23 – 25, 2019.

October 30, 2019
Andrew gave a presentation titled "Case Study: Institute of Asset Management (IAM) & International Society of Engineering Asset Management (ISEAM)" at IMA conference in Lugano, Switzerland. The presentation was co-authored with Professor Joe Amadi-Echendu.

November 4-8, 2019
Andrew presented and attended University's annual Physical Asset Management program, Chestnut Residence, Toronto. Chi-Guhn gave a guest lecture in the course on Machine Learning for physical asset management.

November 13, 2019
Andrew was appointed as a member of the program committee for WCEAM 2020 (World Congress on Engineering Asset Management), Bonito, Brazil 16-19 August, 2020.

November 21, 2019
Chi-Guhn attended the Korea Asset Management Forum (KAMF) Workshop to represent Deep Learning for PAM.

December 9, 2019
Andrew gave a presentation titled "An Analytic Toolbox for Optimizing Condition Based Maintenance (CBM) Decision" at International Maintenance Conference (IMC), Florida, December 9-13, 2019.

C-MORE leadership activities

Chi-Guhn Lee, Director

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Somayeh Alizadeh, Visiting Professor

Somayeh is an Associate Professor in the Industrial Engineering faculty at Khaje Nasir Toosi University in Iran. She joined C-MORE as a visiting scholar in July. Since her arrival, Somayeh has been researching Association Rule Mining and Sequence Pattern Mining. She has used Sequence Pattern Mining algorithms on CEA data produced through the maintenance of hydroelectric generating units. The patterns' relevance to maintenance activities, especially sequenced activities, have been extracted using Sequence Pattern Mining algorithms. These patterns reduce downtime by determining the occurrence of the next maintenance activity or next component outage. The method helps to predict the future events of generating units and the next outage. There is a concern about a time gap among discovered events in patterns. For example, the sequence of two events (outages) with a one-month gap cannot be accepted as an interesting sequence. Therefore, she has focused on the time constraint problem in Sequence Pattern Mining. She is looking at Sequential Pattern Mining algorithms which could be able to consider the time gap problem.

Overall project direction

Janet Lam, Assistant Director

Goals and retrospectives

This section highlights the some of the main achievements in C-MORE for the period June 2019 – December 2019. This year, C-MORE's staff and students made steady progress on all projects with members, and attended conferences and courses across the globe. In particular, PEMAC's MainTrain conference in Edmonton was a great opportunity to share C-MORE's research with Canadian maintenance practitioners.

We submitted a grant proposal for DND's All System's Go challenge on connected maintenance on army equipment. The title of this proposal is "A multi-dimensional optimal health model strategy for condition-based maintenance."

C-MORE has entered into an agreement with the School of Continuing Studies to formally offer a Physical Asset Management 2 course that emphasizes emerging technologies and acts as the continuation of the existing PAM course. In November, TAMS and C-MORE hosted the first joint PAM course at Inha University in Korea.

Activities

Theoretical work

This section on theoretical work is oriented toward students' and postdoctoral fellows' research topics.

Name	Activity
Li Yang, postdoctoral fellow	Since the last meeting, Li attended the 11th International Conference on Mathematical Methods in Reliability and gave a presentation titled "Operations &Maintenance of Wind Farms Incorporating Multiple Impacts of Wind Conditions." He also met with GE Grid Canada to discuss the overall health management control system of smart grid network, and their smart manufacturing process. Li is currently working on two research topics: prognostic of remaining useful lifetime integrating statistical model and machine learning process,

	and prognostic technology via fusion of multiple sensor data. He has submitted two journal papers; they are under review and appear in the list of publications.
Kuilin Chen, PhD candidate	Kuilin continues his research in digital twin for reheat furnace. He is currently working on probabilistic sequence-to-sequence learning models. A more detailed review of this work is included in the Report and will be presented at the December consortium meeting. He is working toward his PhD qualifying exam in the near future.
Michael Gimelfarb, PhD candidate	Michael is currently working on the problem of Bayesian region identification and policy transfer in reinforcement learning (RL) with multiple source tasks to improve the sample efficiency of modern state-of-the-art RL methods. In this framework, a reinforcement learning agent is presented with multiple solved source tasks (both dynamics models and optimal policies) and uses transitions data collected in the new target task to reason about local task similarity with respect to the source tasks in each state. Only dynamics differ between source and target tasks. This posterior distribution over source tasks is parameterized as a deep neural network, in order to allow efficient and scalable inference. This posterior is then used to sample actions from the source tasks to help guide the agent to promising regions of the state space and learn a good policy more efficiently. He is planning to submit this work to the International Conference on Machine Learning (ICML) in January 2020. A more detailed write-up of his proposed idea is provided later in the Report.
Aakash Iyer, MEng student	Aakash is a 2nd year graduate student pursuing his Master's of Engineering degree in Mechanical & Industrial Engineering with an emphasis on Data Analytics, and an MEng certification in Financial Engineering. His main research project under the supervision of Professor Chi-Guhn Lee and Dr. Li Yang deals with developing a hybrid approach to RUL estimation using Deep Learning algorithms and stochastic processes. Since September 2019, he has been able to analyse data driven and model driven approaches in RUL estimation. He is also volunteering with Dr. Li Yang in the KPI analysis for Kinross Gold.
Scott Koshman, PhD candidate	Scott Koshman is on an academic leave of absence to enjoy being a full time parent to his newborn daughter. He will be returning to academic research for the fall semester of 2020.
Saravanan Kumar, MEng student	Saravanan is currently working on his MEng project with the Toronto Transit Commission (TTC) to help optimize the re-inspection schedule for TTC's rail defects. He has pre-processed inspection data from TTC's Non-Destructive Testing (NDT) team from years 2015-18 to develop statistics that can be used to build a re-inspection optimization model.

	Further, he will use the defect priority transition data to optimize the re-inspection schedule with the objective of maintaining current track reliability. His study will provide for future scope to include defect modes, geometry of track, and location of defects for sensitizing the re-inspection schedule.
Arun Shanmugam, MEng student	Arun is an MEng student in Mechanical and Industrial Engineering. He is working on a reliability study of Propulsion Diesel Engines in Halifax Class frigates for the Department of National Defence (Navy).
Avi Sokol, PhD candidate	As a flex-time PhD student and a full-time employee, Avi continues to research integration of Reinforcement Learning and Inventory Control to reduce waste in supply chains. In the past 6 months, Avi did a literature review of inventory control theory and practice, along with the emerging trends in reinforcement learning. As a proof of concept, he developed 2 reinforcement learning inventory models applying deep Q-learning and policy gradient methods. Both achieved near-optimal solutions.
Bin Yang, Visiting PhD student	Bin is a visiting PhD student from Xi'an Jiaotong University. His research focuses on applying transfer learning to automatically recognize the health states of machines such as locomotive bearings and wind turbine gearboxes. In the past two years, his key results are as follows: His paper "An intelligent fault diagnosis approach based on transfer learning from laboratory bearings to locomotive bearings" was published in *Mechanical Systems and Signal Processing*. It is about a multi-layer adaptation network to extract transferrable features both from the vibration data of laboratory motor bearings and locomotive bearings. As a result, the diagnosis model determined by the data from laboratory motor bearings can also be reused to recognize the health states of locomotive bearings through the transferrable features. His paper "A polynomial kernel induced distance metric to improve deep transfer learning for fault diagnosis of machines" was published in *IEEE Transactions on Industrial Electronics*. In this paper, he proposed a distance metric to estimate the distribution discrepancy of the cross-domain data from different machines. This metric improves the computation efficiency of traditional Gaussian function-based maximum mean discrepancy and is more robust to kernel parameters and shows better transfer performance when it used to construct deep transfer learning models.
Zihan Zhang, MASc student	Zihan began her MASc program in September 2019. In addition to completing three courses (Linear Programming and Networks, Stochastic Processes, Engineering Asset Management), she has made progress as follows: finished a

project proposal for TITAN with Li; processed vibration signals and analysed them in both time and frequency domain; gave a rough research proposal for her thesis with Li's help; continued studying GNN and other AI techniques and tried to define the system graph network.

Collaboration with companies and site visits

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

Member	Collaborations
Defence Science & Technology Laboratory	We continued progress on the long-term procurement project; we looked at the effect of a probabilistic distribution among the parameters and computed the equivalent project values and durations, in other words, the required relative yield of a shorter project to have equal value to a longer project. Tim Jefferis also proposed a project inspecting different types of maintenance projects that require different levels of investment at the management level. Both projects will be presented at the December C-MORE meeting.
Department of National Defence	The DND team and C-MORE have been working diligently on the propulsion diesel engine health analysis project. Defining a failure that can be identified in the data was a challenge that the team overcame together. As detailed information is not easy to extract, we have worked on alternative methods that can act as a proxy to clear definitions.
Kinross	Kinross invited C-MORE to speak at its bi-annual asset management conference at Niagara on the Lake. Janet spoke to the group about applications of C-MORE's work in the mining industry. Li, Aakash and Jiayue are working on the new KPI project – determining the KPI factors that affect equipment availability. This project will be presented at the December meeting.
Teck	Graeme Dillon proposed a project on determining the late-life of engines in haul trucks. The question is to decide whether an asset should be retired or refit at about 60% of the expected life, based on its previous performance. Two engines that are the same age may have a different result, if one has performed well in its youth, while another has caused a lot of headaches and has clocked in many hours in the shop.
Toronto Transit Commission	Since the last meeting, C-MORE and TTC have continued progress on the re-inspection project. In October, there was an important discovery that when defects change status from low-priority to high-priority defects that they are re-entered into the system as a new defect. These pairs of entries had to be linked and identified as one defect to allow proper analysis. This project will be presented at the December meeting.

Machine learning driven prognosis and condition-based maintenance

Zihan Zhang

Background

The advancement of sensor technology enables practitioners to monitor health status of industrial assets online. With multiple sensor data, health and lifetime prognostic can be adopted to support safety-critical and cost-optimal condition-based maintenance. Current prognostic methodologies can be substantially classified as data-driven approaches and model-driven approaches. With big data size, data-driven prognostic, particularly machine learning-driven prognostic, has drawn extensive attentions due to its superiority of: (a) less dependent on physical or statistical model, (b) powerful learning ability, and (c) capacity of handling high-dimensional data.

Nevertheless, the application of machine learning in real-world asset prognostic and maintenance still face some challenges due to the size/complexity of assets. First, how to define system failure based on multiple sources of sensor data is still unknown. Second, the failure and structure dependence between separate components/failure mechanisms is rarely addressed in current research, which may mislead maintenance decision-makings. Third, maintenance optimization of multiple-component systems with both structure and failure dependence is heavily restricted by state explosion problem, which cannot solve within conventional analytical frameworks.

The above mentioned challenges are also the source of TITAN's demands – how to acquire prediction result of higher accuracy and further schedule reasonable maintenance strategies. To address these challenges, our research will develop several advanced machine learning approaches to cure the curse of dimension and capture dependence between data/structure/failure.

Graph neural network (GNN), a booming deep learning approach, is adopted to solve the system-level prognosis and maintenance optimization problem. The core idea is to formulate a "graph" to capture dependence, where each component/failure mode is treated as a node, and the correlation between different components/failure is seen as the edge. As such, both sensor data and structure properties can be sufficiently harnessed for model training.

Vibration analysis

In order to depict the degradation of machines, we need to analyse the raw vibration signals collected from sensors to dig out their characteristics and correlations to help us have a deeper understanding of data. Here, we adopt the following procedure to conduct analysis:

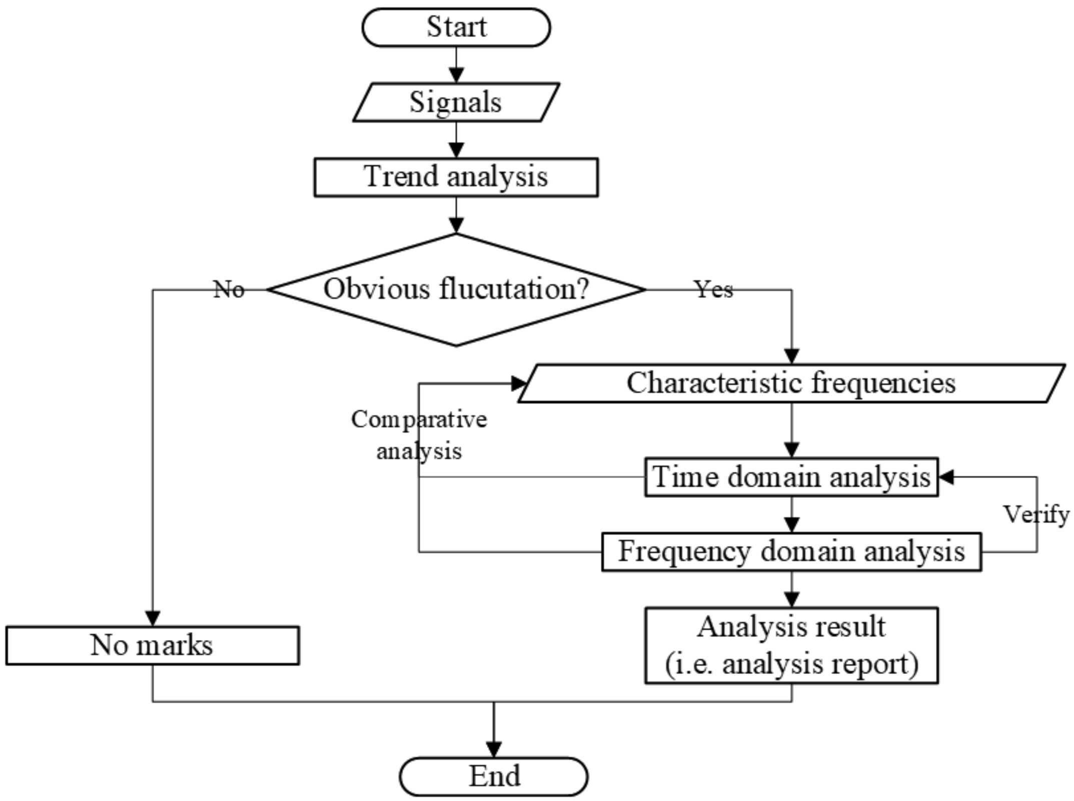
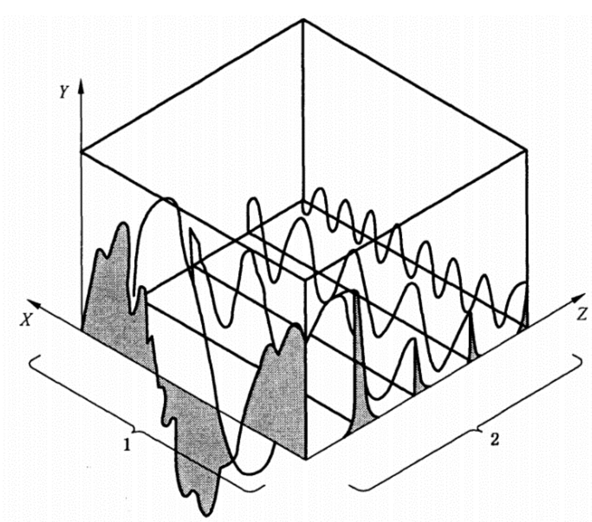


Fig 1. Flow chart of analysis process



1 – time domain
2 – frequency domain
X – time
Y – amplitude
Z – frequency

Fig 2. Relationship between time domain & frequency domain

Trend analysis

If signals have no obvious fluctuation, the machine will be still in "healthy state," or it will need further analysis – time domain analysis and frequency domain analysis.

Time domain analysis

In time domain, abnormal signals will have diverse periodic shock pulses in the waveforms, where a type of pulse contains a kind of fault information.

