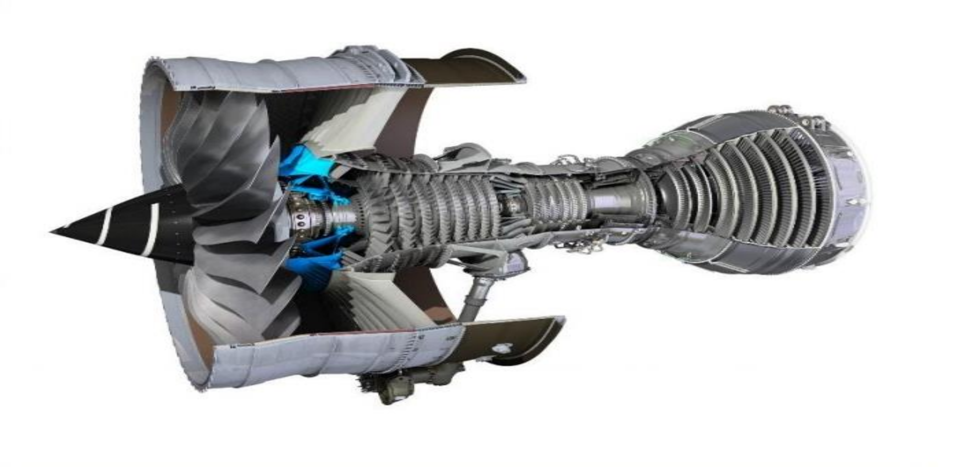
IND5001 Group Project

Members:

Elvis Ayroso, Lim Meng Hock Roger, Stanley Poh Wee Chin, Wong Sin Wee

Company Introduction

- Pioneer cutting-edge technologies that deliver the cleanest, safest and most competitive solutions to our planet's vital power needs
- One of the top Aircraft engine maker
- In the aviation market for many decades
- Global footprint with manufacturing, assembly, MRO, customer services facilities
- Operations in more than 50 countries and customers in over 100
- Engines powered small, medium, large and defense aircraft
- Keeping up with the changing world with growing passenger numbers and mounting environmental pressures
- Net to Zero Carbon emissions by 2050 – operations, facilities, products and technologies

