Opportunities for Data Analytics in Power Generation

Prognostics: The Final Frontier

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XMPLR Energy
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- **Consulting**
  - Business Strategy
  - Disruptive Technology Introduction
  - M&A
- **Technology Liaison**
  - Licensing & Technology Transfer
  - Foreign Market Introduction
- **Data Analytics**

Key Opportunities for Data Analytics

- **Efficiency**
  - Fuel Costs
  - Capacity/Output
- **Reliability**
  - Availability
  - Capacity/Output
  - Load Factor
  - Maintenance
- **Emissions**
  - Compliance
  - Optimization
- **Flexibility**
  - Operational
  - Economic

Focus of Today's Talk

Data Science & Prognostics

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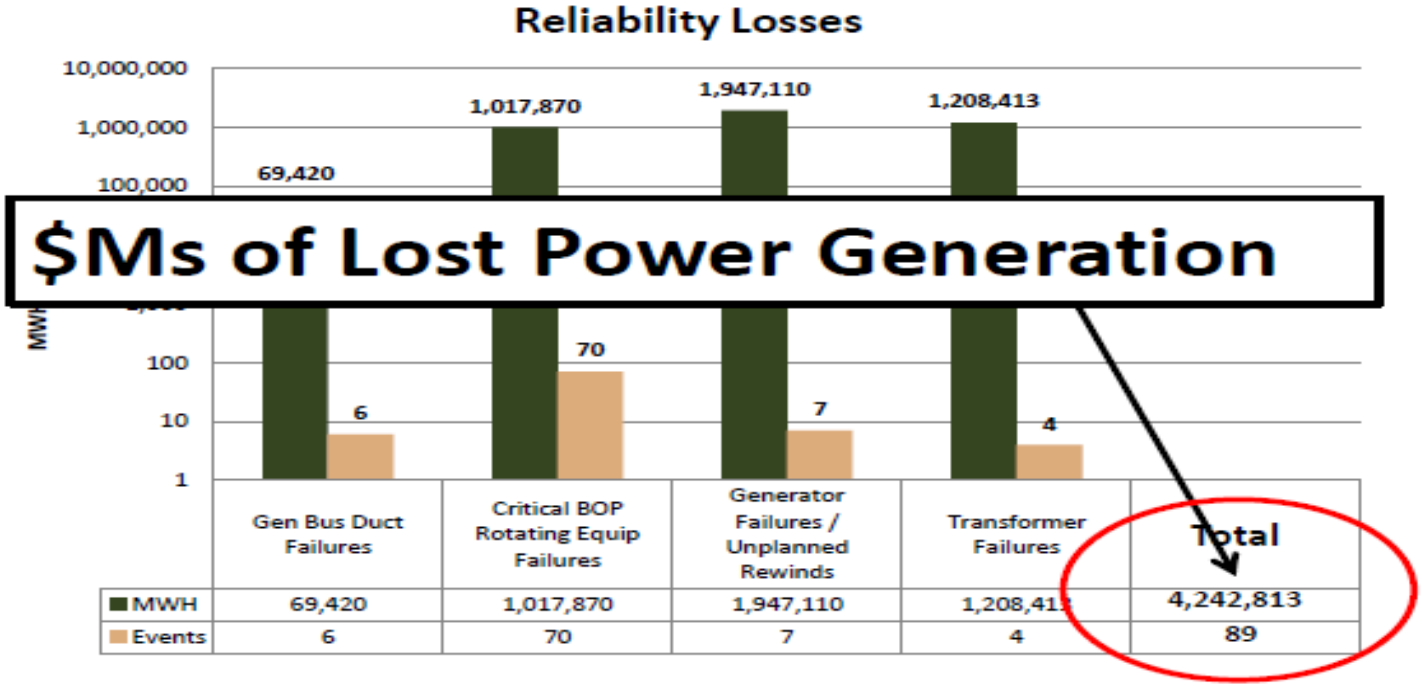
Why is this Important?