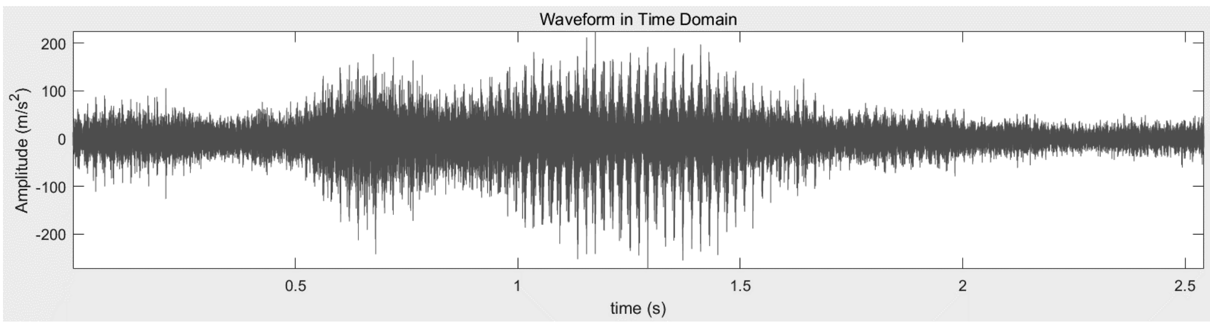


Fig 3. Waveform in time domain

Frequency domain analysis

Similarly to time domain, each fault has its corresponding characteristics in frequency domain. Imbalance and misalignment are shown in "base frequency" and "double frequency" respectively, whereas looseness is shown in all frequencies. Compared with machine's characteristic frequencies, we will find the possible its faults. Besides, the amplitude of the signals will also tell us the severity of the faults.

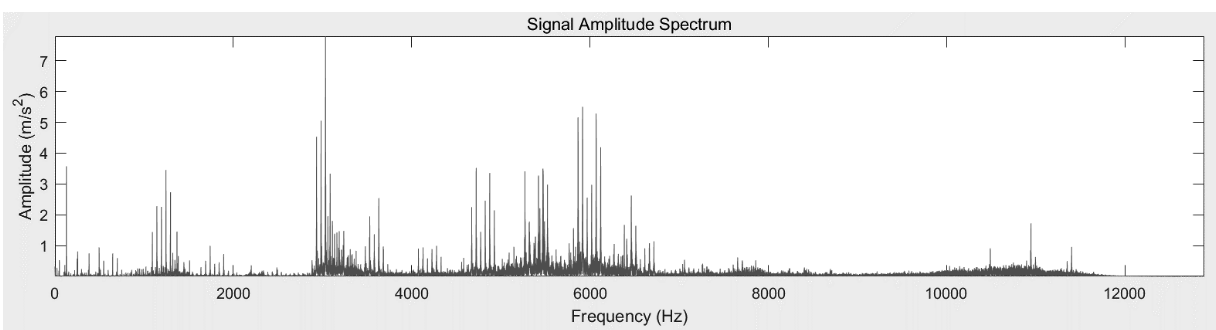


Fig 4. Signal amplitude spectrum

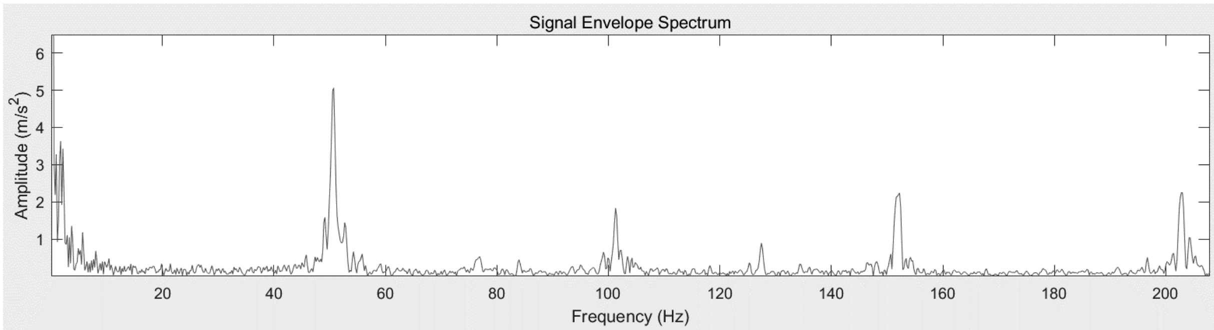


Fig 5. Signal envelope spectrum

Objectives

Based on data and demands, this research aims to develop an advanced diagnosis, prognosis and health management framework for industrial devices such as rotary machine (bearing, gearbox) with a higher accuracy of diagnosis/prognosis and reduce failure downtime. To this end, we proposed to integrate machine learning approaches with domain knowledge (e.g., physical failure mechanism, degradation evolution law) and statistical processes. Specific objectives are specified as below:

- GNN-based lifetime prediction based on dependence of sensor data;
- System diagnosis based on degeneration dependence among components;
- Condition-based maintenance optimization for multi-state systems.

Research proposal

1. GNN-based lifetime prediction based on dependence of sensor data

Abundant degeneration information is hidden in the sensor data. Conventional statistical methods either adopts a certain signal as the health index or fuse multi-sensor information based on a certain statistical indicator, whereas AI methods input several sensor information into the network via weight processing without digging out the underlying relationship among signals. In contrast, we apply GNN structure to explore the potential physical and statistical relationships among signals to help engineers to have a deeper understanding of degenerating process, leading to a higher accuracy of RUL prediction. The relationship between different signals is formulated via statistical regressions, and signals with closest relationship is chosen for training. In this research, physical correlation is used to define the mutual influence among sensors to improve the interpretability of the sensor graph. Besides, we can even infer the missing signals based on the relationships among sensors.

2. System diagnosis based on degeneration dependence among components

Traditional AI methods have not considered degeneration dependence among the components from the perspective of mechanical structure. In contrast, GNN can help us analyse the state of system from mechanical operating relationship. In this research, we integrate three dependence into our system graph network – structural dependence, stochastic dependence and functional similarity dependence.

Structural dependence descripts components' relationship in mechanical transmission structure; stochastic dependence tires to find the degeneration relationship among components from statistical perspective; while functional similarity dependence considers the similarity in function, such as replaceable components with spares. Based on the informed graph, we can predict remaining lifetime of the entire system with better interpretation in system level.

Furthermore, after we obtain RUL of system, we can leverage the graph structure to find the fault origin and infer possible effect of initial degeneration or failure on other components via tracing the defined relationship in graph.

3. Condition-based maintenance optimization for multi-state systems

For large industrial systems with multiple components, the volume of system's state set is huge, even when each component is subject to binary state (either normal or failure) assumption. If maintenance strategy sequence of system is regarded as a Markov decision process, a high-dimensional transition probability matrix is unavoidable once changing the system from a state to another via maintenance. It is a curse of dimensionality. In this research, GNN is utilized to solve this problem by formulating the transition probability matrix to a graph. For a specific maintenance action, the set of possible next states is limited, so we can reduce computation and simplify our problem by searching the most possible states to find the optimal maintenance actions instead of searching the whole state sets.

One step further, maintenance of systems with multi-state or even with continuous-state components can also be solved within in our GNN framework. Without the limitation of large state space, more timely and accurate maintenance decisions can be made to reduce the production loss of the entire system and increase its operation safety.

Evaluating long term projects of differing length under uncertainty (DSTL)

Janet Lam

Background

In heavy investment projects such as infrastructure or military, it's possible that the operative timelines are not 6 months to a year, but more along the lines of 5 to 20 years. When considering very long projects, there are a range of variables to consider. A short project may be more expensive in terms of labour but more flexible in terms of technology. The duration of a project will also affect the feasibility of certain features, as well as the quality of the build.

In this project, we considered ways to compare projects of differing lengths against one another. We included analysis for uncertainty in the parameters, and equated the values of the projects of different lengths. The result was a table of equivalent project values depending on the duration.

Project setup

In order to get an idea of the relative project values, each project started with a value of 100, and steadily lost value over the years. The rationale was to consider the projects to have full value at inception, and as time goes on and the project progresses toward completion, the project loses value each year due to time value and technological progress.

Additionally, every year there was to be a small probability of a significant or catastrophic event occurring that would severely reduce the value of the project. A real-life example of this might be the invention of the smartphone, as it has fundamentally changed the way we operate in our daily lives.

In comparing the short and long projects, the idea is that a long project will allow a larger scope, so may have a higher starting value, but it will face more incremental lost value during the development cycle, and more exposure to the chance of a catastrophic event.

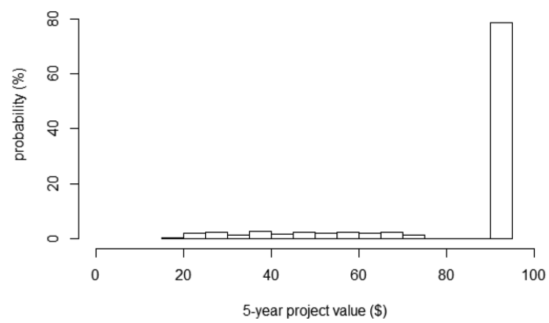
Simulation parameters

For the purposes of this project, a few parameters were considered:

- Annual depreciation rate: U[0.01, 0.02]
- Annual probability of a catastrophic event: 0.05
- Percentage project value lost in the event of a catastrophic event: U[0.2, 0.8]

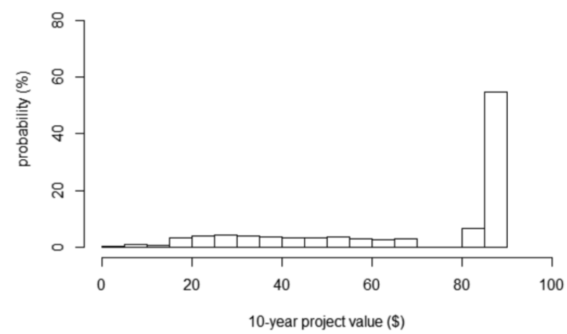
The project durations to be compared were 5, 10, and 20-year projects. In each project, once a step event occurred no more step events were permitted. The resulting project value histograms are seen below.

As expected, in all cases the vast majority of the projects retain their regularly depreciated values, while some projects suffer a step loss and result in a final value between 0 to 75%, depending on the duration of the project.



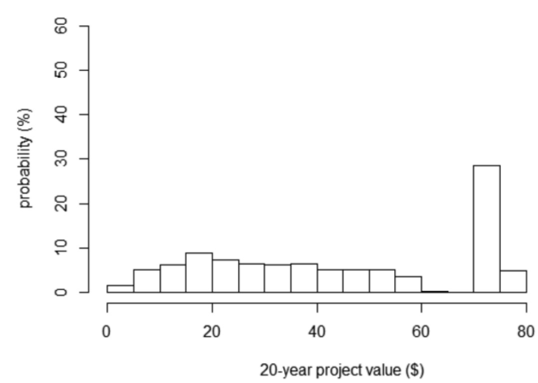
The small differences in value distribution between the project durations can be explained as follows.

The mode in all three cases represent the projects that did not suffer a step loss. Since the annual depreciation amount can range from 1 to 2% each year, the 10 and 20-year projects have a lower mean value for those that did not suffer a step loss.



The longer the project runs, the more opportunities there are to experience a step loss, so in each successive project lengths, there are proportionally more projects that experience step loss. Once a step loss is experienced, the project experiences regular annual depreciation until the end of the project.

These simulations were run on 1000 replications with uniform distributions. It would be interesting to see how changes in the distribution would also affect the final value histograms.



Analytical project value comparisons

Once we understood how the projects behave over the years, it was of interest to determine the conditions under which the projects were equivalent to one another. That is, how much does a shorter project have to be worth, in order to be equivalent to a longer project?

For this part of the project, we considered ways to evaluate a project of n years. We computed the expected value of a project of 5, 10 and 20 years, and equated them to each other.

The parameter values that we used were:

Annual depreciation	1%
Annual probability of step event	5%
Value lost at step event	50%

First, let's consider a 5-year project with no step event. The project's value after 5 years will be

$$100(0.99)^5 = 95.099$$

Now, considering the probability of experiencing a step event. If there's an annual probability of 5% to experience a step event, then the probability that there will be at least one step event in 5 years is

$$1 - 0.95^5 = 0.2262$$

Using total probability, the expected value of the project after 5 years is

P(step event) × value with step event + (1-P(step event)) × value with no step event

So $(1 - 0.95^5)(100)(0.99)^5(0.5) + 0.95^5(100)(0.99)^5 = 84.3424$

Similarly for the 10 and 20-year projects, we get 72.2935 for a 10-year project and 55.5558 for a 20-year project.

To determine project equivalence, we let x be the proportional value of a 5- year project to a 10-year project. Then, $84.3424x \geq 72.2935$, which gives us $x \geq 0.8571$. In other words, a 5-year project whose value is 86% of at 10-year project will be equivalent.

Similarly, a 10-year project whose value is 77% of the value of a 20-year project is equivalent.

To wrap up this stage of the project, we considered comparing all project durations between 5 and 20 years. We generated an equivalence table, seen on the next page.

Project equivalence table

Select the project you'd like to evaluate in the leftmost column.
Select the project you'd like to compare against in the top row.
The intersecting entry is the relative value of the column project required for equivalence with row project.
For example: a 5-year project whose value is greater than or equal to 0.85714244 of the value of a 10-year project will have equal or greater value.

Project duration	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
5	1.0000	0.9684	0.9384	0.9099	0.8829	0.8571	0.8327	0.8094	0.7873	0.7662	0.7461	0.7269	0.7087	0.6912	0.6746	0.6587
6	1.0326	1.0000	0.9690	0.9396	0.9117	0.8851	0.8598	0.8358	0.8129	0.7912	0.7704	0.7506	0.7318	0.7138	0.6966	0.6802
7	1.0656	1.0320	1.0000	0.9696	0.9408	0.9134	0.8873	0.8625	0.8389	0.8165	0.7950	0.7746	0.7552	0.7366	0.7189	0.7019
8	1.0990	1.0643	1.0313	1.0000	0.9703	0.9420	0.9151	0.8895	0.8652	0.8420	0.8199	0.7989	0.7788	0.7596	0.7414	0.7239
9	1.1327	1.0969	1.0629	1.0307	1.0000	0.9709	0.9432	0.9168	0.8917	0.8678	0.8451	0.8234	0.8027	0.7829	0.7641	0.7461
10	1.1667	1.1298	1.0948	1.0616	1.0300	1.0000	0.9715	0.9443	0.9185	0.8939	0.8704	0.8481	0.8268	0.8064	0.7870	0.7685
11	1.2009	1.1630	1.1270	1.0928	1.0603	1.0294	1.0000	0.9721	0.9455	0.9201	0.8960	0.8730	0.8511	0.8301	0.8101	0.7911
12	1.2355	1.1964	1.1594	1.1242	1.0908	1.0590	1.0288	1.0000	0.9726	0.9466	0.9218	0.8981	0.8755	0.8540	0.8334	0.8138
13	1.2702	1.2301	1.1920	1.1558	1.1214	1.0888	1.0577	1.0281	1.0000	0.9732	0.9477	0.9234	0.9002	0.8780	0.8569	0.8367
14	1.3052	1.2640	1.2248	1.1876	1.1523	1.1187	1.0868	1.0564	1.0275	1.0000	0.9738	0.9488	0.9249	0.9022	0.8805	0.8597
15	1.3403	1.2980	1.2578	1.2196	1.1833	1.1489	1.1161	1.0849	1.0552	1.0269	1.0000	0.9743	0.9498	0.9265	0.9042	0.8829
16	1.3757	1.3322	1.2909	1.2518	1.2145	1.1791	1.1455	1.1135	1.0830	1.0540	1.0263	1.0000	0.9749	0.9509	0.9280	0.9061
17	1.4111	1.3665	1.3242	1.2840	1.2458	1.2095	1.1750	1.1422	1.1109	1.0812	1.0528	1.0258	1.0000	0.9754	0.9519	0.9295
18	1.4467	1.4010	1.3576	1.3164	1.2772	1.2400	1.2046	1.1710	1.1389	1.1084	1.0793	1.0516	1.0252	1.0000	0.9759	0.9529
19	1.4824	1.4356	1.3911	1.3489	1.3087	1.2706	1.2344	1.1999	1.1670	1.1358	1.1060	1.0776	1.0505	1.0247	1.0000	0.9764
20	1.5182	1.4702	1.4247	1.3814	1.3403	1.3013	1.2641	1.2288	1.1952	1.1632	1.1327	1.1036	1.0759	1.0494	1.0241	1.0000

Attentive-GP for probabilistic Seq2Seq Learning

Kuilin Chen

Background

Sequential models are widely used in manufacturing, finance and robotics, where future outputs are predicted by past endogenous and exogenous data. Besides one-step-ahead prediction, it is more desirable to have models predict time-series multi steps ahead or generate time-series over long horizons. Such models can be applied for high fidelity simulation in digital twins of manufacturing processes, power planning in a smart grid and so on.