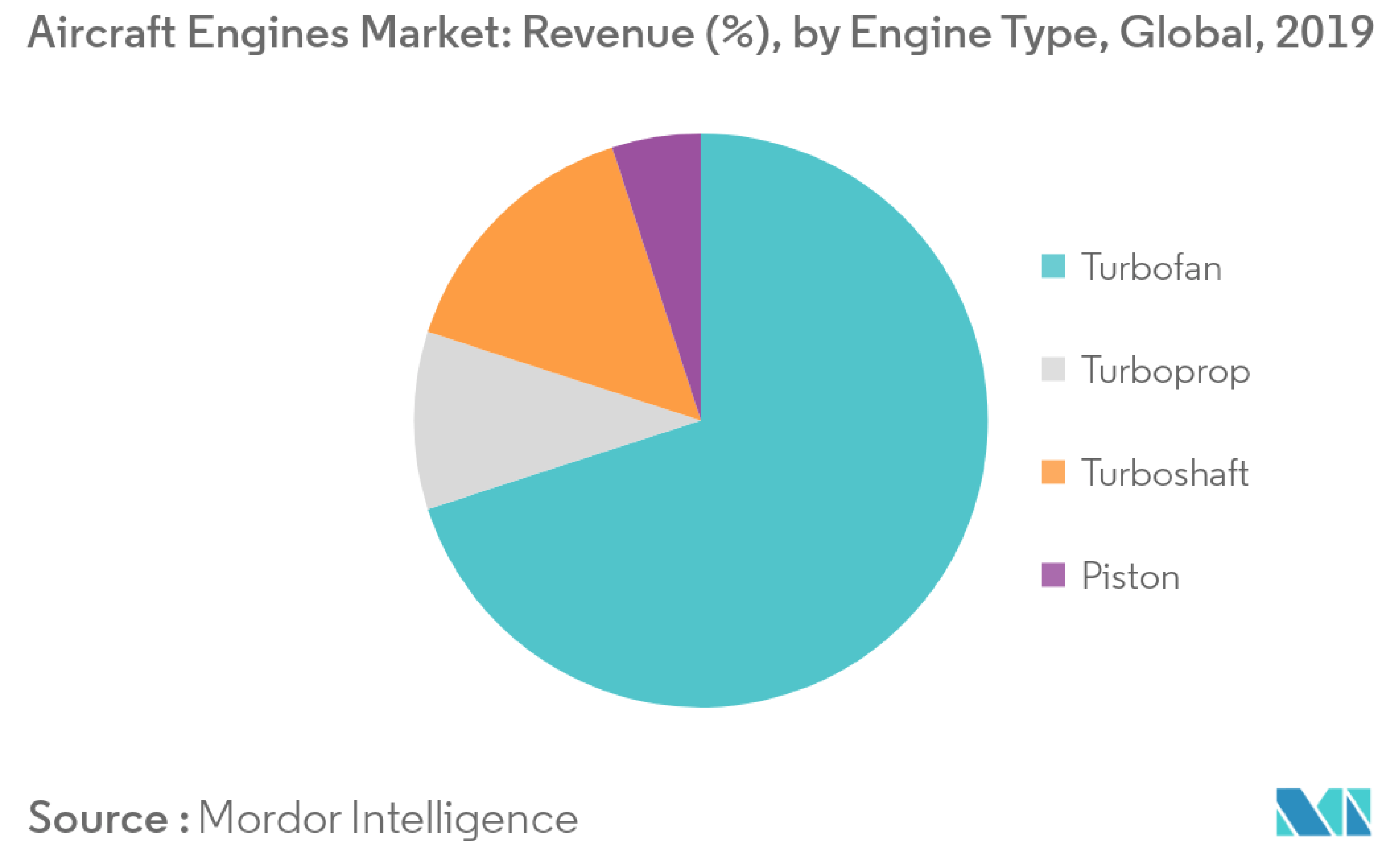


Industry Overview (Engine Market)

- Airlines are revamping their fleet by procuring new aircraft generating the demand for new engines with forecast period (2020 to 2025)
- Anticipated registration of over 5.5% Compound Annual Growth Rate (CAGR) in aircraft engines market
- Demand is the Highest for Turbofan Engines and holds a major share in the aircraft engines market
- New aircraft programs, like COMAC C919 and Boeing 777X, are powered by newer generation turbofan engine in supporting the growth and development of lightweight, advanced propulsion systems

Studies from (pre-Covid): https://www.mordorintelligence.com/industry-reports/aircraft-engines-market

Industry Overview (Engine Market)



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Industry Overview (I4.0 Engine Business)

Data-powered Business Model

Increasing use of data in every segments of the business through digital threads.

Data-driven engine preservation

Increasing use of IoT sensors, data analytics to preserve engine through real time monitoring of engine performance.

Data-managed product lifecycle

Increasing use of engine data to improve product design for more efficient engine.

Data-Commitment for environment

Increasing market pressures of reducing carbon footprint which aviation industry committed to play a part environmentally.

Overview of Current Operations

A completed and tested aircraft engine takes 25 days to complete a total of 6 processes before delivering to the value customer.

The last process that each engine undergoes is an engine test which will last for a day. This critical testing will determine if the engine is fit for flying.