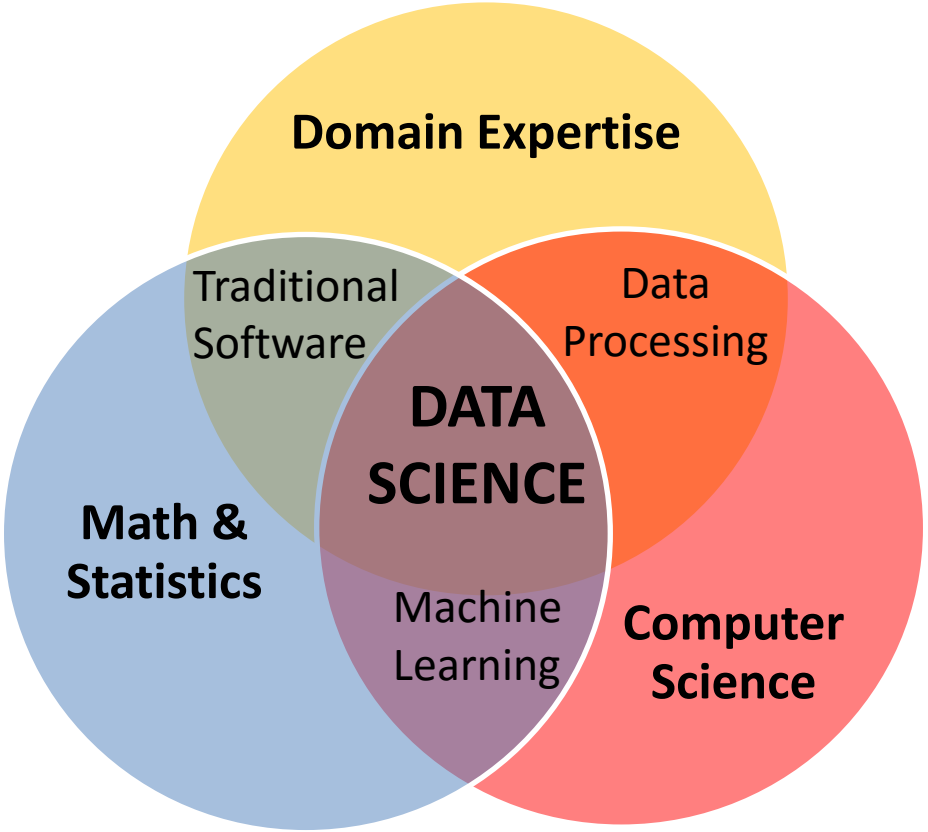


Source: Duke Energy. 2007-2012

Why is this Important?

MIT Study:
Bearing Failures in Rotating Equipment cause $240B in downtime and repair costs EVERY YEAR!

How can Data Science Help?



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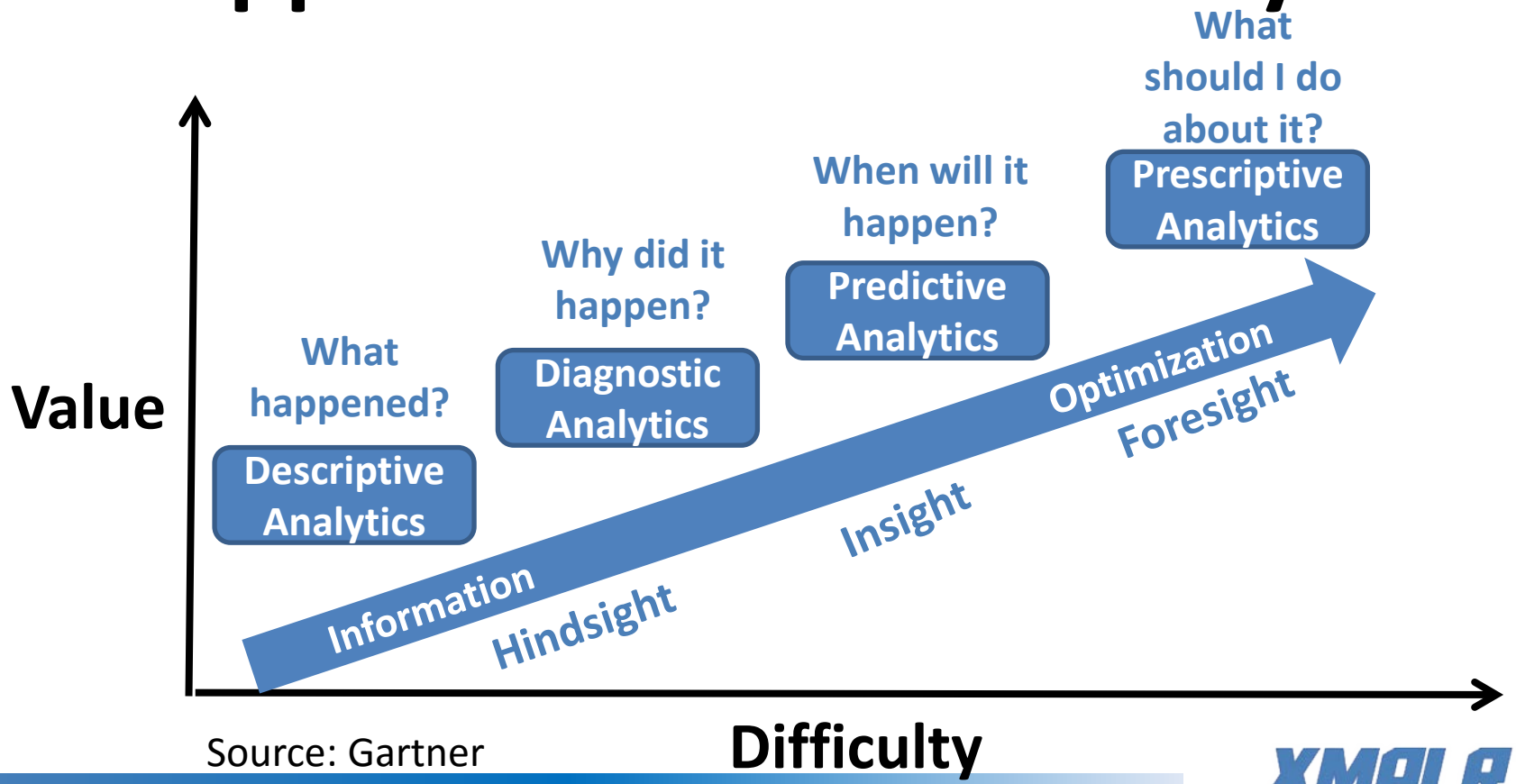
Approaches to Data Analytics



