AI-enabled Predictive Maintenance
Digital Twins for Industrial Systems

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- and all members of the MLAI group at GE Research

Key References

- Huang, H. Xu, C., Yoo, S., “Bi-Directional Causal Graph Learning through Weight-sharing and Low-rank Neural Network”, IEEE International Conference on Data Mining (ICDM19) Nov 2019
- Publications on Uncertainty in PHM - https://ti.arc.nasa.gov/tech/dash/groups/pcoe/uncertainty-prognostics/publications/
OUR MISSION ... “Research to Reality”

GE’S INNOVATION Ecosystem

- **Ideas** to scale
- **1000+ Researchers** - 600+ PhDs
- **3,000** patents across the company each year, 60K+ portfolio
- **Contemporizing model** ... market test everything
- **Delivering** sustainable tech differentiation

**BUSINESSES**
- Gas Turbines: 12,000
- CT scanners: 13,000
- Engines: 70,000
- Wind turbines: 40,000
- Oil & Gas: 150,000+
- Additive: 1,400

**GLOBAL NEEDS**

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Artificial Intelligence Group
GE Research

• 30+ years of Research, Development & Commercialization
• Over 50+ PhDs (computer vision, machine learning, knowledge representation, big data, & human system interaction)
• Broad spectrum of technology coverage:
  • Medical Image Analysis, Industrial Inspection, Aerial Inspection (drones & satellite-based) and Video Intelligence
  • Natural Language Processing, Knowledge Representation, and Reasoning
  • Diagnostics, Prognostics, Health Monitoring, and Time-series Analysis
  • AI-based Optimization & Controls and Workflow Automation
  • Science of AI: Robustness, Commonsense Reasoning, and Explainability.
• Integral partnerships with GE businesses, government, and academic institutions
Industry Value: Drivers and Dynamics

**Drivers**

1. **Increased Productivity**
   - Keep 300k people in the sky/hr.
   - Engine $70k
   - Gas & Steam Turbines $12k

2. **Faster Growth**
   - 1/3 of the world electricity
   - Wind Turbines $40k

3. **Risk-Managed Adaptability**
   - 16k scans per minute
   - HC Scanners 400k

4. **Improved Safety**
   - Digital - ↑ capabilities @ lower cost
   - E.g. Online, tele, autonomous
   - Blurring markets and government influences
     - E.g. Bezos, Musk, US/China

**Dynamics**

- Deeper customer engagement
  - E.g. Emirates, ENEL

- Blurring markets and government influences
  - E.g. Bezos, Musk, US/China

- Digital - ↑ capabilities @ lower cost
  - E.g. Online, tele, autonomous

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Maintenance Practices and Applications of AI

**Run to Failure**
- 1940: Liberty Ships
- 1920: Griffith Model
- 1956: Comet Aircraft
- 1957: Rotor Burst

**Preventive Maintenance**
- 1960: Paris Law
- 1970: RCM, CMMS

**Predictive Maintenance**
- 2000+

**Digital Twin**
A continuously learning model

**System Availability**
- 1930: Run to Failure
- 1950: Inspection
- 1970: CMMS
- 2000+: PHM, CBM, RCM

**Source:** Readiness & Sustainment Programs, Robert Cranwell, Sandia
Remote Monitoring Today

- Prevent Forced Outages
- Condition-Based Maintenance
- Performance Optimization

High-Value Assets
- Aircraft Engines
- Power Plant Equipment
- Manufacturing Systems

Sense
- Existing Sensors
- Inspection
- Advanced Sensors
- Advanced Inspection

Predict
- Advanced Signal Processing
- Artificial Intelligence
- Model-Based Diagnostics
- Sensor & Data Fusion

Assure
- Prevent Forced Outages
- Condition-Based Maintenance
- Performance Optimization

Improve Safety
Improve Availability
Maximize Performance
Improve Reliability

High-Value Assets

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Digital Twin

definition

Engineering models that continuously add insights into each asset to deliver specific business outcomes

1. Per asset model
2. Business outcomes
3. Continuously tuned
4. Scalable
5. Adaptable

**Inspection Optimization**
- Inspection Delay & Avoidance

**Work Planning**
- Workscoping
  - Maintenance, Repair, Inventory
- Workforce / Inventory Planning

**Work Optimization**
- Optimize Shop Maintenance
- Outage Mgmt. & Reduction

**Service Optimization**
- Shop & Region cost reduction + Per Asset Fleet Mgmt.

**Design Impact**
- Design for Service
- Design for Performance

**New Service Creation**
- Optimizing Controls
- Operations Optimization (N+1)
- Business Optimization (N+2)
Digital Transformation with Digital Twins