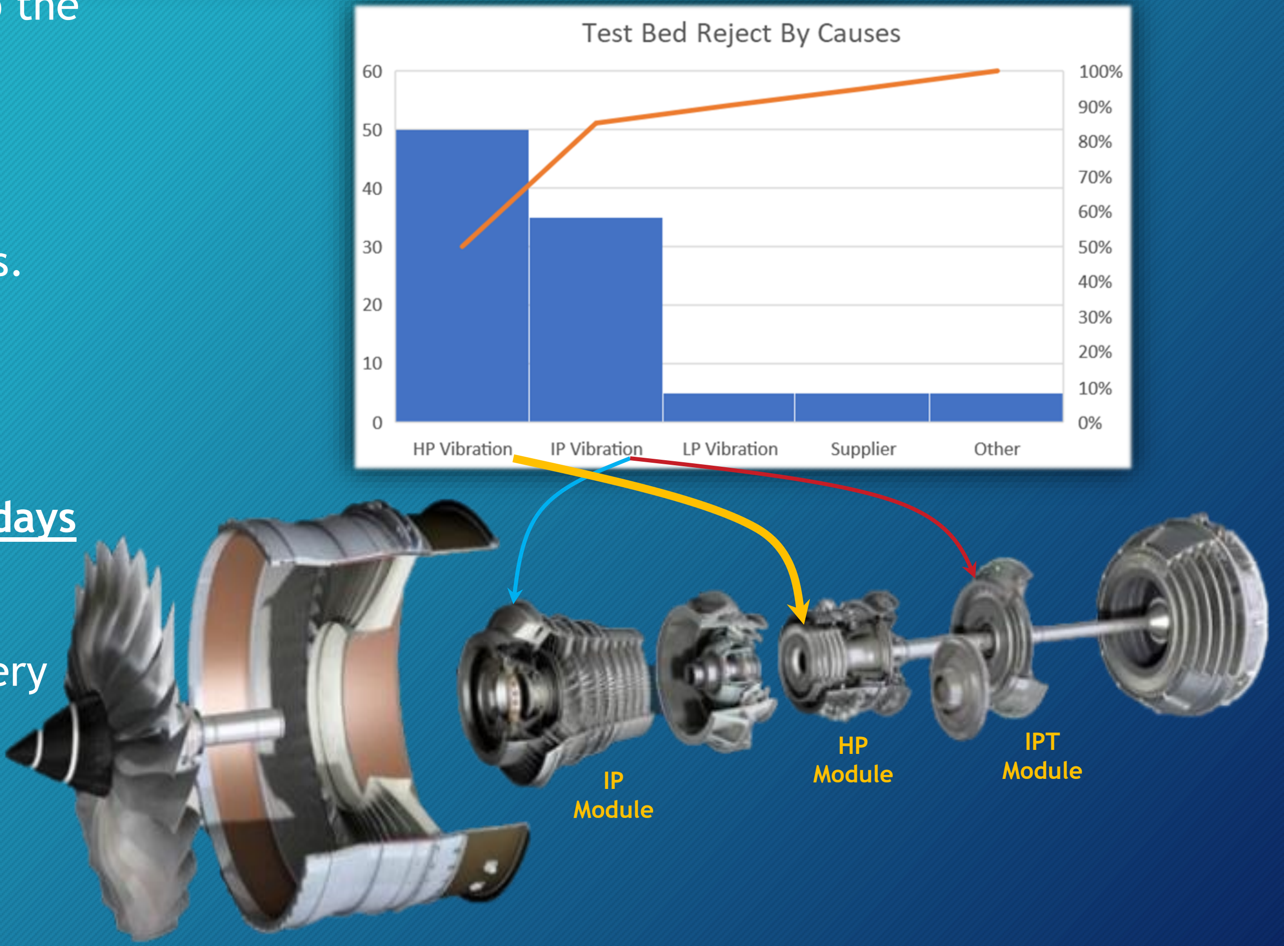
One of the key requirement during the test is to ensure vibration of the engine falls within the margin.

Vibration results are only available after the final build and engine test.

Within each process, dimensional data are measured and input to the manufacturing execution system (MES) for records purposes.

Challenges in Current Operations

- Machines and Systems are **not connected** and integrated to the network.
- **Manual** intervention of dimensional results into MES.
- Key dimensional outputs only use during engine test process.
- Test bed pass rate is about **80%,** with 40 engines rework on average output of 200 engines per year.
- On each engine been rejected, the rework lead time is **20 days** and direct cost more than **100k**.
- The engine is built-to-order, any reject will delay the delivery to airplane factory and cause the airplane delivery delay to airline.
- The top failure modes are HP and IP vibration.

