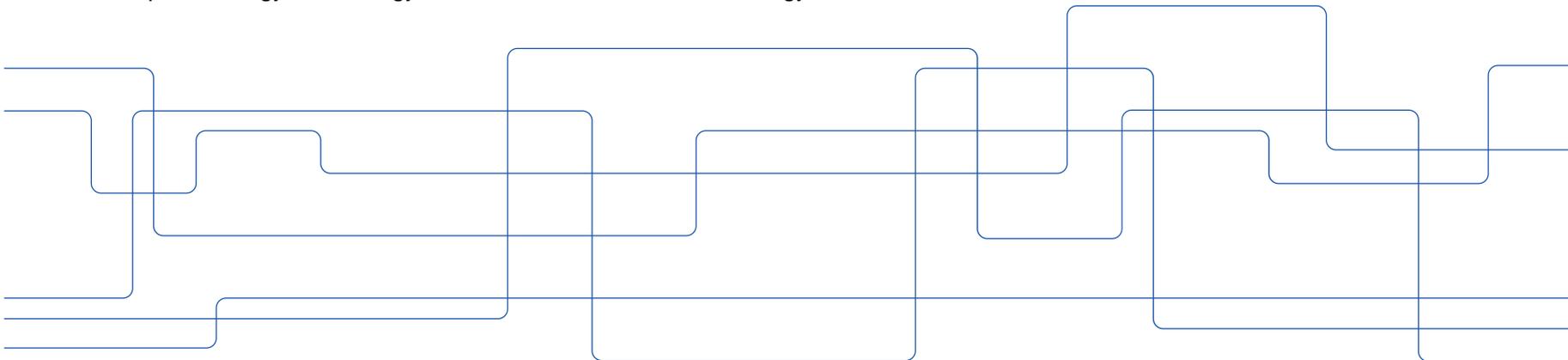


Health monitoring for highly reusable launch vehicles using Machine Learning

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Introduction

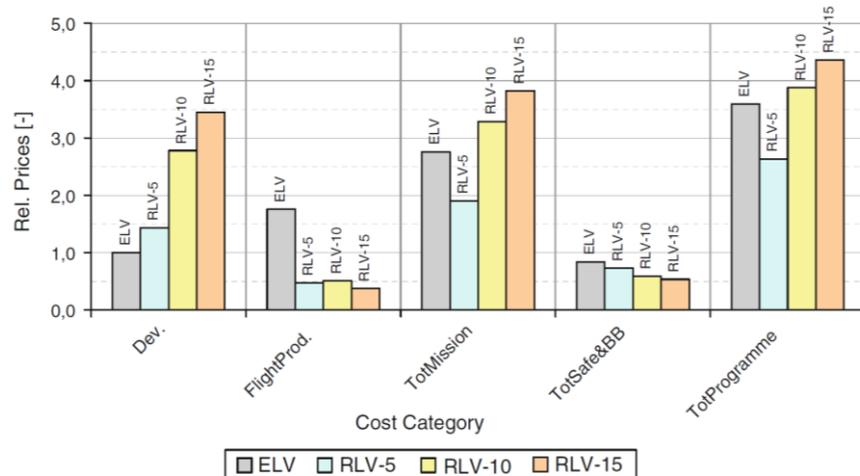
- Sweden has **many assets and capabilities**, linked to strong knowledge and experience, that let it profit from the growing (commercial) space market
- **Independent EU access** to space is of strategic importance, and **Sweden is uniquely positioned** to provide many parts of the value chain
- **Reusability** can support both **economic** and **strategic aspects**
 - Reduced launch service costs
 - Rapid response capabilities



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Reusability & Financial sustainability



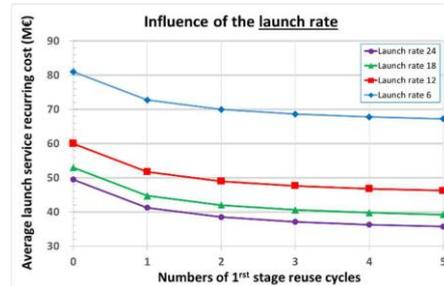
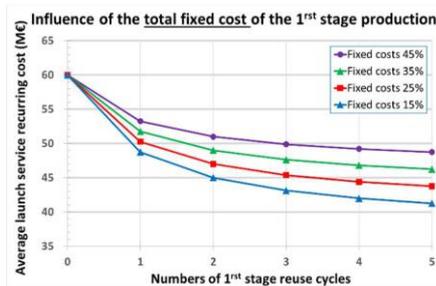
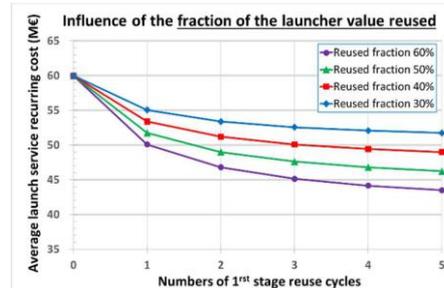
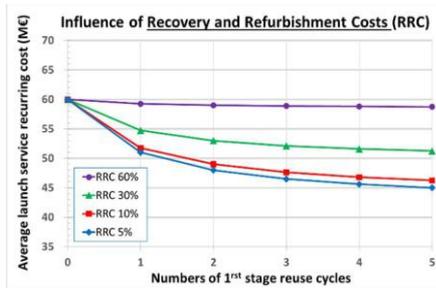
From: Preclik, D. et al, 2011 [1]