Source: Gartner

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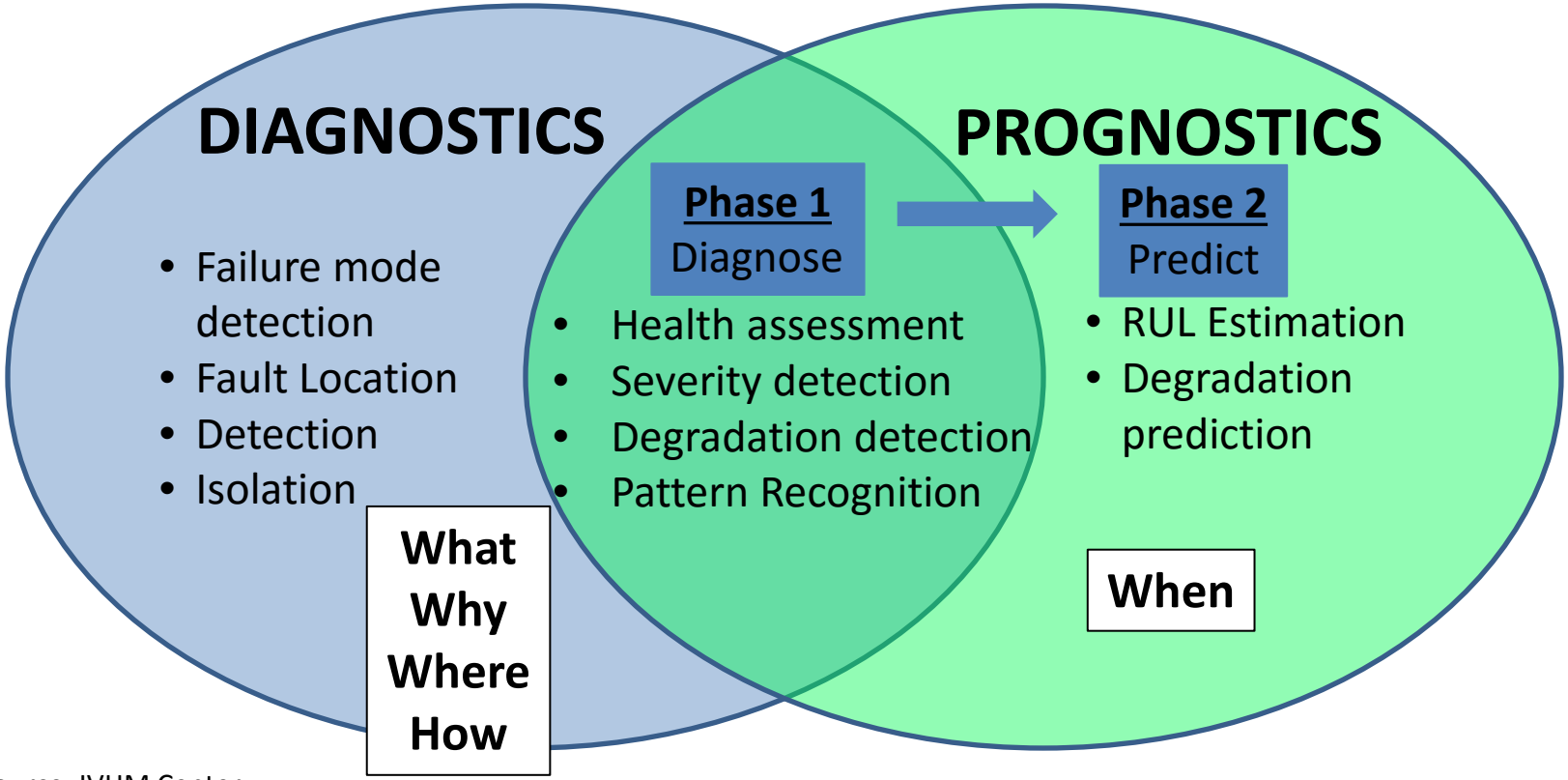
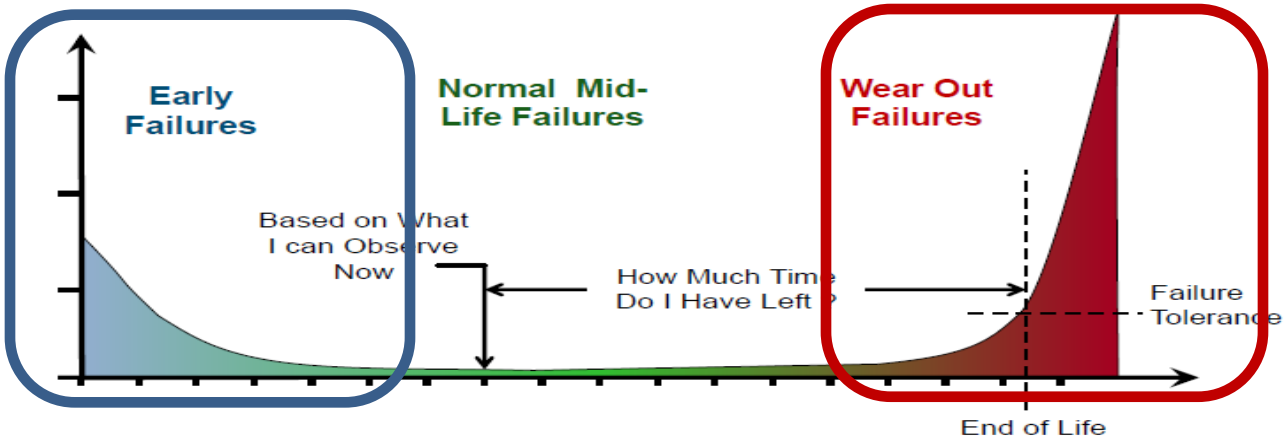
Diagnostics vs Prognostics