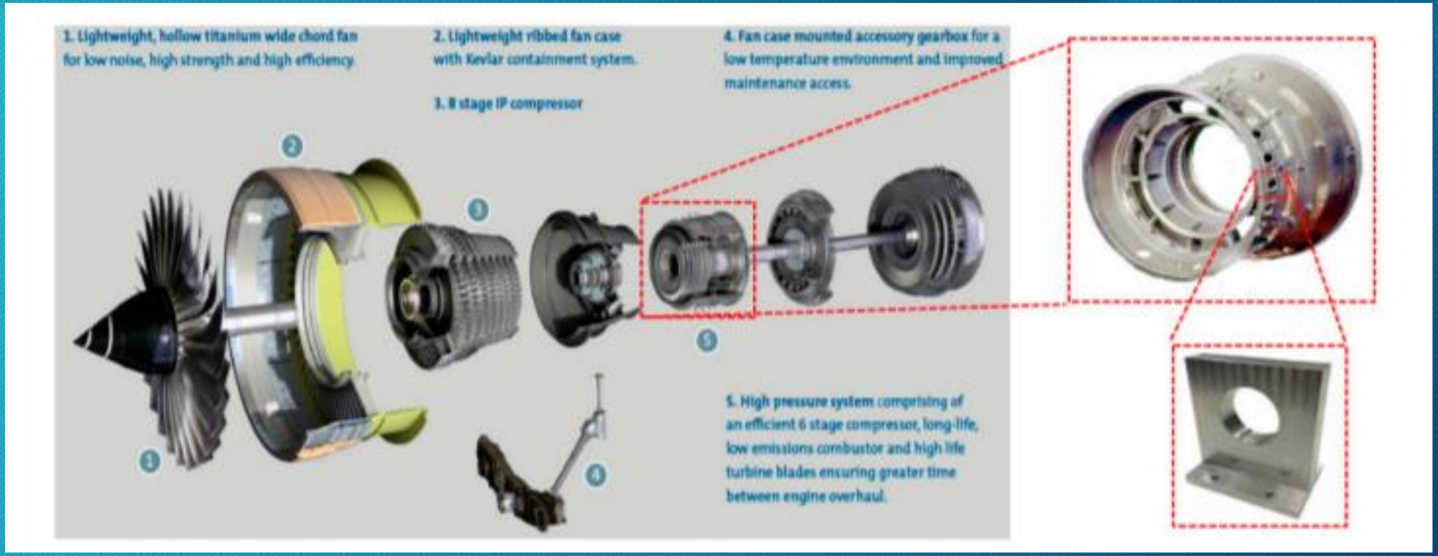


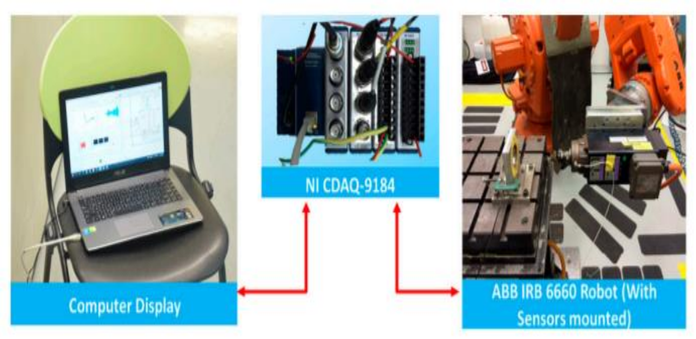
Technology Case Studies

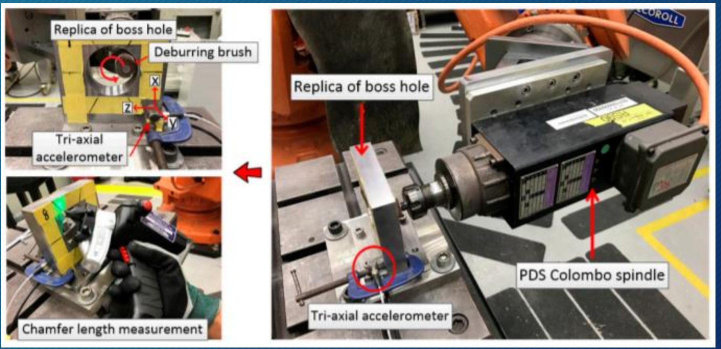
Machine learning is being tested out on individual module operational level

For this case study, deburring process was focused upon, and sensors were attached to a ML model to provide in-process monitoring.

This shows some companies are already doing small scale pilot projects and shows feasibility of integrating ML and I4.0 into the workspace







Caesarendra, W. et al. (2018).