Due to RNNs' excellent performance on sequence modelling, they have been further integrated as encoder-decoders for sequence-to-sequence learning tasks [1]. The core idea behind encoder-decoders is to encode input sequences as a fixed-length hidden state and use a decoder to sequentially generate outputs and update the hidden state. However, it is difficult for the basic encoder-decoder model to deal with long sequences when all the necessary information is compressed in a fixed-length hidden state. As a result, time-series prediction accuracy could deteriorate rapidly as prediction horizon increases. The encoder-decoders with attention mechanisms are the current state-of-the-art for sequence-to-sequence learning tasks [2]. The attention mechanisms within encoder-decoders search for the most relevant information from the input and output sequences to predict future outputs. Traditional encoder-decoders employ recurrent neural networks (RNN) to embed the input and output sequences, but the recurrent structure precludes the massive parallel computation on GPUs [3]. Recently, the Transformer architecture is developed by computing dot-product attention multiple times (multi-head attention) directly on input and output sequences without RNN embedding, leading to significantly improved efficiency and accuracy [4].

Uncertainty quantification in time-series prediction and generation is as important as point estimation. Bayesian neural networks offer mathematically grounded framework to reason about model uncertainty by introducing prior distributions over network weights [5]. Training Bayesian neural networks essentially requires inference for the posterior distributions of model weights, which can only be approximated by computation-intense variational inference (VI) [6], gradient based Markov chain Monte Carlo (MCMC) [7], or their variants. In addition, it is non-trivial to extend VI and MCMC to complex model structures, such as encoder-decoders. Bayesian neural networks are still within the framework of parametric models, and the extent of prior knowledge and uncertainty (from data) expressed in a finite number of parameters is relatively limited. Nonparametric Bayesian approaches, such as Gaussian processes (GPs), provide richer representation of uncertainty through kernel (covariance) functions [8]. Given the intuitive value of combining GPs and neural networks, such hybrid models have been considered in different contexts. For example, deep belief nets are trained to extract features from images in an unsupervised way [9]. Such features are fed to GPs to generate superior classification results. Meanwhile, GP regression can be integrated into feedforward and recurrent neural networks as the last layer for probabilistic regression tasks [10]. Although hybrid models outperform standalone neural networks, currently there is no standard training algorithms for such hybrid models to get optimal performance.

To tackle the existing challenges in probabilistic time-series prediction and generation, we propose a new encoder-decoder architecture to generate time-series with predictive distribution. The new method, termed Attentive-GP, is based on the combination of Transformer architecture and GP regression. The original time-series are encoded into a feature space via a linear transformation layer and combined with positional encoding. The attention mechanism searches the most relevant information across all time steps between the features of input and output sequences. The output layer is replaced by a GP regression layer to map the featured attentions to output sequence with a probabilistic Bayesian representation. In addition, a block-wise greedy training algorithm is developed to train the proposed model effectively.

Attentive-GP

A new encoder-decoder architecture for probabilistic time-series generation is proposed. The new method, termed Attentive-GP, is based on the combination of Transformer architecture and Gaussian process regression. The last layer in the Transformer architecture is replaced by a Gaussian process regression layer $f(\cdot)$ to retain a probabilistic Bayesian representation. Meanwhile, the penultimate layer in the Transformer serves as a feature extractor $\phi(\cdot)$. The input sequence $\{x_1, \dots, x_N\}$ and the past output sequence $\{y_1, \dots, y_{i-1}\}$ are propagated through the feature extractor $\phi(\cdot)$ to get a feature vector $\bar{x}_{\mathrm{i}}$ that contains the most relevant information to predict next output y_i.

$$\bar{x}_i = \phi(\{x_1, \dots, x_N\}, \{y_1, \dots, y_{i-1}\})$$

Then $\bar{x}_i$ is mapped to y_i through the Gaussian process regression layer $f(\cdot)$ as follows:

$$y_i = f(\bar{x}_i) + \epsilon_i$$

where ε_i is Gaussian noise with zero mean and variance σ^2. The proposed method not only calculates point estimation of y_i but also provides complete predictive distributions over y_i through a kernel function. The popular Gaussian kernel function is used in this study because it is known to be universal approximators to any continuous functions within an arbitrarily small epsilon band.

Due to the probabilistic nature of the Gaussian process regression layer, the negative log marginal likelihood function is used as the loss function for the proposed method. Let W be parameters in $\phi(\cdot)$ and θ be parameters in $f(\cdot)$. The proposed model is trained by minimizing the loss function w.r.t. W and θ. However, the gradient w.r.t. to θ need be calculated using the entire training data set. As a result, the mini-batch based stochastic gradient descent (SGD) algorithms cannot be used in this case because the training data cannot be factorized. It is possible to train the proposed model using the full-batch gradient descent algorithm without factorizing the training data set [11]. However, the full-batch gradient descent algorithm requires a large amount of memory in the training process and is not scalable to large training data. Another more scalable approach is to use the semi-stochastic gradient descent algorithm, where W is updated by mini-batch data and θ is updated by full-batch data, asynchronously. Notice also that it is not desirable to update θ in the early stage of training process because $\bar{x}_i$ is not stable while W is not converged. We propose a simple and effective training method inspired by transfer learning. After initialization of W and θ, W is updated using the stochastic gradient descent algorithm while holding θ constant. After W converges, θ is fine-tuned using the full-batch gradient descent algorithm.

Algorithm 1

Initialize parameters $\boldsymbol{\theta}_0^0, \mathbf{W}_0^0$
for $k = 1, 2, 3, ...$ **do**
  for $\tau = 1, 2, ...T$ **do**
    Update $\mathbf{W}_{k-1}^{\tau-1}$ based on mini-batch data
  end for
  $\mathbf{W}_k^0 \leftarrow \mathbf{W}_{k-1}^T$
  for $\tau = 1, 2, ...T$ **do**
    Update $\boldsymbol{\theta}_{k-1}^{\tau-1}$ based on full-batch training data
  end for
  $\boldsymbol{\theta}_k^0 \leftarrow \boldsymbol{\theta}_{k-1}^T$
end for
return $\boldsymbol{\theta}, \mathbf{W}$

Experiments

Sequence data from different applications is used to demonstrate the effectiveness and reliability of the proposed Attentive-GP approach. The details of the selected data sets are described below.

Robot arm: We want to learn the inverse dynamics model of a 7-degree-of-freedom anthropomorphic robot arm, collected at 100Hz from the actual robot performing various rhythmic and discrete movement tasks. The inverse dynamics model of the robot is strongly nonlinear due to a vast amount of superpositions of sine and cosine functions in robot dynamics.

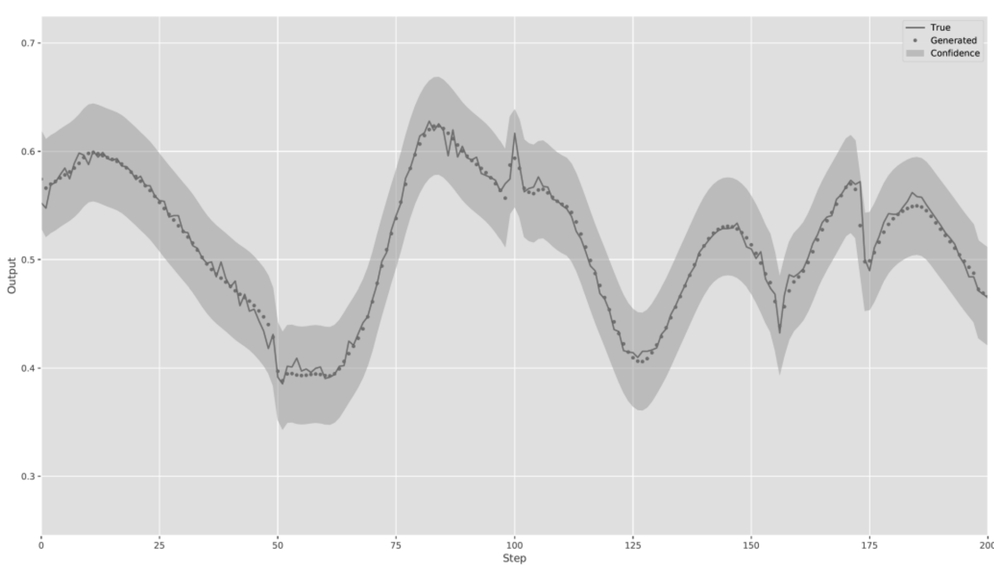
Suspension system: Mechanical oscillating processes constitute an important set of nonlinear dynamic systems. Examples include e.g. suspensions in motor vehicles, where shock absorbers and progressive springs are important components. The data is generated from a 2nd order linear time-invariant system with a 3rd degree polynomial static nonlinearity around it in feedback.

Smart grid: The smart grid data consist of 11 input sequences of hourly temperature measurements at 11 different cities in USA, and an output sequence of total power load in that area between 2004 and 2008.

For each data set, 80% of samples are used for training, 10% of samples are used for validation and the remaining 10% of samples are used for test. In addition, the proposed method is compared against RNN, LSTM, GRU, RNN encoder-decoder and Transformer (Attention). Optimal model structure, including number of layers and number of neurons in each layer, is selected for each method using grid search based on the root mean squared error (RMSE) of validation data set.

RMSE	Robot Arm	Suspension System	Smart Grid
RNN	4.924e-2	4.474e-2	9.714e-2
LSTM	4.704e-2	4.284e-2	8.624e-2
GRU	4.799e-2	4.176e-2	8.672e-2
RNN Enc-Dec	1.353e-2	1.903e-2	3.564e-2
Attention	7.069e-3	1.495e-2	3.325e-2
Attentive-GP	6.573e-3	1.304e-2	3.242e-2

As shown in the table above, the proposed method outperforms a range of alternative approaches on sequence-to-sequence regression tasks. In addition, the generated sequence for torque in robot arm with 95% confidence interval is plotted in the figure below.



Conclusions

A new encoder-decoder architecture for probabilistic time-series generation is proposed in this paper. The multi-head attention based encoder-decoder with a GP output layer, termed Attentive-GP, has strong feature extraction capability, while retaining the probabilistic Bayesian nonparametric representation. The proposed method outperforms a range of alternative approaches on sequence-to-sequence regression tasks. The Attentive-GP not only works on data with low to high noise levels, but also is scalable to problems with different dimensions using straightforward and generally applicable model specifications. The proposed block-wise greedy training scheme can train the Attentive-GP model efficiently and effectively. In short, the Attentive-GP provides a natural mechanism for Bayesian encoder-decoder, quantifying predictive uncertainty in sequences while harmonizing with the neural networks based encoder-decoder. Predictive uncertainty is of high value in Industrial 4.0, such as digital twin, and can also be applied to financial modelling and autonomous driving.

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DND: Propulsion diesel engine reliability modelling

Arun Shanmugam

Background

The Canadian Department of National Defense has twelve Halifax-class (aka City-class) frigates in operation that have served the Navy since 1992. The propulsion system on these vessels consists of a Propulsion Diesel Engine (PDE) and two Gas Turbines that work in a Combined Diesel Or Gas (CODOG) arrangement, with the PDE functioning during cruising speeds and the turbines serving high speed dashes. The Propulsion Diesel Engine (PDE) will be the object of this reliability modelling study.

Current procedures in maintenance activity & information management

The PDEs are subjected to an Oil & Coolant Conditioning Analysis Program (OCCAP) once every 30 days which involves offsite analysis of oil & coolant samples by a third party while maintenance decisions are made by the Fleet Maintenance Facility (FMF). Disparities have been observed between results of the OCCAP analysis and recommendations of the maintenance technicians and these disparities have proven challenging while making decisions regarding scheduling of maintenance activities.

The maintenance activities of the PDE are carried out in conjunction with the Defense Resource Management Information System (DRMIS) – an SAP-based integrated information system that supports maintenance activities and replacement part procurement among other business processes. The DRMIS generates work orders for scheduled preventive maintenance actions and keeps track of corrective maintenance orders. The integrated system generates purchase orders for replacement parts that need to be procured towards completing corrective maintenance. This introduces a significant challenge in analysis since orders are not indicative of failure or suspension events but associated part replacements that could be one or many depending on the maintenance activity.

Problem Statement

The objective of the project is to develop a model to predict engine failure with the use of a Weibull Proportional Hazards model. This will involve constructing an event history of failures and suspensions of the PDEs that will be used with OCCAP data to construct a Transitional Probability Model on EXAKT Condition-Based Maintenance software. The analysis also has the scope to assess & refine current maintenance policy with the inclusion of costs involved during corrective and preventive maintenance activity.

Data cleaning

Jamie Dreyer in collaboration with Nicolle Kilfoyle prepared three files towards the analysis: the DRMIS work order dataset with 4678 orders from November 2012 to March 2019; OCCAP oil and coolant conditioning data from December 2012 to January 2019; and month-wise PDE odometer reading data.

Since the DRMIS generates work orders that double as procurement orders, this introduces great ambiguity in determining the number of events. Further, the dataset of work orders also contains quite a few orders for replacement that are not critical to the functioning of the engine such as the replacement of bulbs. This necessitated a case-by-case analysis of work orders in close collaboration with DND, which has been an ongoing process in the project.

The dataset contained orders for multiple parts associated with the same failure or suspension event which would have potentially resulted in an over-estimation of the number of failures/suspensions. This necessitated grouping of orders based on how close they are with each other chronologically, odometer running hour and most importantly, DNDs input so that the Weibull model would closely mirror reality.

The DRMIS generates orders codes for different classes of orders that link to preventive/corrective maintenance. However, this distinction is not always consistent since preventive maintenance orders generate “dummy” corrective maintenance orders to pull spare parts associated with the PM action. The characterization of a failure or suspension event is therefore, not a straightforward task due to the nature of the data and the complexity of the PDE as an asset.

Characterization of failures & suspensions

The costs associated with the procurement of replacement parts is a metric that we relied on to distinguish failure/suspension events critical to functioning. The hypothesis was that critical failures and/or suspensions would be characterized by a relatively higher total cost of replacement and hence, can be used to focus the analysis on the orders that link to engine functioning.

During the first phase of analysis, the cost threshold for a significant failure was determined to be 35000 CAD for corrective maintenance actions. It was also imperative to the analysis that all maintenance actions under consideration would bring the engine to a "good-as-new" working condition. Based on DND input, it was understood that all corrective actions resulted in restoration of PDE to good as new while not all preventive maintenance actions did not. 12K and 15K preventive maintenance actions and 24K overhauls brought the PDE to "as-new" condition and therefore, it was decided that orders linked to these PM actions would be considered significant and relevant for analysis. This resulted in the reduction of orders relevant to Weibull analysis from the initial number of 4678 to 80. This was followed by preparation of the data for EXAKT Weibull analysis.