Source: IVHM Center

Traditional Failure Curve



Source: EPRI

- Failure rate are high in the early life – “infant mortality”
- Failure rates are high at the end of life
- Remaining useful life can be predicted.
- Based on assets that have regular & predictable wear
- The Rise of Predictive Maintenance!

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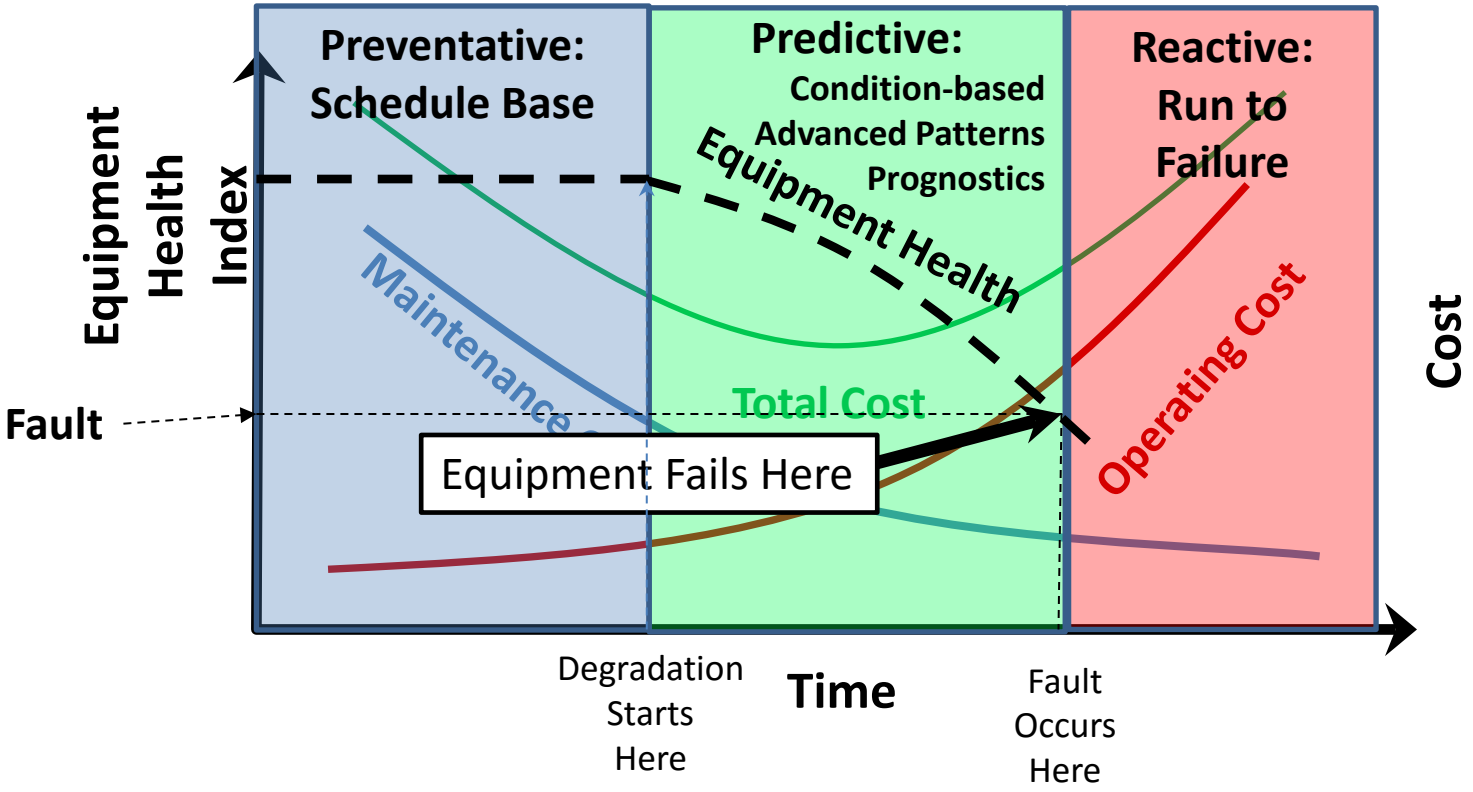
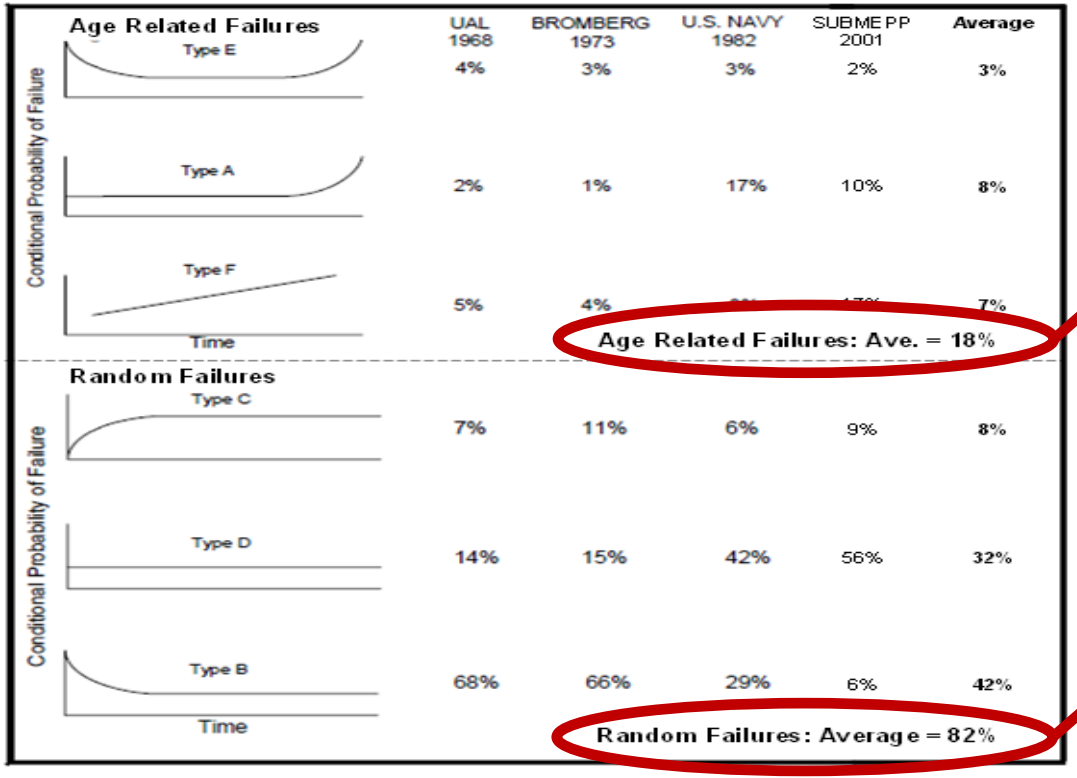
Predictive Maintenance