Technology Case Studies

Cloudera currently has an ML enabled digital platform for MROs and is currently being utilized by Lufthansa Technik

This project will aim to leverage machine learning models technology for engine turbine lead time improvement.

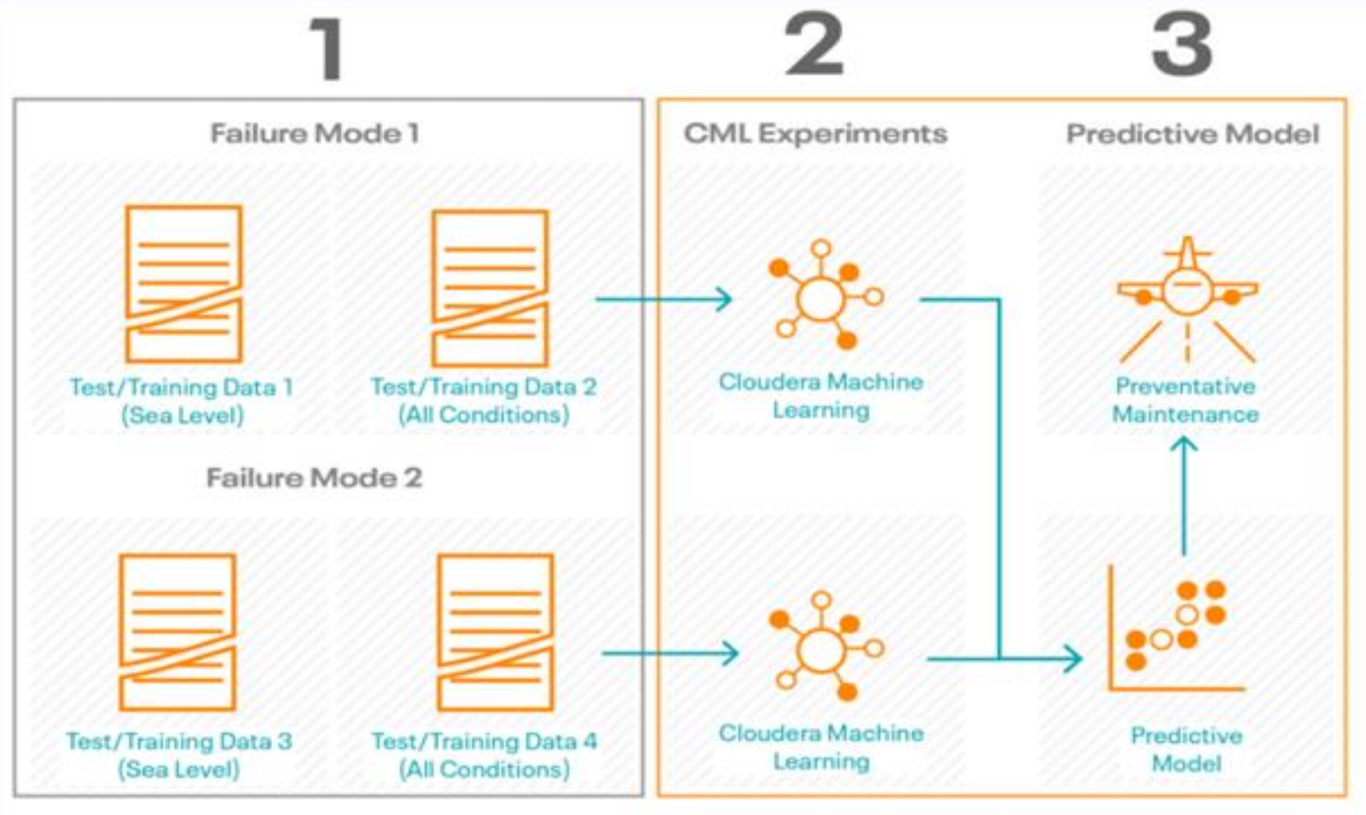
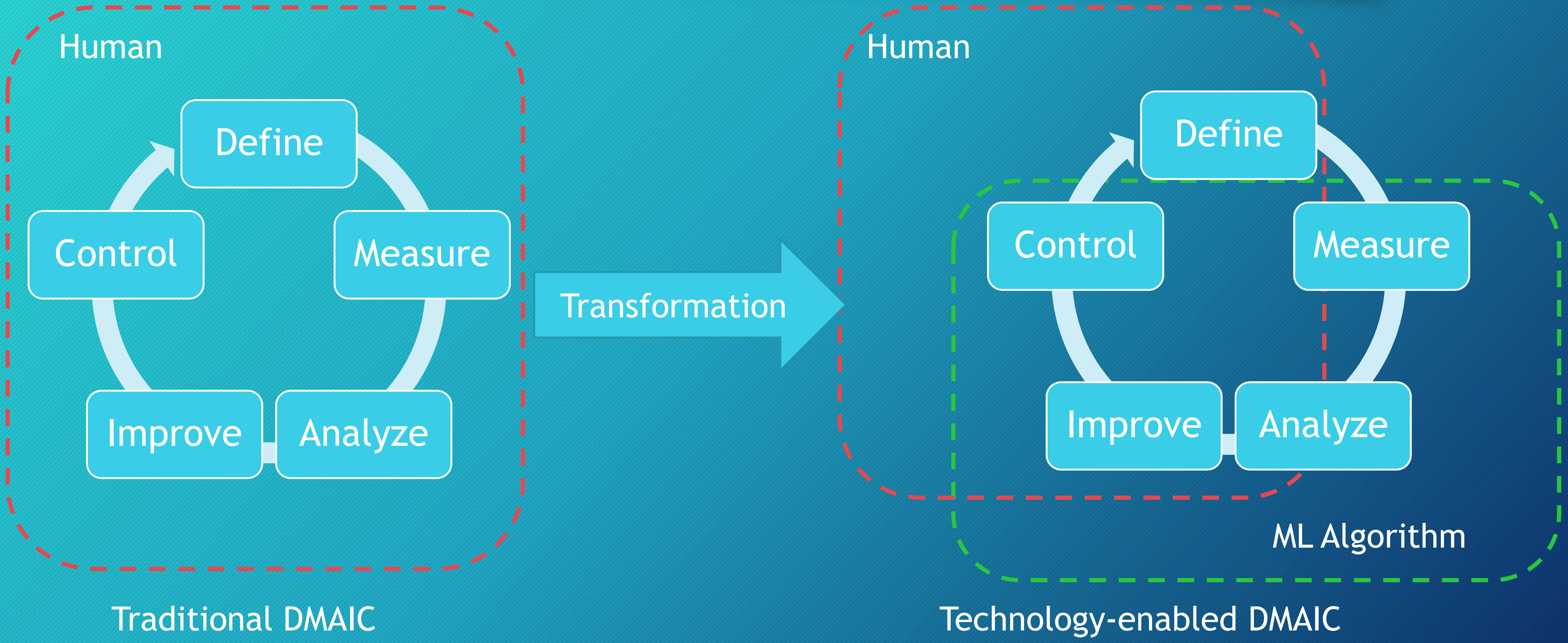