- The **key financial feature** of reusable launch vehicles is the **reduction in vehicle costs per flight**.
- **Development costs will rise** due to increased design and analysis efforts, as well as the need for more testing due to more difficult validation requirements
- Further **cost increases** occur due to new **inspection** and **maintenance tasks**
- Due to this there **may be a minimum in costs**, which reflects the **current state of technology**
- **Technical solutions** to the above issues will therefore become **increasingly valuable**



Reusability & Financial sustainability

- The impact of recovery and refurbishment activities on launch service costs is on the same order as
 - that of the **fixed costs** and
 - the **fraction** of the launcher value that can be **reused**
- Optimization of **recovery** and **maintenance** processes will therefore likely become an **important** source of competitive advantage



From: Oswald et al., 2020 [2]



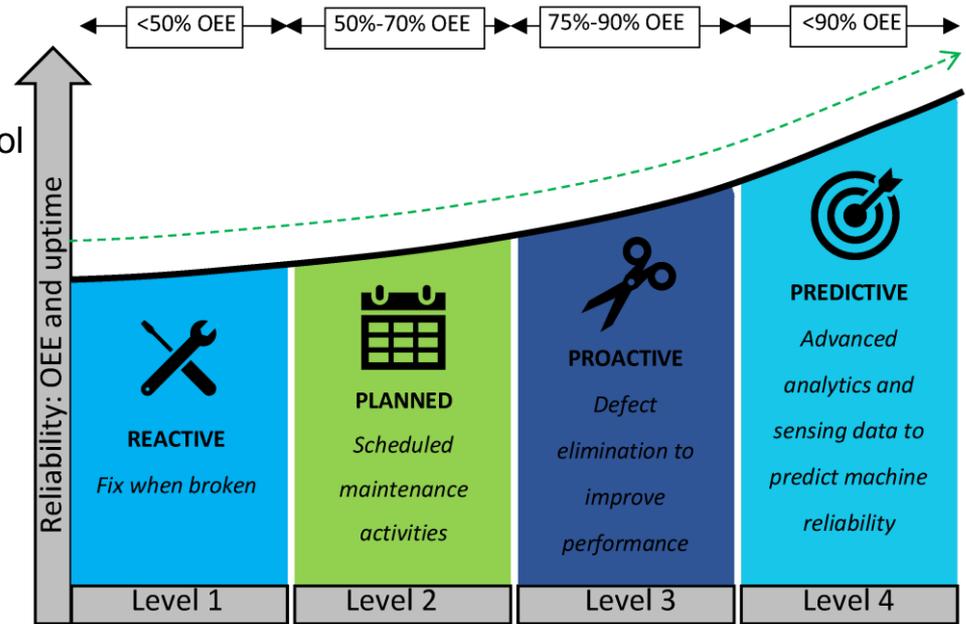
Space Shuttle Main Engine – Lessons Learned [3-4]

- High costs related to maintenance processes due to:
 - Up to 120h of maintenance work with large team
 - > Suboptimal accessibility makes maintenance difficult and slow, increases reassembly time and risk
 - > Large inspection burden due to limited health monitoring
- Lessons for second generation reusable engines
 - Design for
 - > Reuse: trade-off between performance and part/system life time
 - > Inspection and maintenance: critical parts need to be accessible
 - Monitor
 - > Provide necessary information for maintenance planning
 - > minimize inspection and maintenance burden



How to decrease cost and increase reliability?