Predicting Failures is Hard



	UAL 1968	BROMBERG 1973	U.S. NAVY 1982	SUBMEPP 2001	Average
Type E	4%	3%	3%	2%	3%
Type A	2%	1%	17%	10%	8%
Type F	5%	4%			7%
Age Related Failures: Ave. = 18%					
Type C	7%	11%	6%	9%	8%
Type D	14%	15%	42%	56%	32%
Type B	68%	66%	29%	6%	42%
Random Failures: Average = 82%					

Only 18% of Failures are age-related

82% of Failures are random

Sources: RCM Guide, NASA, Sept. 2008, and U.S.. Navy Analysis of Submarine Maintenance Data 2006

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Using Predictive Analytics for Remaining Useful Life (RUL)

- **Condition Monitoring**
  - Identifies anomalies in data trends
  - Typically, provides little warning of a fault (hrs to days)
- **Advanced Pattern Recognition**
  - Specific signal patterns (features) linked to faults
  - Gives indication of likely future fault
  - Generally, more focused on diagnostics than prognostics
- **Mean time to failure**
  - Based on “average” life of particular asset
  - Needs large set of “crash test” data
  - But is your asset “average”?
- **Prognostics**
  - Predicting the time at which a system or a component will no longer perform its intended function
  - Includes a confidence level associated with the time prediction.
    - (i.e. RUL of 3 months at 60% confidence level

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Predictive Analytics vs Prognostics

Predictive Analytics

Something will happen at some point

Prognostics

Explicit time window until failure with confidence level

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Prognostic Approaches

Experienced-based Models
Advantages
• Based on actual failure experience • Rules-based • Simple • Little data required
Disadvantages
• Little prediction capability • Requires subject matter experts • Needs continued observations • Difficult to scale to other assets

Experience Based Models

Generic, statistical life, mean time to failure

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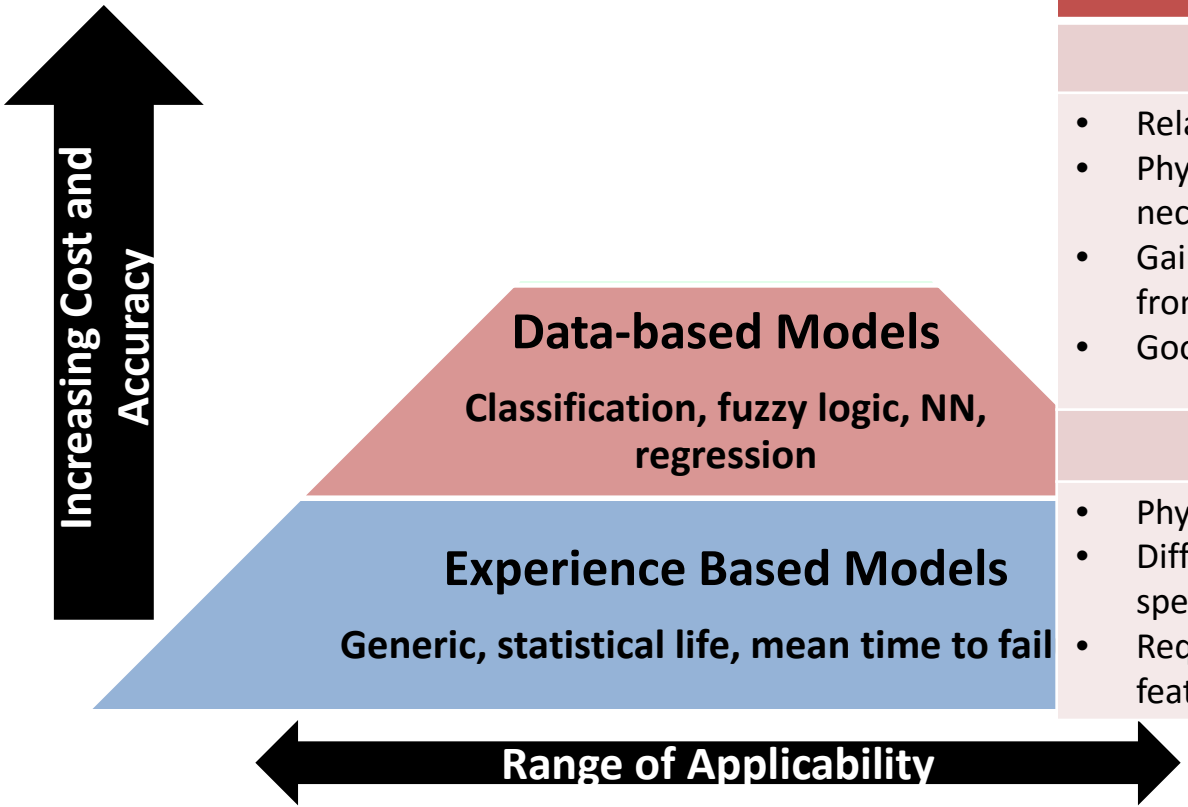
Prognostic Approaches