Fig 2: Diagram showing how CML is used to build ML training models

Leauanae, T. (2020, Oct).

Technology Recommendation and Process Improvement



Design Thinking for Solution

EMPATHY

- High Reject at Engine Test
- High cost of non-quality due to the reject, each reject cost 100k and 20 days of delay delivery of the engine to airframer.
- To get a good quality module, specification tighten and subsequently high reject at module build.

DEFINE

- Major Test Reject is Vibration (HP and IP)
- Vibration come from modules.
- To improve the Test yield, the quality of the module need to be improved.

IDEATE

- What if we can filter bad module during module build to eliminate costly reject at test bed?
- What if we can predict the module vibration signature with the features from the module?

PROTOTYPE

- A Machine Learning model of 180 engines data has been performed on the HP module.
- The model able to predict the Pass or Fail by using the HP build measurement and balancing data.

TEST

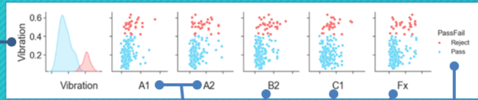
- Test the prototype model with simulation data.
- With the model, the Rejects can be reduced in 4 ways.

Prototyping Using 180 Engines Historical Data

Data Collection

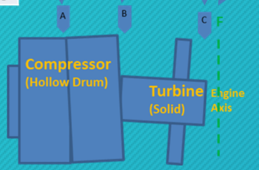
	Label	Label	Flatness Measurement								Balancing Measurement							
	Label	Label	A1	A2	B1	B2	C1	C3	D1	D3	Ax	Ay	Bx	By	Ex	Ey	Fx	Fy
Index	Pass/Fail	Vibration	um	um	um	um	um	Deg	um	Deg	um	Deg	um	Deg	um	Deg	um	Deg
1	Pass	0.23	5	25	12	20	42	154	10	100	39	227	85	63	38	312	60	221
2	Reject	0.11	25	21	16	6	76	156	8	121	70	98	109	73	51	131	66	262

	Label	Label	Flatness Measurement						Balancing Measurement			
Index	Pass/Fail	Vibration	A1	A2	B1	B2	C1	D1	Ax	Bx	Ex	Fx
1	Pass	0.23	5	25	12	20	42	10	39	85	38	60

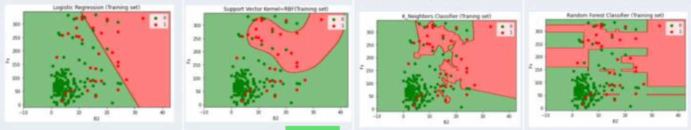


	Label	Regression Features				
Index	Vibration	A1	A2	B2	C1	Fx
1	0.23	5	25	20	42	60

	Label	Classification Features				
Index	Pass/Fail	A1	A2	B2	C1	Fx
1	Pass	5	25	20	42	60



Machine Learning Model

	Classification Models			
	Logistic Regression	Support Vector	K_Neighbors	Random Forest
Characteristics	- Parametric model. - Find the best fit based on the statistical probability. - Sensitive to outlier - Suitable for small dataset.	-Try to maximize the margin between the closest support vectors based on geometry distance. - Not sensitive to outlier. - Suitable for small dataset.	- Non Parametric model. - Use geometry distance to separate the cluster. - Features shall be scaled. - Suitable for large dataset.	- For classification, it use decision tree Yes or No . - Able to provide probability interpretation. - Can handle complex features.
Baseline	Bench mark: 149 Pass, 31 Reject. Accuracy predict: "Pass"=82.7%, "Reject"=17.3%			
CV Accuracy	82%	81%	78%	78%
CV F1 Score	36%	49%	41%	42%
AUC	0.908	0.865	0.810	0.835
Precision _Recall	60%	40%	55%	40%
Train	Accuracy: 83 F1 Score : 42	98 94	91 75	99 96
Test	Accuracy: 86 F1 Score : 29	86 44	86 55	83 40
Separation of Training Dataset				

Overfitting:
Train set almost perfect scores but not the case for test set.

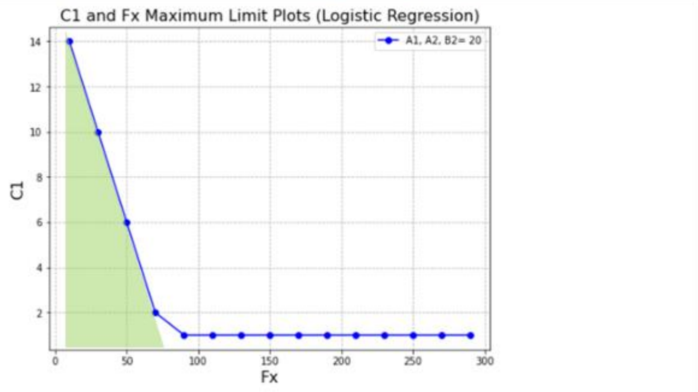
Predict the Engine Vibration at Test

```
# Measurement data input:
A1=25   #<25
A2=25   #<25
B2=25   #<25
C1=10   #<25
Fx=350  #<250

measurement = pd.DataFrame({'A1': [A1],'A2': [A2],'B2': [B2],'C1': [C1],'Fx': [Fx]})
measurement = sc.transform(measurement)

#perdict the Vibration of the measurements
prediction=pd.DataFrame(LR_classifier.predict(measurement))
#print(prediction)
result=prediction[0].map({0:'Pass', 1:'Reject'});
print(f'The Vibration predicted by Logistic Regression classifier is: {result[0]}')
```

```
The Vibration predicted by Logistic Regression classifier is: Reject
```