Weibull analysis and further investigation

The Weibull analysis yielded a shape parameter that was not commensurate with assets such as the PDE. This was largely owing to the practical complications surrounding the data – the orders do not have a one-one correspondence with events as described earlier and multiple events with the same running hours in the reduced order set were considered to be one in the EXAKT analysis since the working age readings correspond to month-wise readings and not hour reading at the time of failure. Consequently, we consulted with DND to revisit the list of events under consideration and this resulted in the second phase of analysis which involved revisiting the cost threshold and consolidation of duplicate/cancelled orders, in an attempt to refine the model.

It was determined that there did exist failure events below the 35000 CAD threshold and so, the cost threshold was moved to 10000CAD, and removal of duplicate/cancelled orders. This resulted in a new list of 209 orders which was subjected to the same EXAKT Weibull analysis as was done before. This resulted in only a marginal increase in shape factor but was still not reflective of the actual reliability behaviour of PDEs.

Inter-failure time analysis

The continued repeat of unexpected outcomes with the Weibull analysis necessitated an Inter-failure time analysis. Time between successive events was analysed using a histogram (see Fig 2) and it was observed that most IFTs could be found in the less than 250 running hours mark. This strikes as abnormal since typically failure events are farther apart and so, it was decided to take a closer look at these orders.

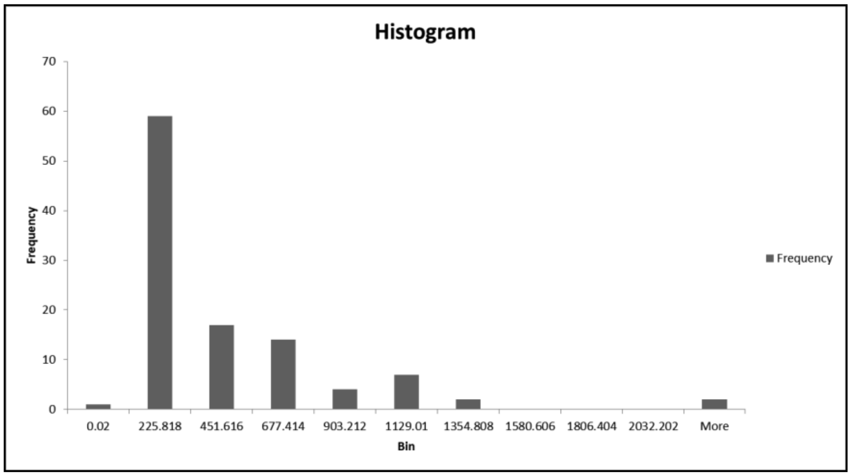


Fig 1: Inter-failure time analysis histogram

This ski-slope shape indicates a shape factor of less than one, which is not consistent with the behaviour of engines. Upon increasing the resolution of analysis of events less than 250 hours, the following histogram (Figure 3) was obtained.

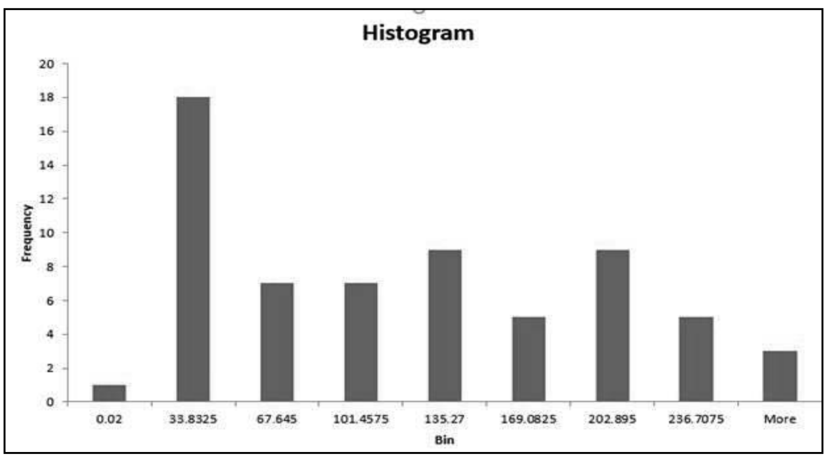


Fig 2: Analysis of orders less than 250 hours

The examination of orders with running hours less than 34 hours (which meant that failure events were not longer than a day apart), two successive failure events on HMCS Calgary stood out since they were merely 4 hours apart. Discussions are ongoing with DND regarding the nature of events such as these and how best to go forward from here.

Future work

In the immediate time ahead, we hope to continue our investigation into the disparities in inter-failure times and resolve them to consolidate the event history. This will then pave way for the next step in the process that involves cleaning and analysis of OCCAP data. The OCCAP data and event history will be used to generate the predictive model for PDE failures. Cost data can be used to assess and refine current maintenance policy.

Kinross Gold KPI analysis

Li Yng, Jiayue Niu, Aakash Iyer

Background

In June of this year, Kinross proposed a project where we investigated the key performance indicators (KPIs) arising from their various mines to determine whether we could identify existing relationships between the variables. Working with KPIs has the benefit of using values that are already being reported regularly, so the quality of the data is relatively high and the acquisition of the data is relatively simple.

Kinross is interested in determining the relationship between their preventive maintenance activities and the resulting availability of their mobile fleet. In other words: are the PM activities having the desired outcome of increasing our fleet availability?

In this report, we describe the steps that were taken to prepare the data for analysis and the initial results.

Variable definitions

The KPIs are reported monthly for each vehicle. For some variables, the are two reported values, one each from the Operations department and the Maintenance department. Upon discussion with Emilio and Theresa, it was determined that the values from the maintenance department should be used. The variables included in the analysis are as follows:

Variable	**Definition**	**Alternate description**
Hours	Unscheduled downtime	
Hours (scheduled)	Scheduled downtime	Time spent in PM
Evts	Number of failures	
Evts (scheduled)	Number of planned outages	Number of PMs
TotalDown	Hours + Hours (scheduled)	
TotalHrs	OperatingTime + OperatingDelay + Standby + Hours + Hours (scheduled)	
Avail	(OperatingTime + OperatingDelay + Standby) / TotalHrs	

Util	OperatingTime / TotalHrs	
UofA	Util / Avail	Effective availability
MTBF	(OperatingTime + OperatingDelay) / Evts	
MTTR	Hours / Evts	
MTTR (scheduled)	Hours (scheduled) / Evts (scheduled)	
MTBS	OperatingTime / Evts (scheduled)	

Preliminary data cleaning

Since we have entries for scheduled down time, unscheduled downtime, and total downtime, we can remove the dependent columns and replace them with new values. Namely,

Total Hours and Total Hours (SCHEDULED)

And subsequently two new KPIs are generated for better exploratory analysis

Failure_Rate = 1/MTBF

Reliability = exp(-Failure_Rate*OperatingTime)

Note: It is assumed that the KPIs provided have been independently obtained and as such have not been recalculated.

In the new dataset obtained, NaN values are subsequently removed and verified.

Weibull analysis

Given the nature of 2 columns in the dataset is unknown, Weibull Analysis was performed on the given data in order to generate insight regarding the optimum maintenance policy. For doing so, standard Python libraries were used including Weibull Library for generating Weibull Probability Plots.

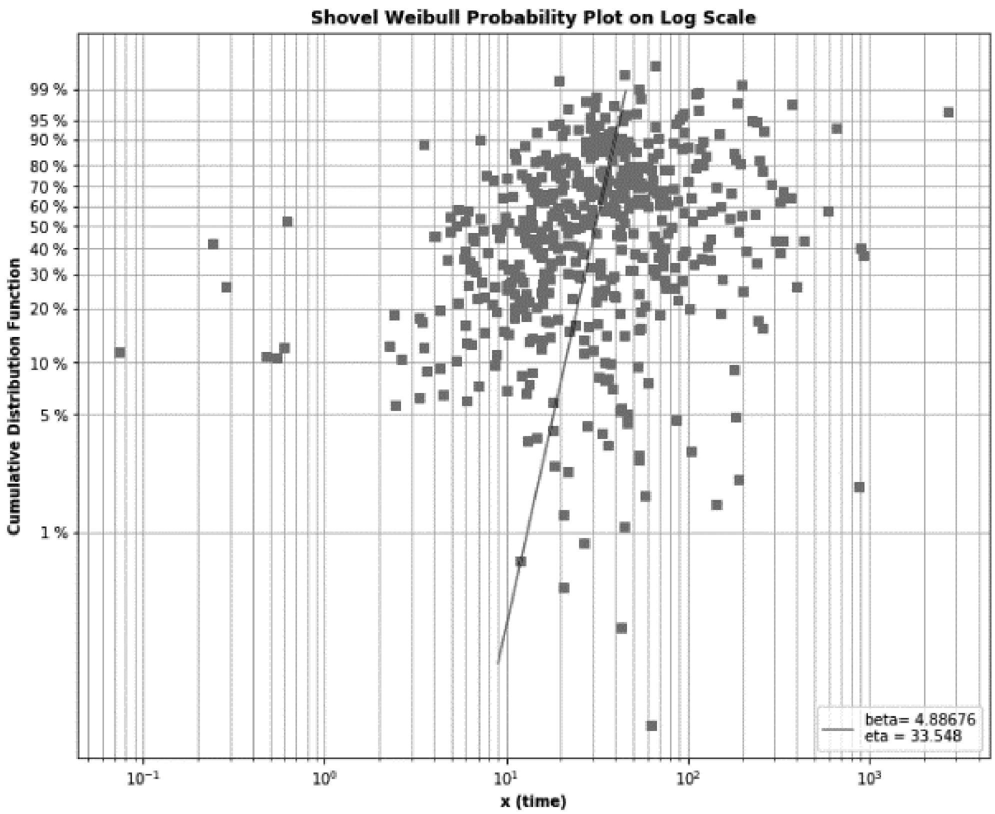
In order to perform the analysis, the data was divided into the two classes: Shovels and Trucks; which will give us insights regarding the fleet wise asset management condition. Then, Weibull analysis was performed for each of the 14 models of shovels and trucks in order to generate further insights. In order to obtain Shape and Scale Factor, Linear Regression was utilized to get near fit and CDF performance was gauged.

1. Shovel fleet Weibull analysis

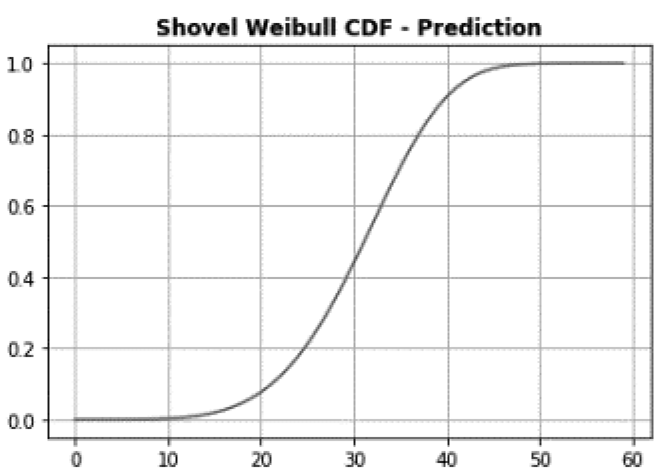
Here, all the data for the Class of Shovel were combined in monthly fashion and the Weibull analysis was performed in order to gauge the fleet performance. Upon using linear regression, the following parameters were obtained:

- r^2 value: 0.04769664440420172
- slope/shape parameter: 4.886764259206796
- scale parameter: 33.547678288351676

The Weibull Probability Plot is given below:



The following graph calculates CDF Prediction with X axis the Number of Months and Y axis the Percentage of Asset Fleet.



Based on the output above, 100% of the population will have failed after approximately 47 months.

Subsequently, Weibull analysis for each model was done; the following table represents the comparative summary.

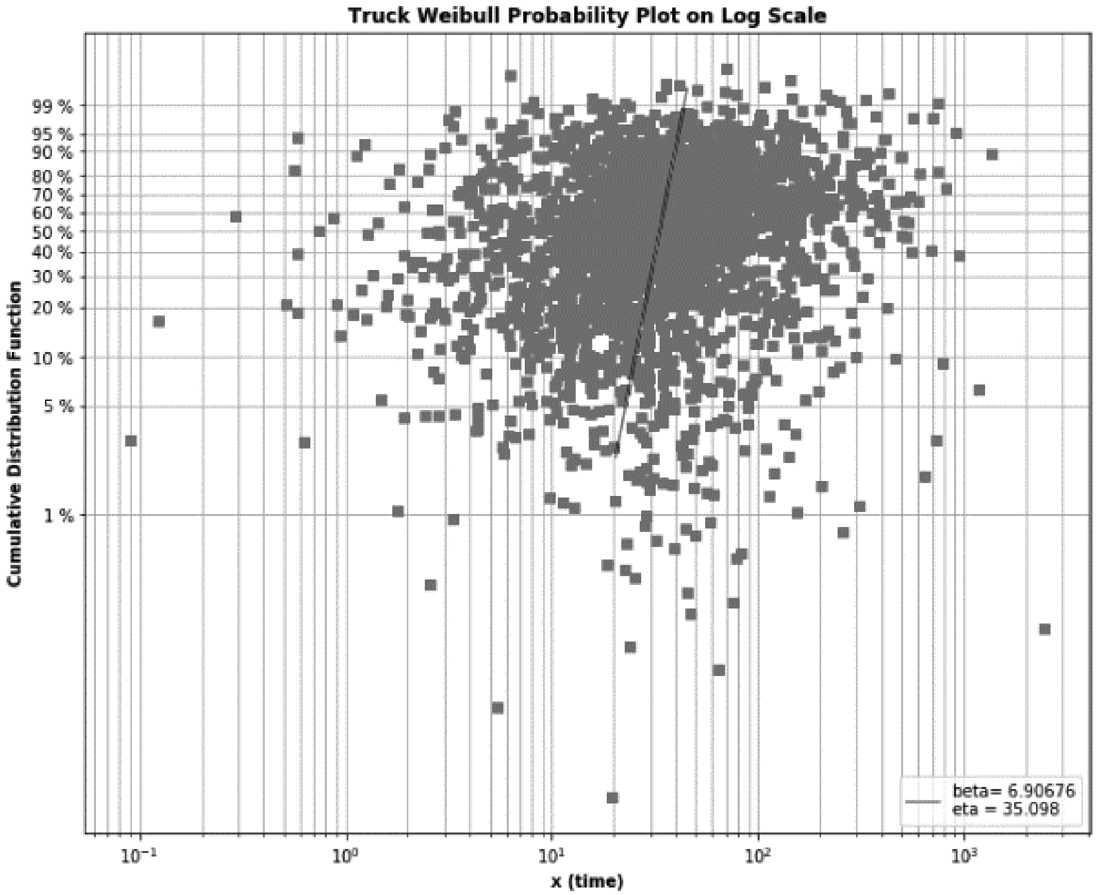
Asset	Shape Factor	Scale Factor	Approximate Months to 100% Failure
Shovel Fleet	4.88	33.54	45
CAT 992 G	3.34	35.75	60
CAT 994	9.01	28.80	35
CAT 994 H	4.69	58.43	80
CAT 994 F	5.76	50.07	65
Hitachi 3600	2.97	24.70	41
Hitachi 3601	5.72	36.45	50
Hitachi 5500	5.03	26.31	36
Hitachi 5600	2.06	28.86	61

2. Truck fleet Weibull analysis

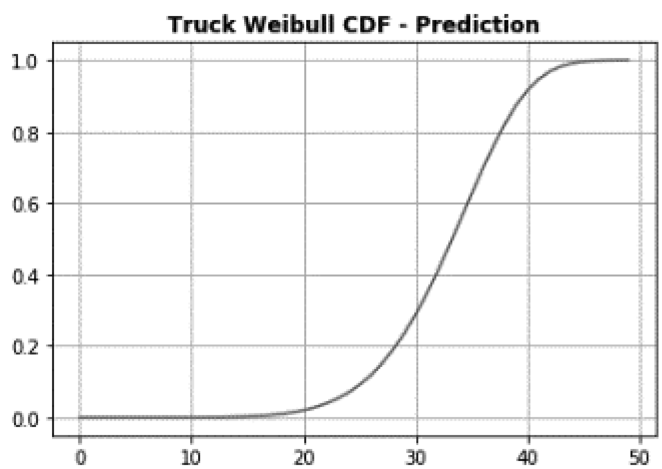
Here, all the data for the Class of Truck were combined in monthly fashion and the Weibull Analysis was performed in order to gauge the fleet performance. Upon using Linear Regression, following parameters were obtained:

- r^2 value: 0.025604608506261
- slope/shape parameter: 6.906764264612196
- scale parameter: 35.097508538347O5

The Weibull Probability Plot is given below:



The following graph calculates the CDF Prediction with X axis the Number of Months and Y axis the Percentage of Asset Fleet.