Sense
Predict
Control/Action
Inspect
Repair
Digital Twin
A Living, Learning Model

Coverage
Outcome

Operations Twin
Industrial Plant Twin
Business Twin
Platform + Digital Twin Applications
Stand-alone applications

Asset Twin
Process Twin

Sense
Predict
Consumer Sector Digital Transformation

**Digital model**
- Female
- Age 25-34
- Income < $70K

**Insights**
- e.g. Demographic

**Business outcome**
- e.g. Segmentation

**System**
- e.g. Books

**Transformation & expansion**

**Platform**

**Psychographic - Model of ONE**
- Female
- Age 25-34
- 1st child, 5-10 months
- Parents live ~ 600 miles
- Spends $1.2K/month online
- Income < $70K

**Profiling, prediction - P&L of ONE**
- Age 25-34
- Income < $70K

**New industries, services - platform for all**
- Amazon
- Google
- Apple

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GE’s Industrial Digital Twin

Digital model
- Flying in Asia-Europe Route
- 2-3 Service years

Insights
- e.g. Fleet

Business outcome
- Flying Singapore-London
- Last inspection distress ranking < 2
- Flies 80% between Coastal Airports
- Temp. T49 delta < 10F
- Due for overhaul in 7.1 months

System
- e.g. Fleet life and performance

Transformation & Expansion

Platform
- e.g. Services & Products

New Services & Products - Platform for all

Per Asset ... Per Flight - Model of ONE

Per Asset Analytics - P&L of ONE

Customized Optimizers
Digital Twin + Platform(s)

- Flies 80% between Coastal Airports
- Temp. T49 delta < 10F
- Due for overhaul in 7.1 months

Individual life and performance
- P(Event)
- Time

System
- e.g. Fleet life and performance

Transformation & Expansion

Platform
- e.g. Services & Products

New Services & Products - Platform for all
Example

**INPUTS**

- Atmospheric Data
- Operational Data
- Inspection & Repair
- Site Events

**GE DIGITAL TWIN**

- Lifting Models
- Health Models
- Thermal Models
- Transient Models

**OUTCOMES**

- Business Optimization
- Operations Optimization
- Asset Performance Management
- Advance Controls/Edge Computing
- Security

**CUSTOMER KPIs**

- Reliability
- Capacity
- Emissions

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Challenges in Predictive Maintenance → AI Opportunities

- Contextual Reasoning
- Industrial Data Quality
- Explainability
- Uncertainty and Trust
- Information to Action - Automation
- Continuous Learning
- Edge-Cloud Continuity
- Unstructured Information
Explainability

Deep Causal Learning
System-wide Monitor and Causality Analysis
Interpretable Deep Learning Model

Typical Deep Learning Model
- Unconstrained low to high level connection
- Hard to interpret influencing factors

DANCE: Deep Analysis Net w/ Causal Embedding
- Constrained & structured low level to high level connection
- Can trace back influencing factors

Modeling

Data Preparation

- Original n-dimensional time series
- Sample i

Test Sample → Trained model → Residuals + Factors (Anomalies)
Deep Causal Learning
• Models causal relationship between parameters of the system
• Does not require parameter subset selection prior to modeling
• Does not require identification of nominal set *apriori*
• Applicable to a variety of time-series formats
• Applicable across fleets, asset models,
Causality/Correlation Matrix

**Input:** Multivariate time series

\[ X(t) = \sum_{\tau=1}^{L} A_{\tau} X(t-\tau) + \varepsilon(t) \]

Granger Causality, Multivariate Linear

Fleet of 600+ engines
18 months of data
260+ parameters

Output: Relationships between timeseries

Fleet

Unhealthy Asset
Causality/Correlation Matrix - 2

**EXAMPLES**

1. Corrected Altitude = measures altitude as a function of total pressure, total air temperature
2. Computed Airspeed is subject to air-density changes,
3. Adjustment of fan air flowrate is affected by fan speed, explains desired cooling outlet temperature.
4. Fan speed, function of engine rotational speeds, is affected by Pressure and Bleed Position.
5. Outflow Valve is the actuator of the Cabin Pressure Regulating System.
6. The change of Valve Position is triggered by the change of altitude and outlet temperature.