Data-based Models

Advantages

- Relatively simple and fast to implement
- Physical cause/effects understanding not necessary
- Gain understanding of physical behaviors from large datasets
- Good for complex processes

Disadvantages

- Physical cause/effects not utilized
- Difficult to balance generalizations and specific learning trends
- Requires large datasets to characterize fault features

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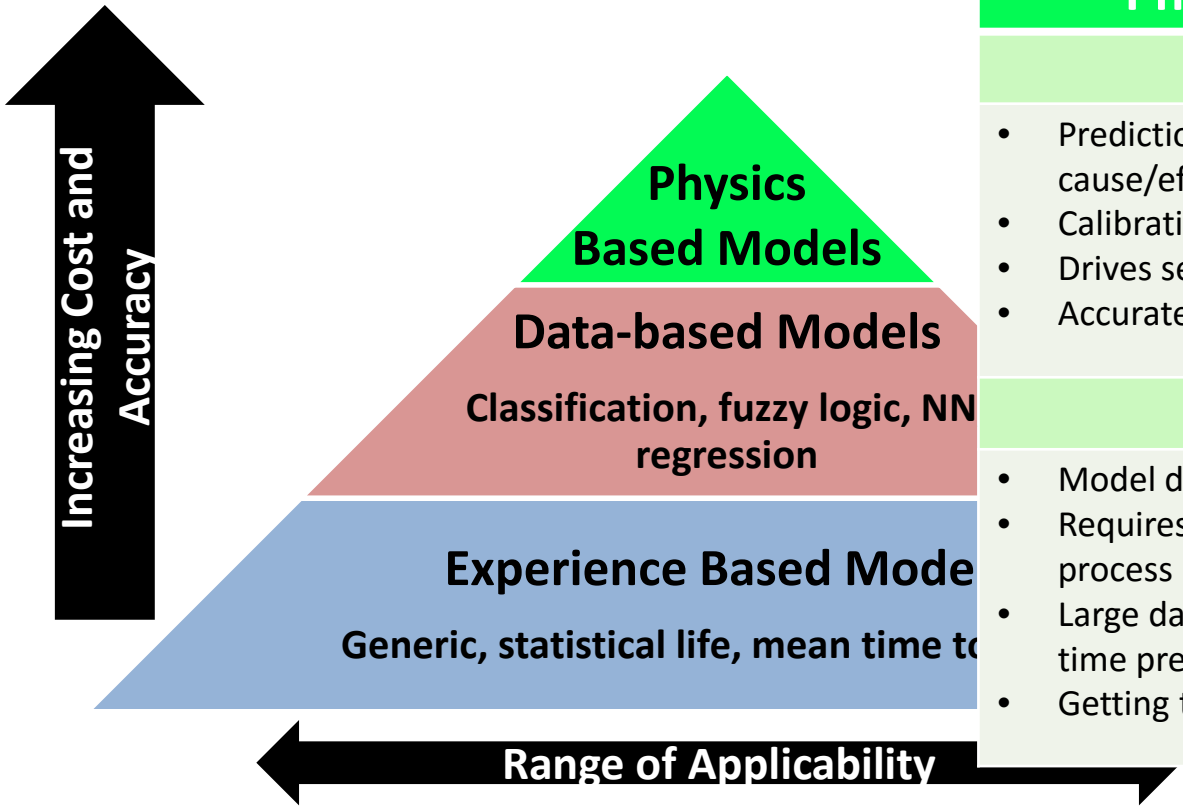
Prognostic Approaches



Physics-based Models

Advantages

- Prediction results based on intuitive cause/effects relationship
- Calibration only needed for different cases
- Drives sensor requirements
- Accurate

Disadvantages

- Model development may be hard
- Requires complete knowledge of physical process
- Large datasets may be unpractical for real-time predictions
- Getting the “right” data may be difficult