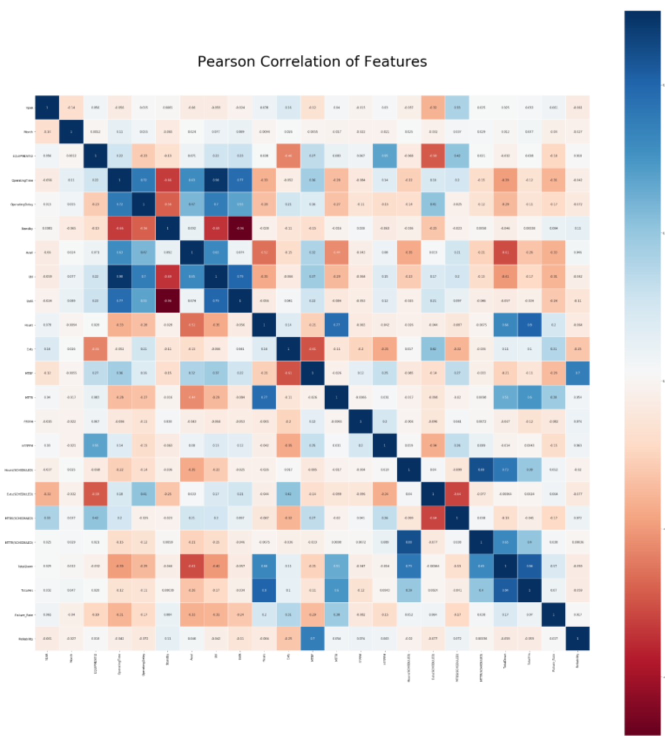
Based on the output above, 100% of the population will have failed after approximately 44 months.

Subsequently, Weibull analysis for each model was done; the following table represents the comparative summary.

Asset	Shape Factor	Scale Factor	Approximate Months to 100% Failure
Truck Fleet	6.9	35.097	44
CAT 785	9.9	39.89	48
CAT 789	15.59	24.14	27
CAT 793 C	6.15	60.018	79
CAT 793 D	2.8	45.79	80
CAT 793 F MARC	-33.07	32.131	0
CAT 793 F MEM	3.77	38.28	59

Exploratory Analysis

To gauge the affect of KPIs for the overall maintenance policy, understanding the relationship between the KPIs is essential. As such, Pearson Correlation of Features is calculated and is denoted via the following heatmap:

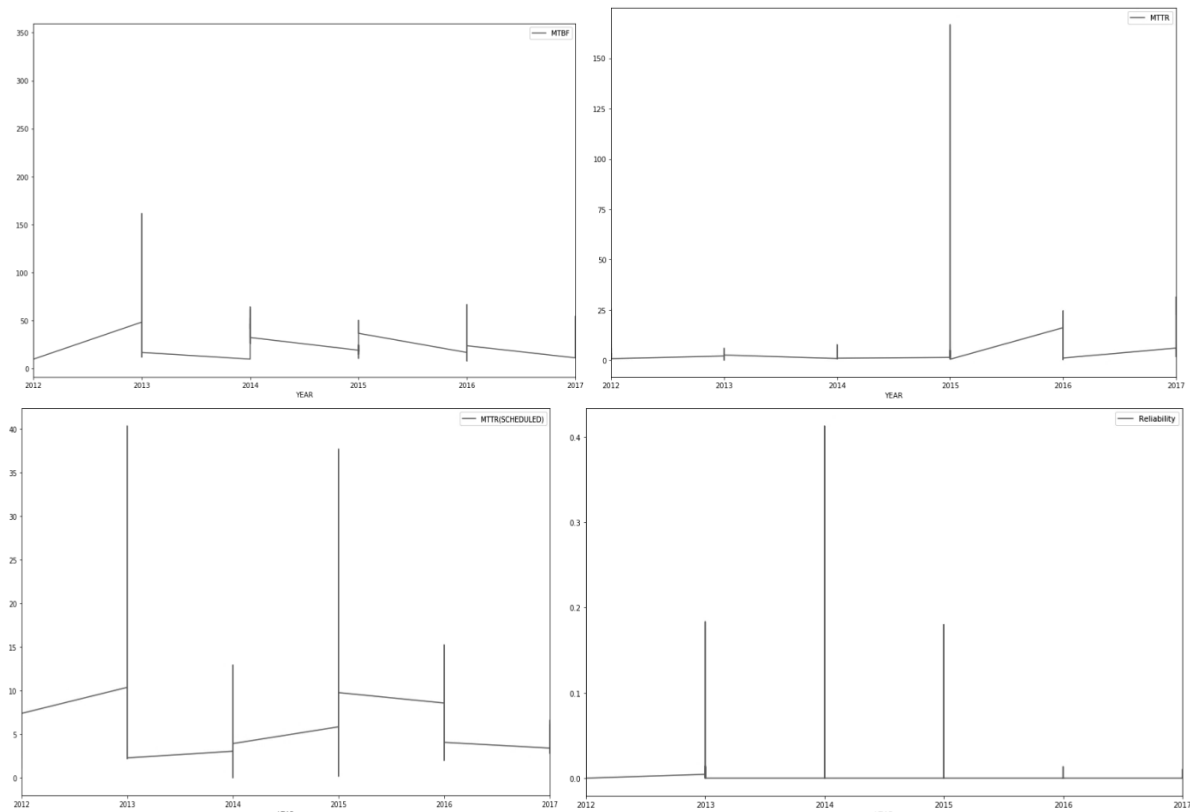


Given the analysis of the correlation of features, many are correlated with each other as they are primarily derived from many initial columns. But one set of features that stick out is that of UofA and Standby hours with a correlation of -0.97 implying strong negative correlation which means that if Standby hours decrease, UofA increases and vice versa. If the dataset has perfectly positive or negative attributes, then there is a high chance that the performance of the model will be impacted by a problem called — "Multicollinearity." Multicollinearity happens when one predictor variable in a multiple

regression model can be linearly predicted from the others with a high degree of accuracy.
Lastly, for each model of both classes, KPIs were plotted out for better understanding. The KPIs include:

- MTBF vs Years
- MTTR vs Years
- MTTR (SCHEDULED) vs Years
- Reliability vs Years

We choose model CAT 992G as an example. The following observations can be made.



Summary

This project is still a work in progress; more direct comparisons between variables are being made and more insights into results are being gained.

AI-based RUL estimation: hybrid approach combining deep neural network algorithms with stochastic process

Aakash Iyer, MEng Student

Background

In my current MEng project, the main objective is to develop a hybrid RUL prediction method utilizing Artificial Intelligence algorithms and stochastic processes. This report will present the problem statement, objectives, a brief literature review, and current progress in the project.

As a secondary project, I have also contributed to the Kinross Gold KPI Analysis report.

Problem Statement

The Remaining Useful Life (RUL) is an important factor related to an engineering asset which is crucial for effective maintenance and Prognostic Health Management (PHM). Many techniques have been developed and applied to degradation modeling. In general, these approaches can be categorized into model-based methods and data-driven based methods. Data-driven approaches employ various machine learning methods, including AI algorithms. Deep neural network (DNN) approaches have been proven effective in RUL estimation due to their capacity in handling high-dimensional non-linear degradation features. However, the applications of DNN in practice face a primary challenge of uncertainties in predicted values which may not be analytically quantified.

Model-based approaches, on the contrary, utilize physical or mathematical models to formulate the degradation process and estimate the model parameters from the measured data. The Wiener process model, the Gamma process model and the inverse Gaussian process model are three popular stochastic process models for degradation modeling. The model-based methods generally require less data to perform accurate RUL prediction, making them promise when the degradation data are not abundant but applicable when conditions are monotonic.

Thus, a combination approach would be able to overcome many shortcomings of both approaches and may provide a more practical solution.

Hypothesis

A major hypothesis considered is that the data used for analysis follow a random path and are thus effective for stochastic programming applications. Other assumptions on data and equipment conditions will be applied as the project progresses.

Literature review

- **RUL prediction of deteriorating products using an adaptive Wiener process model [1]:** This 2016 IEEE paper gives detailed insight into the application of model-based approach utilizing Weiner Process for estimation of RUL. The paper provides insights into PHM and showcases application of adaptive drift where the adaptivity of the future rate is easier to be accounted for in the proposed models. However, the procedure fails to identify the role of features of dataset and their role in the estimation of RUL. The procedure is applied on NASA's Lithium-ion battery data where a comparative analysis is performed in order to gauge the methodology's effectiveness.

- **Estimation of bearing remaining useful life based on multiscale convolutional neural network [2]:** This 2018 IEEE paper introduces an MSCNN model structure, which keeps the global and local information synchronously compared to a traditional convolutional neural network (CNN). The effectiveness of the presented method is validated by the experiment data from PRONOSTIA in the IEEE PHM 2012 Data Challenge. Compared to traditional data-driven and different CNN-based feature extraction methods, the proposed method shows enhanced performance in the prediction accuracy.

Proposed method

For the analysis, the NASA Turbofan dataset is utilized for method evaluations. The project comprises of 3 main stages, namely:

1) Data-driven approach comparative analysis
2) Model-driven approach
3) Hybrid approach development

At a later stage, new datasets will be incorporated to gauge the method's effectiveness. All processes discussed have been performed on Python.

1. Data-driven approach

The data-driven approach mainly deals with the use of machine learning methodologies such as deep neural networks for estimating RUL. Thus, the main aim of this stage is to perform a comparative analysis of various DNN methods.

Before using a model, the dataset needed to be prepared. The following steps were undertaken in data preparation:

- **Data cleaning:** Removing columns and rows with NaN values.

- **Feature selection:** There are 21 sensors and 3 optimal setting values provided in the dataset, but upon performing feature selection techniques on the dataset which included Outlier Statistic Analysis, Pearson Correlation Analysis, and Feature Importance via Random Forest Regressor, ideal sensors were identified, and the unnecessary feature columns were removed.

- **Data preparation:** The feature data had to be normalized to be eligible for regression and hence scaling was performed using MinMaxScaler. In order to obtain a target variable, new features were created, including Max Cycles per Unit, Time to Failure (TTF), and Fraction time to failure.

$$TTF_i = max(cycles) - cycles_i$$

$$fTTF_i = \frac{TTF_i - min(TTF)}{max(TTF) - min(TTF)}$$

After the necessary data preparation, 5 neural network techniques were used:

- **Convolutional neural network (CNN):** Here, I utilized Keras library where ReLU activation function is used and Adam is the optimizer. The neural network tha has 18 input neurons, 6 intermediate neurons, and 1 output neuron since it is a regression problem, estimating the remaining useful lifetime.

- **CNN long short-term memory networks:** I used a 1D convolutional layer followed by a max pooling layer, the output is then flattened to feed into LSTM layers. The model has two hidden LSTM layers followed by a dense layer to provide the output. I used mean squared error loss function and Adam optimization

- **Bayes by Backprop (BBP):** Using Pytorch, Bayes by Backprop inference is where the mean and variance of activations are calculated in closed form. Activations are sampled instead of weights. This makes the variance of the Monte Carlo ELBO estimator scale as 1/M, where M is the minibatch size. Sampling weights scales (M-1)/M.

- **Bayes by Backprop (BBP) + MC dropout:** A variant for the Bayes by Backprop, using “Dropout as a Bayesian Approximation: Representing **Model**

Uncertainty in Deep Learning" [3], was used to predict RUL. A fixed dropout rate of 0.5 is set.

- **Bayes by Backprop (BBP) + stochastic gradient Langevin dynamics:** Another variant for the Bayes by Backprop, in Bayes by Backprop (BBP) + Stochastic Gradient Langevin Dynamics the true posterior over w is converged, but here done with a fixed learning rate. The main reference used for this technique is the paper "Bayesian Learning via Stochastic Gradient Langevin Dynamics" [4]

After the model is run, the score for the test set is calculated. The fraction of remaining life (0.00-1.00) is re-converted to remaining useful life as expressed in number of cycles. Knowing the predicted remaining life (fraction), the predicted total number of cycles per unit is estimated in the testset. This can be done with the following function:

$$max(predictedcycles_i) = \frac{cycles_i}{(1 - predictedfTTF_i)}$$

The maximum cycles per unit is subtracted from the predicted total number of cycles in the test set to obtain the RUL, remaining useful lifetime:

$$RUL_i = max(predictedcycles_i) - max(cycles)$$

The models were utilized to predict RUL, and using given RUL dataset, the effectiveness of each technique was gauged using RSME.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

Parameter	**CNN**	**CNN + LSTM**	**BBP/BNN**	**BBP + MCD**	**BBP + SGLD**
RMSE	30.57	29.12	23.14	24.63	28.83

2. Model-driven approach

For the second stage, I am currently working on developing a model-driven approach using the Weiner process. The Weiner process is preferred for non-monotonic heteroscedastic data [5] in many publications and hence was chosen. The steps involved in developing this approach consist of:

- Parameter estimation using maximum likelihood estimation. Here, main assumption of single-dimensional Gaussian is considered.

- The drift generated due to Step 1 will be updated by Kalman particle filter, one of the most popular particle filter methods.

- Remaining Useful Life will be calculated using the particle filter via Wiener process.

3. Hybrid approach development

After the data-driven and model-driven approaches are done, combination approach trials shall commence.

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Sequence pattern mining with generating unit data

Somayeh Alizadeh

Background

In today's increasingly connected world, equipment sensors are ubiquitous, and large volumes of data are created automatically. There is no difference in the area of electricity generation, as the operation of hydroelectric and fossil generating units produces large amounts of data on unit health. By inspecting the resulting records using data mining and machine learning algorithms, we may be able to detect patterns that may indicate equipment health. The extracted knowledge may provide information on the occurrence of the next maintenance activity or component outage. In other words, data mining could be used to unlock hidden patterns in the data that is already being collected, empowering us to identify signals indicating an imminent failure.

Generating unit data

The current Equipment Reliability Information System (ERIS) data records are continuous and show the operating and outage or derated status of each unit at all times. Along with timestamps, some codes give further insight into the equipment health, including component codes, amplification codes and the state code.

Frequent pattern mining

Frequent patterns are patterns like itemsets (set of items) or subsequences that frequently appear in a data set. For example, a set of items, such as "cheese" and "pasta" that often appear together in a transaction data set is a frequent itemset. In itemsets, time is not essential; however, in subsequence, time is a crucial concept. Imagine someone goes to a computer shopping center and buys a PC, then a mouse, and then an external DVD. If it frequently occurs in a shopping history database, is a (frequent) sequential pattern. And it is obviously clear that time has an important rule here. Here are some of the basic concepts of frequent patterns, associations and sequence patterns.