\[ L_{\hat{N}} = \frac{1}{nmce} \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{c} (X(t)(i, t_{j+k}) - \hat{X}(t)(i, t_{j+k}))^2 + \lambda \| \hat{N} \|_2, \]

\[ L_{\hat{A}} = \frac{1}{nmce} \sum_{i=1}^{n'} \sum_{j=1}^{m} \sum_{k=1}^{c} (X(r)(i, t_{j+k}) - \hat{X}(r)(i, t_{j+k}))^2 + \lambda \| \hat{A} \|_2 + \gamma \| \hat{A} - \hat{N} \|_2, \]

\[ |\hat{A} - \hat{N}| = \text{Anomaly causal factors} \]
Information to Action & Trust

**Humble AI**
Understand Model Competence and Region of Trust for Safe Prescriptive Analytics – EXTRAPOLATION?
Motivating Examples from Industry

Fault Classification for Wind Turbines

I know this is fault class 1, please authorize to take appropriate actions.

The wind turbine generator might have fault 1 or 3, but not 2, I need more evidence to resolve confusion.

Treatment Prescription or More Tests?

The patient has symptoms of disease x, here is the evidence, I recommend to begin treatment.

The patient might have symptoms of disease x, but I need more evidence, please collect more data.

I don’t know if patient has symptoms of disease x, partner can you look into it.
# Identification of Model Competence

<table>
<thead>
<tr>
<th>Context</th>
<th>Example of Conceptual Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>On input side</td>
<td>Anomaly detection based on training distribution</td>
</tr>
<tr>
<td>On output side</td>
<td>Size of prediction intervals to detect unstable extrapolation</td>
</tr>
<tr>
<td>Jointly with input and output</td>
<td>Concept drift detection using residuals between actual and predicted outcomes</td>
</tr>
<tr>
<td>Internal model parameters</td>
<td>Epistemic models</td>
</tr>
</tbody>
</table>

**epistemology**

/əˈpɪstəˌmɒlədʒi/ (n)  
noun PHILOSOPHY

the theory of knowledge, especially with regard to its methods, validity, and scope. Epistemology is the investigation of what distinguishes justified belief from opinion.
Why Look at Epistemology of ML?

“How can we theoretically characterize what an AI "knows" and what it doesn’t?”

Epistemology is the study of the nature of knowledge, justification, and the rationality of belief for humans and human psychology, we explore to extend it for machine learning systems.

Machine learning provides statistically impressive results which might be individually unreliable:

- “My validation accuracy was high, so trust my belief”
- “Soft-max value for predicted class is high, so trust my belief”

Can we understand the limitations of ML due to:

- Observability (or separability)?
- Unreliable or brittle extrapolation?

If AI is aware of its own knowledge and limitations, then it can provide that information for reliability/safety as well as ask for help (Humble AI)
Epistemology in Machine Learning
Support from Geometric Neighborhoods

Characterizing region of trust, region of overlap, and region of extrapolation to generate Justification-based Reliability

KNOWLEDGE = JUSTIFIED TRUE BELIEF

Behavior of IK, IMK, and IDK regions as a function of $e$

References:
Learning-based Optimization for Wind Turbines

- Get the right data
- Deploy action
- Find optimal decisions
- Machine learning-based predictive and prescriptive models with continual learning
- Sensor data
- Control signals

Wind Farm
Humble AI with Digital Twin
Realizing full value of data-driven analytics by putting information to action

**Humble AI**

- Data → Model → Optimization under competence constraint → Prediction
  - Outcome with uncertainty

- Self learning → Learn from others → Learn from simulation → Continuous learning

- Optimal solution → Infeasible → Robust baseline

**Prediction**
- Control input or strategic action or feedback policy

**Prescription**
- +1% AEP

**Defining capabilities**
- understand region of trust
- quantify uncertainty
- ask for help when incompetent
- continuous learning from multiple sources

**Model**

- Continuous learning
- Learning mode selection
Final thoughts...

AI is already starting to create significant value

Trust is key to adoption

- Data quality and assurance
- Model assurance
- Explainability

Leverage physics and domain knowledge for AI

- Improves accuracy and capability
- Adds Explainability