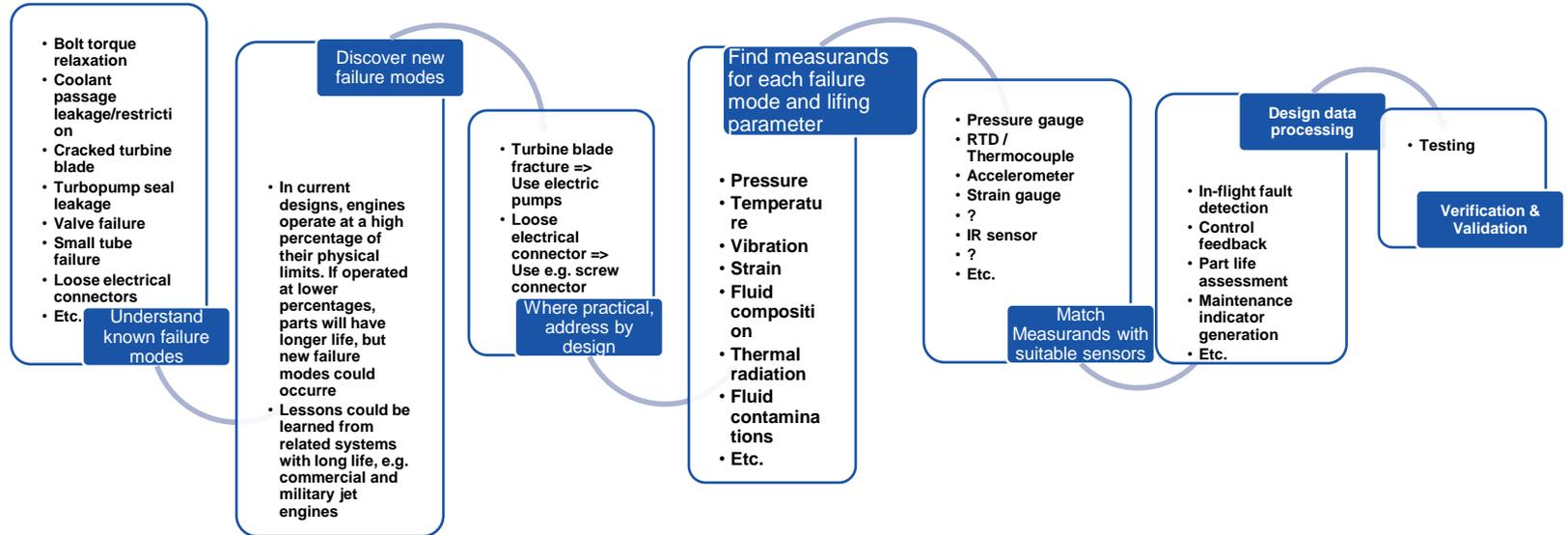
- Use advanced sensor data and intelligent on-board processing to:
 - Detect faults quickly
 - Implement Damage Limiting Control
 - Asses maintenance needs
 - Report system reliability status



From: Carvalho et al., 2019 [5]



Approach and challenges



Key challenges:

- New failure modes
- Lacking sensors
- Lacking data to test algorithms



Sensors

- Sensors will be necessary for
 - In-flight, onboard and real-time diagnostics
 - > Selected based on performance metrics and failure modes
 - On-ground inspection and maintenance
 - > Select sensing capabilities that cannot be placed onboard but are highly value adding to inspection and maintenance.
- Many ‘commercial of the shelf’ sensors could be used
- New sensor technologies may enable advance predictive capabilities
 - Example: Online detection of fuel decomposition in engine cooling channels, which may lead to elevated wall temperature due to solid carbon depositions.
 - > Currently under development at KTH





Machine Learning (ML) using neural networks (NN)

- Machine Learning has been successfully applied to [5]:
 - Heat transfer predictions in rocket cooling channels
 - Fatigue life estimations
 - Discovery of suitable precursors to combustion instability
 - Optimized engine control
- Advantages
 - Similar accuracy as high-fidelity CFD or FEM simulations
 - Low prediction time (a NN only has to multiply the input vector with its weight matrices to generate the output)
 - NN can scale to large data sets and capture the behavior of complicated functions with high-dimensional inputs and outputs
 - Data fusion and assimilation techniques allow to integrate multiple data sources and combine simulations and experimental data in a systematic way
- Disadvantages
 - Depending on the complexity of the problem, the construction of a precise approximation model can require a huge number of data samples
 - NNs are not able to extrapolate, but only provide reliable predictions within the region of the input space that is populated with “training points”