Association rule mining

Frequent pattern mining searches for recurring relationships in a given data set. We begin by presenting an example. There are some transactions in some colours. If we see orange colour in a transaction, we will be sure that the blue colour would be there.

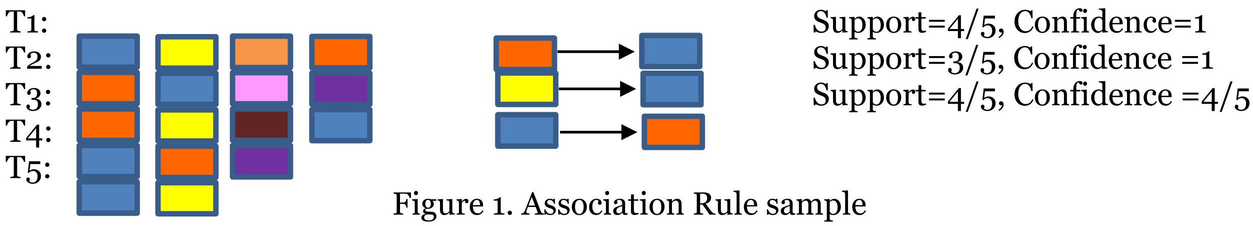

Figure 1. Association Rule sample

Rule ***support*** and ***confidence*** are two measures of rule interestingness. They respectively reflect the usefulness and certainty of discovered rules.

Support, *s*, probability that a transaction contains X and Y
Support $(A \Rightarrow B) = P(A \cup B)$

Confidence, *c,* conditional probability that a transaction having X also contains *Y*
Confidence $(A \Rightarrow B) = P(B|A) = \text{support}(A \cup B)/\text{support}(A) = \text{support count}(A \cup B)/\text{support count}(A)$.

Sequence pattern mining

Sequence data consist of long sequences of event, which are not observed at equal time intervals. Sequential pattern mining has focused extensively on mining sequences. A sequential pattern is a frequent subsequence existing in a single sequence or a set of sequences. A sequence database consists of ordered elements or events. This is an example of sequence :<a(abc)(ac)d(cf)>. It means (abc) happened after <a> and (a,c) happened after (abc) and etc.

Database of sequences is input for sequence pattern mining, and some user-specified constraints can be used to reduce the search space in sequential pattern mining and derive only the patterns that are of interest to the user. It is constraint-based sequential pattern mining. And these constraints are *minsup (minimum support)* or the time-gap between rules or the other constrained defined by users.

Sequence pattern mining with generating unit data

Looking back in time, equipment history can be processed through machine learning algorithms to predict interruption or outage behavior. Data mining algorithms can be used to identify the dependencies between the outage component code, amplification codes and unit state. Furthermore, sequence pattern mining can help to predict the next “outage code” or “state code,” or when the next outage may occur. In other words, future events of generating units may be predicted using these methods.

Data preprocessing

There are some huge data produced through the maintenance of hydroelectric and fossil generating units. We have **continuous records** of the operating and outage data of each unit. (2013-2017).

In this project, we have focused on the "*State Code*" field with this value

- Forced outage (21)
- Maintenance outage (24)
- Planned outage (25)

And "*OCIDGE*" codes were developed from the System Classification Index (SCI) used to identify equipment, systems, and conditions.

Figure 2 shows that about 80% of frequency is only for 20% of data. After investigating this issue, we found that some codes are very generic. For example "*OCIDGE= G199999*" is used solely for external conditions and only if no other cause applies, or "*OCIDGE= G142100*" is a generic code too. Therefore, we omitted all of these codes.

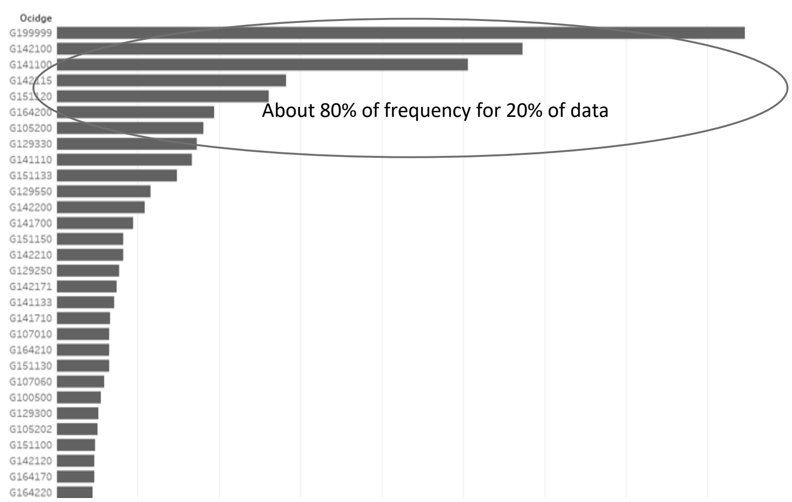

Figure 2: OCIDGE: Outage Component Codes

Modelling

We have used association rules and sequence pattern mining to find out any relationship among "OCIDGE Outage Component Codes" and "State Code" with more frequently. We have used *the Apriori* algorithm in association rules, and these are the parameters for this algorithm.

- Maximum number of antecedents: 5
- Minimum antecedent support (%): 20.0
- Minimum rule confidence (%): 70.0

The number of rules are 67; here are some samples of these rules:

- (Excitation) → Generator And Auxiliaries (c=74%)
- (Excitation) → Generator Power Transformers (c=71%)
- Generator And Auxiliaries →Generator Power Transformers (c=71.5%)
- Circuit Breakers - Generator Voltage → Generator Power Transformers (c=80%)
- (Circuit Breakers - Generator Voltage) and (Generator Power Transformers) → (Brushes and Brush Rigging) (c=72%)
- (Headgates) → Brushes and Brush Rigging (c=73%)

For sequence pattern mining, we have used GSM algorithm and here are parameters for algorithms:

- Number of Valid Transactions: 476
- Minimum Support: 21.218%
- Maximum Support: 98.739%
- Minimum Confidence: 60.366%
- Maximum Confidence: 99.099%

The number of rules are 476, here are some sample of these rules for sequence pattern mining:

- (Brushes And Brush Rigging) and (Circuit Breakers - Generator Voltage) → Brushes And Brush Rigging (c=78%)
- (Brushes And Brush Rigging) and (Generator And Auxiliaries) → Brushes And Brush Rigging (c=70%)
- (Brushes And Brush Rigging) and (Turbines) → Brushes And Brush Rigging(c=74%)
- (Headgates) → Brushes and Brush Rigging(c=61.9%)
- (Brushes and Brush Rigging) and (Generator Power Transformers) → Generator Power Transformers(c=73.9%)
- (Brushes and Brush Rigging) and (Circuit Breakers - Generator Voltage) → Forced Outage (c=95%)
- (Generator And Auxiliaries) and (Generator And Auxiliaries) → Forced Outage (c= 93.6%)
- (Cooling Water Systems) and (Maintenance Outage) → Forced Outage (c=93.3 %)
- (Maintenance Outage) and (Turbines) → Forced Outage (c=93.2 %)

Conclusion

In this research, we have found some interesting patterns based on association rules and sequence pattern mining. These knowledge show the frequent patterns related to an outage of a component which are considerable. Moreover, the sequence patterns which have happened frequently could reveal some impressive knowledge about the time and sequence of a frequent outage of some components. Sequence pattern mining helps us not only to find dependencies between the outage component code and unit state but also to predict the next “outage code” or “state code.” However, these patterns need to be converted to knowledge by experts. On the other hand, while sequence pattern mining is an exciting topic with a high level of research activity, there are some challenges associated with this method. In particular, when two events occur with a moderately long time gap, they cannot be considered as being part of the same sequence. For future research, we have planned to propose a method that enables the incorporation of time gaps in sequence mining by defining the time gap as a parameter. A specified gap among events or outages in the pattern would limit the extracted pattern in sequence pattern mining. By defining both a minimum gap and a maximum gap, only events that fall within a defined time gap would be extracted, enabling the analysis of events such as outages that should not have multiple occurrences within a short period.

Reinforcement learning approach to finite inventory problem

Avi Sokol

Background

In the recent overview of Inventory Management for the Special 50th Anniversary issue of INFOR, Edward Silver (2008) mentioned "... one could argue that inventory management principles can be traced back at least to biblical times as evidenced by the story of Joseph interpreting the Pharaoh's dream as being seven years of plentiful harvests followed by seven years of crop failures and his associated advice to the Pharaoh to stockpile enough harvested grain during the plentiful years to ensure adequate food during the subsequent famine" (p. 16).

Indeed, the theory of Inventory Management is possibly as ancient as the human civilization itself. Nonetheless most researchers (Silver, 2008; Nahmias 2009; Axsäter 2015) tend to consider the article by Ford Harris (1913) on Economic Order Quantity (EOQ) formula to be on the first published material. Interesting enough Donald Erlenkotter (1990) explored that, up until 1988 the original article was "forgotten" and for many years Ford's different publication of 1915 "was erroneously cited" (p. 942).

Classical inventory problems

According to Silver (1981) classification of inventory problems, "classic" EOQ and its variations is a "single item with deterministic, stationary conditions" (p. 634). In addition to the advantage of relative simplicity to understand and to use, the EOQ family of models has a distinct trait of unchanging linear demand (for example, 18 units per hour). This assumption allowed solving more complex problems such as quantity discounts, budget or space constraints for multiple products, production planning, and many others.

A special development of EOQ - classical dynamic lot sizing problem - deserves an exclusive attention in the history of inventory control. In this problem, parameters (such as demand) for a single item are still assumed to be deterministic but time varying (for example, 72 units per day during first month, 90 units per day during second month, 54 units per day during third month etc.). According to Axsäter (2015), .".. [this] problem is relatively easy to solve exactly. The most common approach is to use Dynamic Programming. This was first suggested by Wagener and Whitin (1958)" (p. 54). It might be intuitive for some practitioners to consider demand to be varying over time, yet many theoretical inventory models still assume demand stationarity. Indeed practice-oriented authors consider the fields of forecasting and inventory control to be interconnected in the framework of supply chain management (Johnson and Pyke, 2000; Axsäter, 2015; Wagner 2002).

Starting 1913 EOQ model and its variations was dominating the emerging field of inventory research for next four decades till 1950s. According to Hans-Joachim Girlich and Attila Chikan (2001), "the increasing practical interest in inventory management after World War II coupled with the development and full acceptance of probability theory as a branch of mathematics have led to such a concentration of combined research efforts of prominent economists and mathematicians [...] the result of which is the "Stanford Studies," an unprecedented landmark in the development of inventory theory" (p. 352). Harvey Wagner (2002) wrote: "The United States Air Force, Navy, and Army funded research efforts aimed at improving the performance of logistics systems. The research impetus driving inventory modeling was in full force by 1954" (p. 217). Edward Silver (2008) added, "...from the 1960's onward there was a rapid proliferation of publications [...] in a wide range of outlets. Text books on inventory management began to appear in the 1960's" (p. 16). It is not uncommon to read about 1950s and 1960s as the era of "path breaking modeling" (Wagner, 2002, p. 218) or even "golden era of inventory theory" (Girlich and Chikan, 2001, p. 353).

Stochastic inventory models

It is during this time we see the formulation of major stochastic (probabilistic) inventory ordering policies (terminology from Axsäter, 2015) often referred to as "R-Q" [also known as "Q-R" by Nahmias, 2008; "Q-r" by Muckstadt and Sapra, 2010; and "s-Q" by Silver, 1981] and "s-S" [also known as "R-s-S" by Silver, 1981]. Both ordering policies can use different ordering systems (terminology from Axsäter, 2015) such as Continuous review (when inventory level or position is monitored continuously) or Periodic review (when inventory level or position is assessed at certain given points in time). Whether Continuous or Periodic review, under "R-Q" policy Q units are ordered once inventory declines to or below the reorder point R; or we order up to level S once inventory declines to or below the reorder point s under "s-S" policy. Similar to EOQ family of models, initial stochastic models were not exempt from suffering considerable assumptions such as infinite time horizon and specific distribution of the demand (for example Normal).

In practice, however, with all the progress in the field of stochastic modeling even the funding organizations often continued do use the classic EOQ theory. For example, according to Larry Austin (1977), "... in 1958 the [U.S.] Department of Defense directed to use of basic EOQ principles in all defense procurement and logistics agencies. Although many changes were made over the years, as late as 1973 Air Force Logistics Command (AFLC) was still using a variation of the basic [...] model to determine optimal ordering quantities for its 250,000-item active inventory of expendable spares"

(p. 1). Why is that? Perhaps the best insight was provided by Stelios Zanakis et al (1980): “A plethora of inventory models has appeared in the literature, based on a multitude of (often unrealistic) assumptions [...] striving for mathematical optimality. [...] Managers want to improve their current operation as cheaply and quickly as possible, care little about the optimal solution to a problem with usually inexact data, and will not accept a new solution they do not understand” (pp. 104, 109). This quote especially resonates with the practical experience of the author of this report. Indeed, many authors acknowledge the split between theoretical orientation of academia and practical interest of the industry in the field of Operations Research starting in 1970s, often referred to as “the natural academic drift” (Corbett and Van Wassenhove, 1993; Meredith, 2001).

Digital era of inventory management

The next chapter of Inventory Theory was influenced by the rapid development of the data processing power of commercially available computers and spread of the Internet in 1980s – 1990s. Even though most theoretical foundations for using more sophisticated techniques such as linear programming, Monte Carlo simulations, or heuristic searches in inventory control appear in back in 1950s, it is during this era we can see the theoretical and practical applications beyond “toy-sized models” (Wagner, 2002). Indeed, a remarkable example of the birth in 1950s and the rapid growth in 1980s of publications on multi-echelon inventory models can be found in the literature review by Ton de Kok et al (2018). A good example of industry applicatoin was reported by Ingrid Farasyn et al (2008) on the development of inventory target settings at Procter and Gamble using spreadsheet models starting 1980s. Authors employed simulations techniques to reach desired service levels and claimed multi-million savings.

In the new world of abundantly available data inventory control professionals faced a new set of challenges (and therefore research opportunities) well outlined by Wagner (2002) in the quote “... list [of data challenges] is long enough to convey why the phrase garbage-in-garbage-out is often used in discussion about demand forecasting and the distribution of forecast errors, and why automated replenishment systems commonly under-perform relative to manager’s expectations” (p. 221). Many existing problems were still not solved by the new technologies (Tiwari and Gavirneni, 2007; Wagner, 2002; Zanakis et al, 1980; Woolsey, 2006).

Looking back at the history of Inventory Theory, one can observe 3 elements that shaped the development of this field: stakeholders’ interests to challenge and fund scientific research, theoretical foundation of algorithms and models, technological sophistication to bring theoretical foundation into mass adoption. Starting in 1910s the “classic era” of inventory control gave birth to the first EOQ models. Four decades later the “golden era of inventory theory” introduced the foundations of stochastic models, shaped by the new realities and technologies of 1950s. And even though many more sophisticated theoretical models were developed during that period – it is the rise of computers and the Internet three decades later inspired a new “digital era” in the history of inventory management in 1980s – 1990s.

Introduction of machine learning

Today, three decades since the dawn of digital era, we are facing a new wave of technological progress in the field of Machine Learning (Neural Networks) and Reinforcement Learning well expressed by Richard Sutton and Andrew Barto (2018): "... the neural network provides the program with the ability to generalize from its experience [...]. How well a reinforcement learning system can work in problems with such large state sets is intimately tied to how appropriately it can generalize from past experience" (p. 14). Needless to say, the theory and application of inventory control routinely deals with the large state and action sets. One can think of inventory levels for 10 products each ranging from 0 to 1000 integer units resulting in the number of states greater than the currently estimated number of stars in the observable universe. Some researchers already experiment with the application of Reinforcement Learning in the field of Inventory Control (Gijsbrechts et al, 2019; Oroojlooyjadid et al, 2017).