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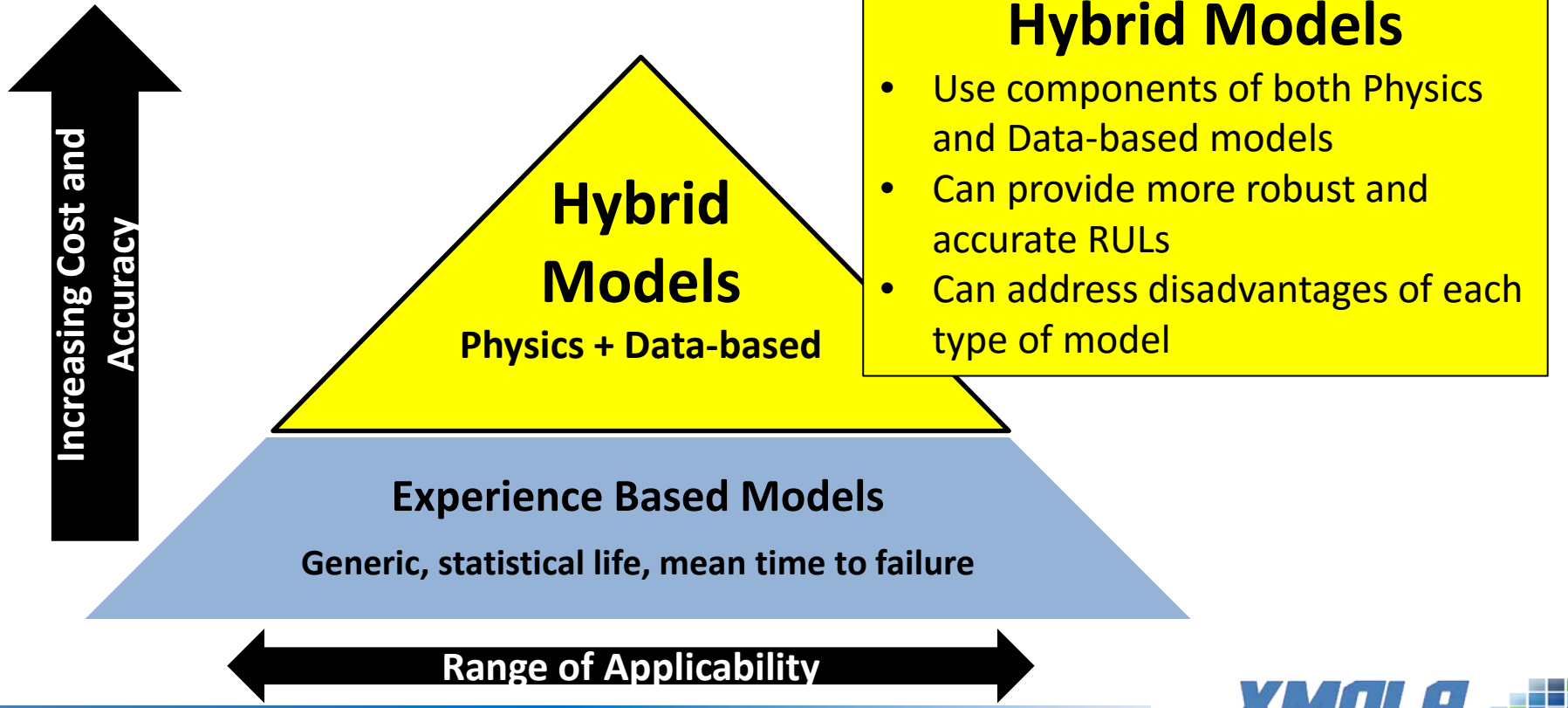
Prognostic Approaches



Hybrid Models

- Use components of both Physics and Data-based models
- Can provide more robust and accurate RULs
- Can address disadvantages of each type of model

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Power Generation Applications for Prognostics

Rotary Equipment

- Turbines
- Pumps
- Generators
- Compressors
- Gearbox
- Bearings
- Fans

Other Possibilities

- Boiler Tubes?
- HRSG?
- Condensers?
- Heaters?
- Valves?

Prognostics Implementation Challenges

- **Data**
  - Measuring the right things
  - Cost of New Sensors
  - Access to multiple data sources
  - Clean data
- **People**
  - M&D centers: leverage expertise
  - In-house vs outsource
- **Accuracy**
  - Confidence in predictions
  - Uncertainty in predictions
  - Validation and verification
- **Data Security**
  - Various data sources
  - Cloud-based or local server
  - Sharing data/information within company

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Conclusions

- Data analytics can help operators manage and improve reliability of generation assets.
- Prognostics can be used to determine a RUL with a time element and confidence level
- Operators can use the RUL to actively manage maintenance schedule and operating conditions in order to maintain reliability.

Thank You.

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