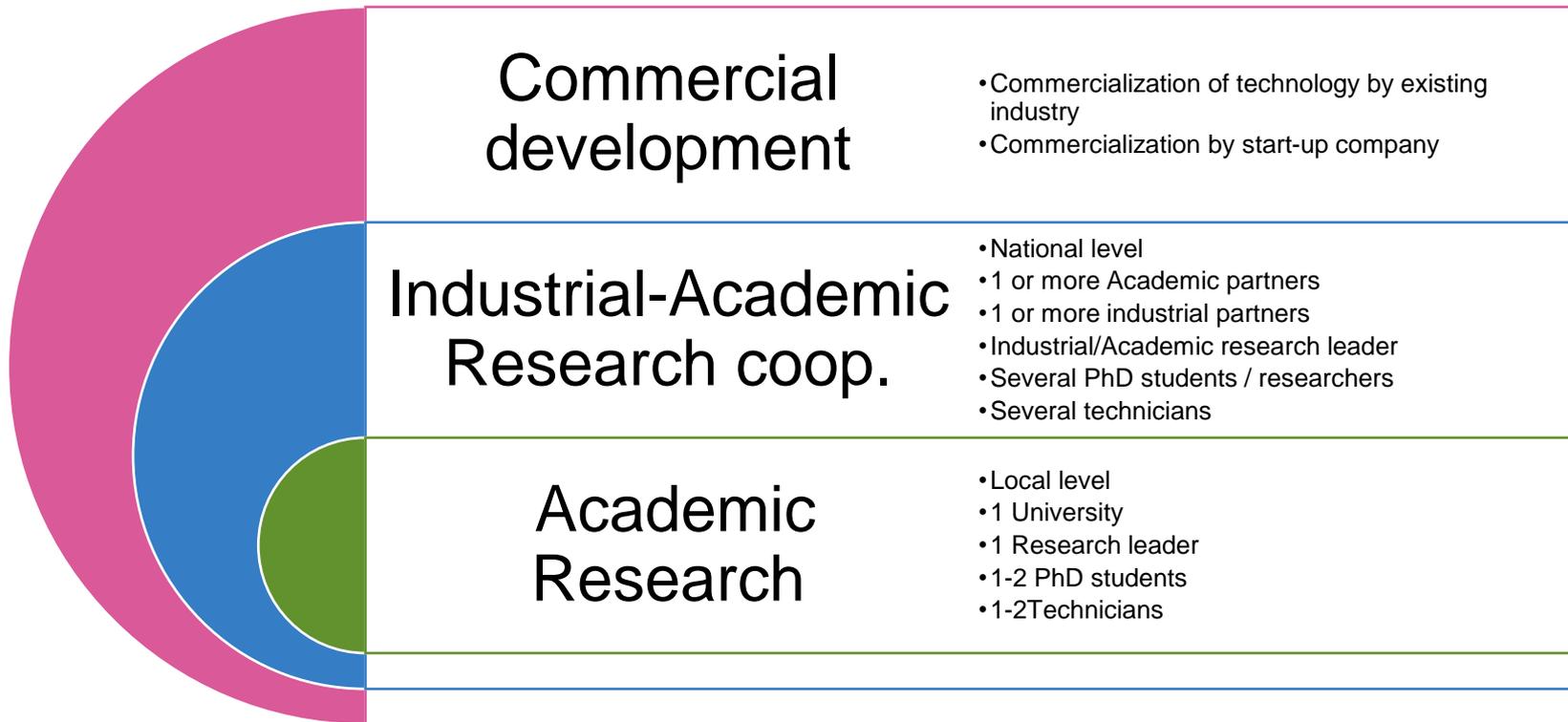


Proposed Idea

- The development of advanced health monitoring and health management technologies are proposed.
- This development is foreseen to have two focal points:
 - First, the continued development of **new sensing methods** for currently unmonitored health indicators, e.g. the thermal decomposition of propellants in cooling channels. This point goes hand-in-hand with the investigation of **failure modes in reusable launch vehicles**;
 - Second, the analysis of health monitoring data through **sensor fusion** and **machine learning** techniques. The developed machine learning algorithms are to be applied to assess the cyclic damage and degradation of system performance of reusable rockets in real-time. This capability supports **in-flight fault detection** and **predictive maintenance**.
- Furthermore, inspection and maintenance techniques will need to be developed to support the process of technology demonstration through sub-scale tests.



Possible implementation formats





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- [1] D. Preclik, R. Strunz, G.Hagemann and G. Langel, Reusability aspects for space transportation rocket engines: programmatic status and outlook, CAES Space Journal, 2011, 1, 71:82
- [2] J. Oswald, K. Kheng, L. Pineau, J.M. Bahu, Economic analysis of a semi reusable launcher for Europe, 71st International Astronautical Congress 2020, IAC-20-D-2.2.4, October 2020
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- [4] I. Cannon, A. Norman and M. Olsaky, Application of SSME launch processing lessons learned to second generation reusable rocket engines including condition monitoring, Rockwell International, AIAA/ASME/SAE/ASEE 24th Joint Propulsion Conference, July 1988
- [5] G. Waxenegger-Wilfing, K. Dresia, J. Deeken, M. Oswald, Machine Learning Methods for the Design and Operation of Liquid Rocket Engines – Research Activities at the DLR Institute of Space Propulsion, Space Propulsion 2020+1 Conference, 2021