Our models

As a proof of concept, we also developed two models. The first model is a Deep Q Learning (Off-Policy Temporal Difference Control) algorithm. An agent (AI) is making a choice every timestep on the inventory procurement for a single item: given the current inventory position, whether to buy more now and if yes - how much. The AI agent doesn't know anything about the distribution of the demand, the delivery lead time, or the cost structure. After several episodes of trial and error, Deep Neural Network eventually learns to recognize the expected consequences of different choices and makes (near-)optimal decisions. Since single item problem is well studied in the literature – we know the optimal answer for this problem to minimize the total cost. Our algorithm found a strategy with the total cost 0.04% greater than optimal solution.

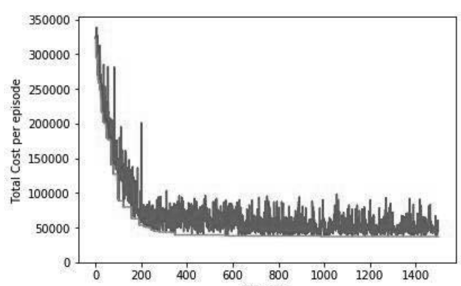

Fig 1: Total costs. Deep Q Learning algorithm. 1 product.

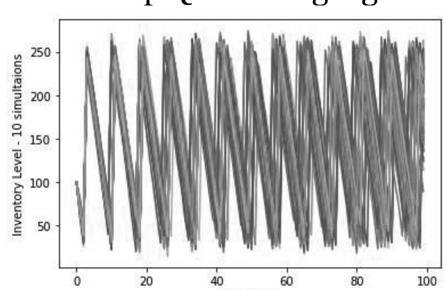

Fig 2: Inventory Level. Deep Q Learning algorithm. 1 product.

Inspired by these results, the first model was extended it to solve a multi-product system (2 items). With the similar settings, an AI agent has no knowledge about the distribution of the demands, the delivery lead times, or the cost structure of both products. Same as before Deep Neural Network is expected to learn the consequences of the different procurement choices. The tricky part of this environment is that ordering costs are shared for both products if procured simultaneously. Thus, the algorithm is challenged to find whether there is an opportunity to buy each product sub-optimally yet achieve system-optimality by saving on simultaneous procurement. Indeed, eventually the model recognized the benefit to buy both products sub-optimally (41.86% and 8.99% above their individual optimal procurement policies), yet save on simultaneous procurement and achieve system-optimal solution that is 18% less expensive than combined expected costs.

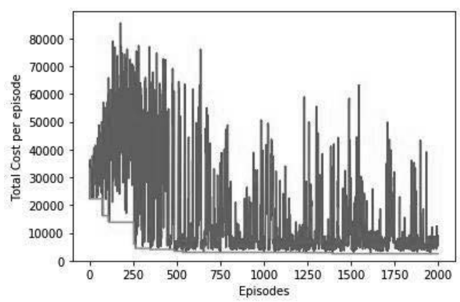

Fig. 3: Total costs. Deep Q Learning algorithm. 2 products.

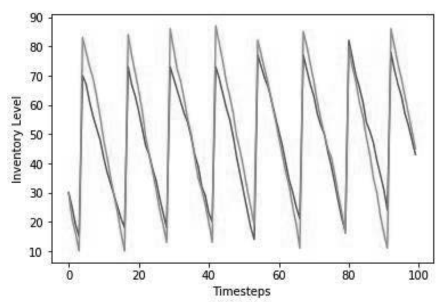

Fig. 4: Inventory Levels. Deep Q Learning algorithm. 2 products.

In the second model Reinforcement Learning Policy Gradient algorithm is used for a single-item stochastic stationary problem. Similar as before an agent (AI) is not given any information about the nature of demand, delivery lead times, or the cost structure. The difference of this algorithm is that the agent makes stochastic decisions about the procurement strategy (such as lot-size and reorder point of “R-Q” policy). After multiple trials and errors algorithm converges on the optimal policy. Indeed, one can observe (figure 6) the convergence of lot-size (Q) and reorder point (R), parameterized by Normal distribution mean and standard deviation, to their optimal values. The corresponding total costs (figure 5) also converging to the optimal value.

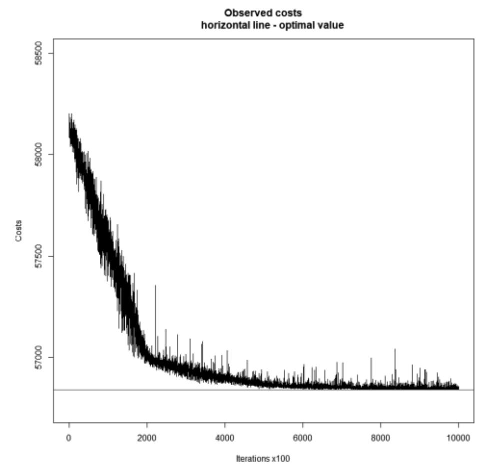

Fig. 5: Total costs. Policy Gradient algorithm.

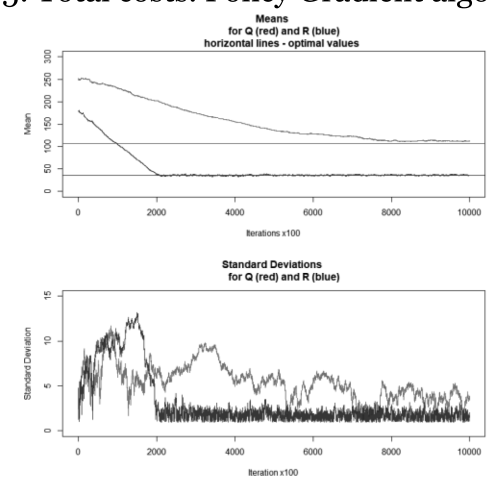

Fig. 6: Policy parameters. Policy Gradient algorithm.

Next steps

The challenge now is to extend these models to solve more practical and more complex problems. One good example can be multi-product system with the stochastic stationary demand and a *shared service level* constraint. Another interesting task can be *time varying* stochastic demand in a multi-product system with the shared set-up costs between some of the products.

Acknowledgement

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Preliminary analysis of DND PDE OCCAP data: missing operating hours

Dragan Banjevic

Background

To successfully analyse maintenance and condition monitoring data for the purpose of building a condition-based maintenance policy, it is necessary to have operating hours (working ages) and dates of every unit collected at any event of interest. The events of interest include installation of a unit, failures, repairs, maintenance actions, suspensions (e.g., taken out of service), and maybe more, and also measurements (inspections, condition monitoring). In our case, units of interest are propulsion diesel engines on 12 ships. Here we discuss completing operating hours for every engine in PDE OCCAP data. This report summarizes the efforts that have been made on the OCCAP data, and the requirements to move forward.

Original data are provided in the row-wise format, that is, every different measurement is provided as a separate record. It might be a convenient method for storing data in a database/spread sheet, but it is inconvenient for analysis, as a lot of information is repeated. It is quite inconvenient to find “missing” values. A standard format to use measurements in EXAKT is “column-wise”; that is, one record include all values measured at once on a given unit on a given day. This record should include engine Id, date/time of a measurement, and values of all variables on the list, so that one variable, say Iron, appears as a single column in the data.

An example of row-wise data (adjusted from original file): all measurements for unit 330 taken on 01/10/2013

Inspections_RW_3				
Ident	**InspDate**	**SampleId**	**CovarName**	**CovarValue**
330	01/10/2013	317604462	%Water	0.11
330	01/10/2013	317604462	Ag	0
330	01/10/2013	317604462	Al	2
330	01/10/2013	317604462	B	0
330	01/10/2013	317604462	Ba	0

Inspections_RW_3				
Ident	InspDate	SampleId	CovarName	CovarValue
330	01/10/2013	317604462	Ca	4412
330	01/10/2013	317604462	Cr	0
330	01/10/2013	317604462	Cu	2
330	01/10/2013	317604462	Fe	12
330	01/10/2013	317604462	Fuel	1.83
330	01/10/2013	317604462	K	4
330	01/10/2013	317604462	Karl_Fisher	1090
330	01/10/2013	317604462	Mg	
330	01/10/2013	317604462	Mn	
330	01/10/2013	317604462	Mo	9
330	01/10/2013	317604462	Na	7
330	01/10/2013	317604462	Ni	0
330	01/10/2013	317604462	**Operating_Hours**	18960
330	01/10/2013	317604462	P	652
330	01/10/2013	317604462	Pb	2
330	01/10/2013	317604462	Pentane	1
330	01/10/2013	317604462	Si	7
330	01/10/2013	317604462	Sn	0
330	01/10/2013	317604462	TBN	13.15
330	01/10/2013	317604462	Ti	0
330	01/10/2013	317604462	Visc_100	16.16
330	01/10/2013	317604462	Zn	765
330	01/10/2013	317604463	Maxigard	15.76

It can be seen that operating hours are included in the records just as any other variable, even if they have special meaning.

There are, in general three types of measurements: Coolant type, Lube Oil type, and Operating hours.

Find duplicates for Test1 Query	
Point_szID Field	NumberOfDups
Coolant Fuel	1
Coolant ISO Particle Count	3
Coolant Maxigard	236
Coolant Nalcool	106
Coolant Spectrography	300
Coolant Soot (FTIR)	1
Coolant Viscosity at 100C	2
Coolant Water and Sediment	188
Coolant Water Test	4

Find duplicates for Test1 Query	
Point_szID Field	**NumberOfDups**
Lube Oil Flash Point	17
Lube Oil Fuel	367
Lube Oil ISO Particle Count	3
Lube Oil Pentane	360
Lube Oil Soot (FTIR)	19
Lube Oil Spectrography	7380
Lube Oil TBN	362
Lube Oil Viscosity at 100C	369
Lube Oil Viscosity at 40C	3
Lube Oil Water and Sediment	16
Lube Oil Water Test	730
Operating Hours	185

In most of the cases, coolant and oil type of measurements are not taken on the same day, but a few days (mostly 1-4) apart, but could be more. In most of cases with oil measurements, Operating hours (OH) are collected, but not with coolant variables. It can be assumed that those OH can be applied to coolant variables, if they are close in date, as well. The problem is that we need OH with *every* measurement, otherwise they would be useless. Luckily, at the end of every month (most of the time), by default, OH are collected and stored. We have combined all available information from OCCAP data, maintenance data (PDEOrders_Cost_Quantity), and OH data (PDE Fleet Running Hours) to recreate an Inspection table that includes column-wise data on measurements. We considered all coolant and oil measurements being taken on the same day, if they are close enough, and assign them appropriate operating hours. If OH for a record was missing, we interpolated it from close record, whenever appropriate. After this analysis, the data in column-wise format looks like the following part (only a few variables displayed).

Ident	Date	WorkingAge	%Water	Ag	Al	B	Ba	Ca
330	10/09/2013		0.01	0	1	0	0	3876
330	01/10/2013	18960	0.11	0	2	0	0	4412

For example, Working Age (OH) on 10/09/2013 is missing. We did not have enough information to interpolate it safely. You may compare this format with row-wise data above.

Below we provide all case for which we cannot use guess work/interpolation for the records. They are listed per unit Id, 330 (HMCS HALIFAX), 333 (HMCS TORONTO), and 337 (HMCS Fredericton)

List of missing values/problems with OH that require DND insight. Other problems solved by interpolation/extrapolation.

Note: %Water was a good indicator for missing or sparse records. The value of 100 is artificially added and used to indicate OH found in maintenance records. The value of 1000 is used to indicate OH found in PDE Fleet Running Hours; you don't see it below, but it made roughly half of all OH records. You may ignore this column.

Comment on 330: In this case, it is clear that 330 was installed much earlier than 08/03/2013, as OH on 17/04/2013 is 18458. Installation date/time (OH = 0) is needed, as well as missing OH (working age). There is an obvious error (typo?) on 30/10/2014. Most dates are too apart to be useful for interpolation.

Inspections_1				
Ident	Date	WorkingAge	WA interpolated	%Water
330	08/03/2013			
330	08/04/2013			0.09
330	17/04/2013	18458		0.14
330	09/05/2013			0.12
330	08/07/2013			0.13
330	17/07/2013			0.12
330	10/09/2013			0.01
330	01/10/2013	18960		0.11
330	17/10/2013			0.11
330	15/11/2013			0.02
330	05/02/2014	19296		0.15
330	11/02/2014			0.27
330	07/05/2014			0.12
330	29/05/2014			
330	07/07/2014			0.07
330	08/08/2014			
330	19/09/2014			0.17
330	09/10/2014			0.21
330	30/10/2014	574	? typo, too small	0.11
330	02/12/2014			0.16
330	03/02/2015			0.2
330	09/04/2015			0.23
330	12/05/2015			2.1
330	06/08/2015			0.23
330	18/09/2015			0.24
330	23/02/2016	20723		0.93

Comment on 333: In this case, it is clear that 333 was installed earlier than 04/11/2012, as OH on 17/10/2013 is 24982. Another problem is that the gap in OH between dates 06/01/2014 and 19/08/2014 is too big (43609 – 25300 = 18309 hours) to be correct for 6 months' time. Similar problems appear two times below.

Inspections_1				
Ident	Date	WorkingAge	WA interpolated	%Water
333	04/11/2012		missing	0.11
333	16/04/2013			0.13
333	15/05/2013			0.14
333	20/05/2013			0.1
333	18/09/2013			0.01
333	17/10/2013	24982		100

Inspections_1				
Ident	Date	WorkingAge	WA interpolated	%Water
333	06/01/2014	25300		0.17
333	21/02/2014			0.08
333	07/03/2014			0.05
333	07/07/2014		? Too large	0.16
333	19/08/2014	43609		100
333	04/09/2014	43609	1	0.14
333	07/09/2014	43609		100
333	21/10/2014	51959		100
333	27/10/2014	51959		100
333	05/01/2015		? Too large	0.06
333	28/01/2015	78563		100
333	28/01/2015	78563	1	0.2
333	03/02/2015		? Too large	0.15
333	11/02/2015	79339		100

Comment on 337: Same problem in date/time conflict with OH, as above, unless OH = 2100 on 11/02/2014 is incorrect. We don't have other records on 337 before 11/02/2014 in the data.

Inspections_1				
Ident	Date	WorkingAge	WA interpolated	%Water
337	11/02/2014	2100		0.05
337	10/04/2014		? Too large	0.05
337	10/07/2014			0.09
337	12/09/2014			0.14
337	18/09/2014		? Too large	0.12
337	30/10/2014	20514		1000

Prognostic RUL estimation integrating statistical model and machine learning

Li Yang

Background

Remaining useful life (RUL) estimation is a crucial technology supporting intelligent predictive maintenance and health management. Deep learning (DL) approaches has been proven effective in RUL estimation due to their capacity in handling high-dimensional non-linear degradation features. However, their applications in practice may face two challenges: (a) online update of lifetime information is unavailable, and (b) prediction uncertainties cannot be quantified analytically.

Our project addresses these problems by developing a hybrid DL-based prognostic approach. Specially, a Wiener-based-degradation model with adaptive drift is employed to characterize the system degradation, among which the further trajectory is learned via an attention-LSTM-CNN encoder-decoder. All parameters are jointly optimized by treating the error coefficient as a special branch of the neural network, and then the drift parameter is updated through Bayesian inference. A high-efficient algorithm is further proposed for the calculation of RUL density function. The applicability is validated by a case study from the degradation data of turbofan engineering. The experimental results state that our proposal outperforms conventional Wiener-based and DL approaches in prediction accuracy.

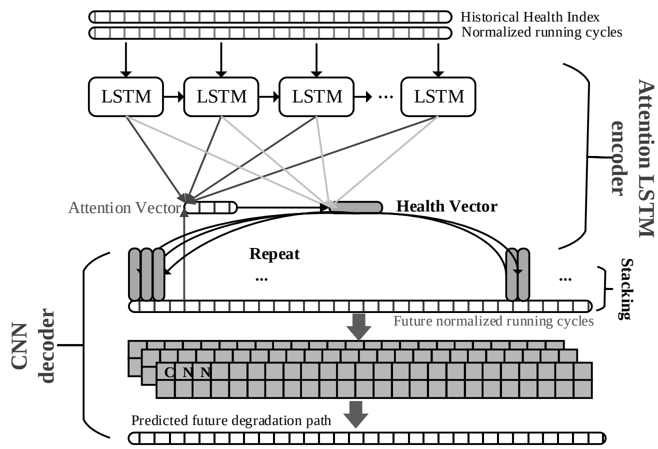


Figure 1 Structure of the attention-LSTM-CNN encoder-decoder

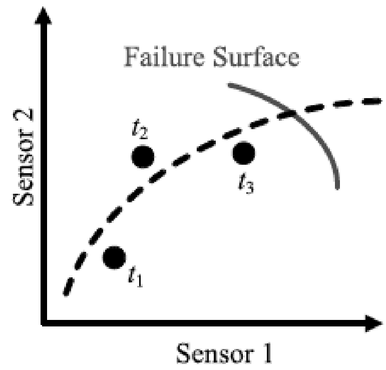
Technology via fusion of multiple sensor data

For diverse industrial assets, massive operational and health data from multiple source can be collected on board. Due to size and power limitations, simultaneous utilization of all data is difficult. Consequently, an essential challenge is how to effectively reflect and interpret the real-time health status of platforms via effective fusion of multiple-dimensional data. The core idea of our research is to construct a global health index, which can significantly reduce the size, weight and dimension limitation. The construction of health index is divided into the following 3 stages.

Stage 1-Feature extraction. Feature extraction from multiple-dimensional data. Technologies such as Functional Principal Component Analysis (FPCA) automation regression model can be adopted for feature extraction.

Stage 2-Data fusion. The second stage is feature fusion, where a comprehensive health index for military platform can be constructed via the combination of selected main features. The weight of each sensor data can be assigned and updated according to filter technology such as Kalman or Particle filter. The constructed HI can be regarded as a single signal, which significantly facilitates visualization and decision making.

Stage 3-Criterion interpretation. The final step is the interpretation of failure criterion using massive monitoring data. Since the criterion is usually hidden and uncertain, we are devoted to extract it by constructing a random surface based on supervised classification probabilistic framework, where the hidden pattern of failure surface is effectively reflected by the hyper-parameters of classifier.



The proposed framework has two notable superiorities.

(1) It is a general framework which can be adopted to diverse assets and platforms, since many data fusion approaches such as linear combination can be viewed as a special case of our classifier.

(2) The proposed framework is easy to implement and able to consider asynchronous data, and capable of solving the feature selection problem.

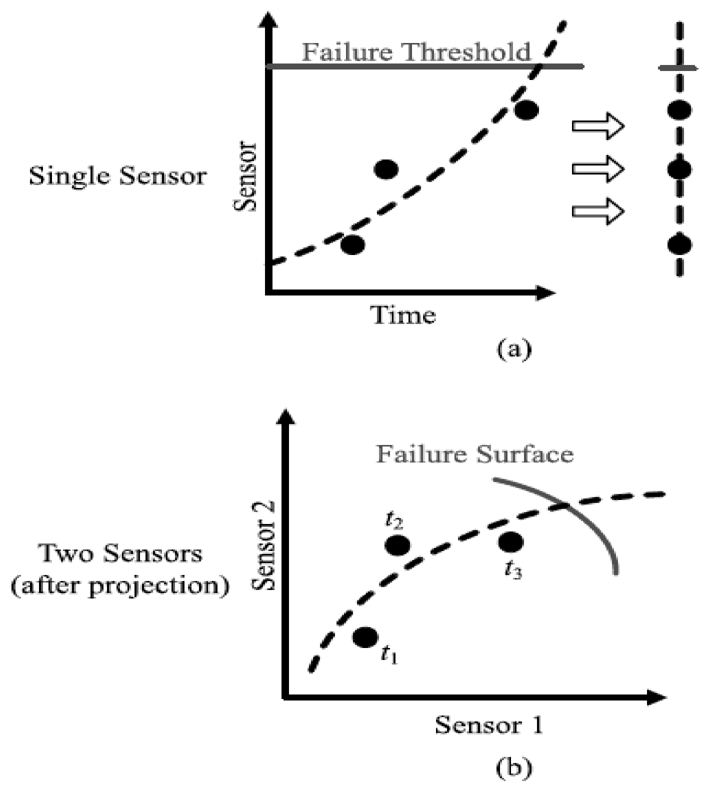


Figure 2 Failure surface construction based on multiple sensor technology

TTC: track re-inspection schedule optimization

Saravanan Kumar, Janet Lam, Dragan Banjevic

Background

At the last progress meeting, C-MORE submitted a preliminary analysis report that was limited to defects that were repaired leaving out the defects that were still open. Further analysis was performed considering all defects, both completed and still open. This report provides a brief summary of the project background, objectives, data gaps, analysis of findings followed by recommendations and scope for future work.

Introduction

The Toronto Transit Commission (TTC) follows the strategy of performing subway track line-tests on the entire system once per year. When track defects are identified, each defect is assigned a priority level with a corresponding time limit in which the defect must be resolved. Maintenance resources are often scarce and, in the event, that they are not available to repair defects on time, the non-destructive testing (NDT) team is assigned to re-inspect the defect to ensure that defects don't transition to higher risks. Every time the NDT team re-inspects a defect, the time limit to resolve the defect is restarted.

TTC feels that over the years, a significant portion of NDT team's resources have been expended on re-inspections. Hence, TTC wanted to review the time limits associated with each priority level and optimize the re-inspection frequency based on evidence.

Objective

The objective of this project was to determine an optimal re-inspection frequency for each defect priority level based on evidence while maintaining the current reliability of tracks.

Preliminary analysis

Priority levels

There are seven different priority levels, designated by colour, with red, yellow and purple being considered "high priority" defects, and blue, brown and gray low priority defects.

In practice, red defects can be related to track failures that demand immediate resolution. Likewise, yellow defects are considered a priority by the maintenance team, and thus are resolved relatively quickly. It is to be noted that gray defects are of least priority and doesn't require re-inspection by NDT team; they are recorded only for information in the event they are upgraded to higher priority.

Table 1 Defect priorities and associated time limits

Priority	Time limit (days)	Time between Re-inspections (actual)
Gray	None	231.64
Brown	365	139.42
Blue	45	36.42
Purple	21	17.38
Yellow	10	5.67
Red	1	1.29

Table 1 lists the priorities in increasing order, their time limits for resolution and actual time between re-inspections in practice. The time between re-inspections shown in the above table is the average of time elapsed between successive re-inspections when a defect stays in the same colour. It is clear from the above table that actual re-inspections are done more often than required i.e. shorter re-inspection time compared to the time limits associated with each priority.

Data gaps

According to TTC's practices, each defect is given a unique defect number and labelled "new" when it is first detected. Each follow-up inspection results in an entry labelled "updated," and a final entry labelled "completed," when the defect is repaired. Data from 2015-2018 was used for this project, and a new unique identifier was added to each data line to track changes from the original data during further data processing. Preliminary analysis identified several data gaps, some of which have been summarized below. The data gaps mandated the need for a data pre-processing and further manual overwriting to eliminate/minimize errors in data analysis.

Apart from the "new," "updated" and "completed" status, around 154 defects had a new status called "not found." Further analysis and discussions with the TTC resulted in the discovery of limitations in MOWIS, the Computerized Maintenance Management System (CMMS) used by TTC, contributing to bulk of the data gaps. For example, when a gray defect transitions to a purple defect, MOWIS doesn't allow an "updated" line with purple priority. TTC manually overrides this by entering "not found" to the current gray defect and opens a new defect with purple priority. It was found that these "not found" entries were crucial to the data analysis. Hence, the data were cleaned with objective to eliminate these "not found" entries with an appropriate status such as "updated" or "completed" and linking newly opened defects with existing defects where required. Other data gaps include errors in update date, defect colour, status, and defect numbers. These gaps were eliminated with mostly manual checking.

Analysis also showed downgrades in priority levels, which when further analysed showed were mostly due to misinterpretation in defect priority level while opening defects. This was also checked manually and overwritten.

Analysis

Transition analysis

For initial analysis, only periods in a defect history with no transitions were considered, i.e. up until a defect had transitioned; the summary of analysis is given in Table 2. The data summarized show the number of times, the average, population standard deviation and sum of days defects stayed in the same colour. This statistical analysis important to decide how to further analyse the data to benefit re-inspection schedule optimization.

Table 2 Summary of re-inspections without transition

Stay in same colour without Transition	Count	Average of stay in same colour (days)	Std. DevP of stay in same colour (days)	Sum of stay in same colour (days)
Blue	76	306.01	264.41	23257
Brown	24	292.33	264.09	7016
Gray	825	495.70	319.35	408950
Purple	364	153.49	138.67	55872
Red	4	2.25	1.09	9
Yellow	54	7.56	10.11	408

The analysis results showed that ratio is count to total time spent in each colour was significantly small. Also, the average was relatively closer to the standard deviation, suggesting a possible exponential behavior. This steered further analysis in the direction of Weibull analysis to account for several censored data.

Table 3 Summary of transitions

Transitions	Count	Average time for Transition (days)
Blue to Gray	5	219
Blue to Purple	4	172
Brown to Gray	4	490
Gray to Blue	3	374
Gray to Purple	32	385
Gray to Yellow	1	332
Purple to Blue	8	203
Purple to Yellow	13	115

Table 3 summarizes the defect priority transition (from-to), count and the average time taken for transition. It was found that *downgrades* were mostly due to interpretation changes and hence was not considered for future analysis. As part of this analysis, a transition rate matrix was also developed for future analysis as shown in Table 4.

Table 4 Priority level transition rate matrix

Colour / Transition Rate	Gray	Brown	Blue	Purple	Yellow	Red	Total
Gray	-8.7×10^{-5}	0	7.3×10^{-6}	7.8×10^{-5}	2.4×10^{-6}	0	8.7×10^{-5}
Brown	5.7×10^{-4}	-1.2×10^{-3}	0	0	0	0	1.2×10^{-3}
Blue	2.1×10^{-4}	0	-1.5×10^{-3}	1.7×10^{-4}	0	0	1.5×10^{-3}
Purple	0	0	1.4×10^{-4}	-5.2×10^{-4}	2.3×10^{-4}	0	5.2×10^{-4}
Yellow	0	0	0	0	-7.8×10^{-3}	0	7.8×10^{-3}
Red	0	0	0	0	0	0	0

Weibull analysis

The results from previous analysis showed good cause to perform a Weibull analysis. The objective of this Weibull analysis is to fit the failure data with suspensions in a Weibull distribution to obtain parameters such as shape and characteristic life. The parameters can further be used to estimate the reliability and hazard of the system over time.

The transitions were treated as "failures," completions and open defects were treated as "suspensions." The last date in the 2015-18 data was chosen as reference to calculate suspension time for open defects. The failure time is the transition time from one priority to any other higher priority.

Weibull analysis was performed only for Gray, Blue and Purple priorities, but not for Brown, Yellow and Red priorities as they did not have transitions to higher priorities i.e. failures.

The results from the Weibull analysis showed that the shape parameter was almost near 1.0 for all 3 priorities, suggesting an Exponential failure pattern. To confirm this behavior, the data was checked for fit with distributions such as exponential, Weibull, gamma and normal. The distribution fitting also suggested best fit with 2 parameter exponential distribution and the distribution parameters for the priority levels are shown in Table 5.

Table 5 Results of distribution fitting

Priority Level	2P – Exponential Distribution	
	Gamma	Lambda
Purple	1	2.34208×10^{-4}
Blue	2	1.73134×10^{-4}
Gray	2	8.83928×10^{-5}

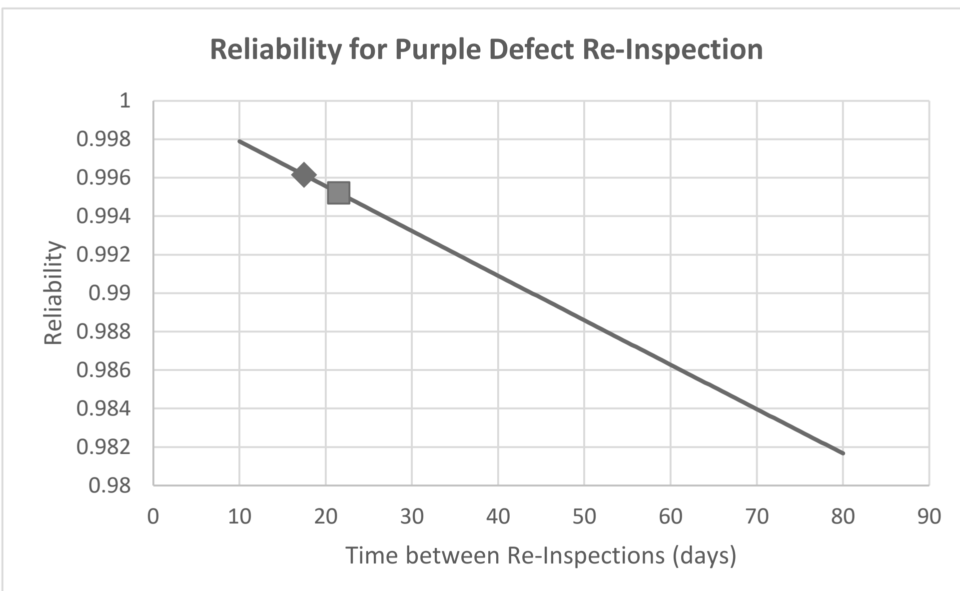
Reliability analysis

The reliability of a rail defect transitioning from one priority to a higher priority can be calculated using the reliability function of a 2-parameter exponential distribution shown below:

$$R(t) = e^{-\lambda(t-\gamma)}$$

It is a valid assumption that the time "t" resets after every re-inspection owing to the memoryless property of an exponential distribution. For example, when the re-inspection interval is set at 20 days, the probability of a defect not transitioning to any higher priority will be the same at 20, 40, 60 days and so on, provided there is no transitions during every re-inspection.   shows the reliability function of purple defect re-inspection with current reliability of ***99.6%*** at ***17.38 days*** re-inspection frequency (current practice) vs reliability of ***99.5%*** at set re-inspection frequency of ***21 days*** (time limit). The graph also shows an expected reliability of ***98.2%*** at **80 days** re-inspection frequency.

Figure 1. Reliability for purple defect re-inspection



This shows that there is not a high reduction in expected track reliability with increased track re-inspection interval. The results of the reliability analysis will be discussed with the TTC and suitable recommendations be made to satisfy the needs of TTC. The recommendations will be based on acceptable reliability levels and consideration of historic behavior of specific priority levels.

Future work

The number of failures i.e. transitions are very less compared to the total number of defects. This deficiency can be further examined to develop better models for determining optimal re-inspection frequency. The comparatively low failures will also pose a challenge while trying to drill down to defect modes for developing inspection frequency and focus in this area can further strengthen the project objectives. The work can also be developed to include cost of inspections and cost of failures to develop a mathematical model for optimizing inspection frequency.