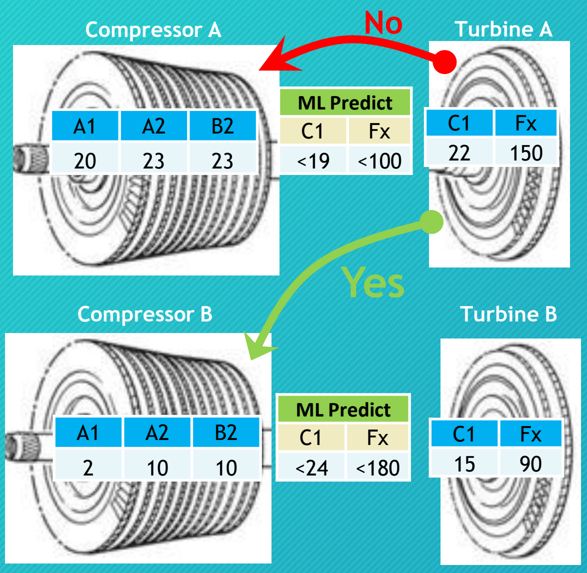
Predict the Build Parameters

```
# Measurement data input from Compressor
A1=20   #<25
A2=20   #<25
B2=20   #<25

# Find the limit of the C1 and Fx on the matching Turbine
C1_list=[]
Fx_list=[]
C1_range=np.arange(1,50,1)
Fx_range=np.arange(10,300,20)
for i in Fx_range:
    for j in C1_range:
        measurement = pd.DataFrame({'A1': [A1],'A2': [A2],'B2': [B2],'C1': [j],'Fx': [i]})
        measurement = sc.transform(measurement)
        prediction=LR_classifier.predict(measurement)
        if prediction>0 :
            break
    C1_list.append(j)
    Fx_list.append(i)

# C1 and Fx predict tramline
plt.figure(figsize=(8,6))
plt.plot(Fx_list,C1_list,'o-',label='A1, A2, B2= 20', color='blue')
plt.grid(linestyle='--')
plt.xlabel('Fx',fontsize=16)
plt.ylabel('C1',fontsize=16)
plt.legend()
plt.title('C1 and Fx Maximum Limit Plots (Logistic Regression)',fontsize=16);
```

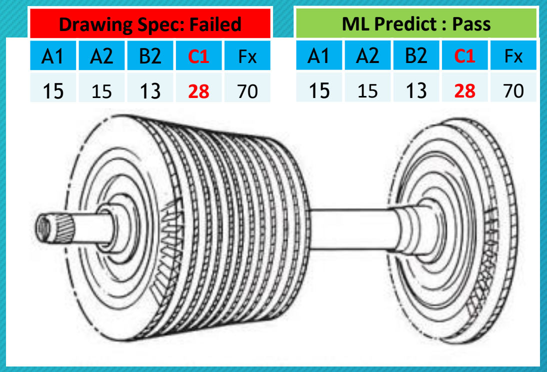


Proposed Deployment Strategies Derived from Prototyping

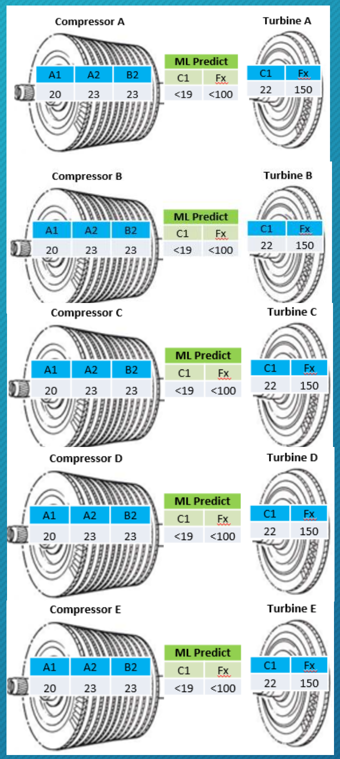
1. Compressor and Turbine Matching
(Improve HP Build Yield)

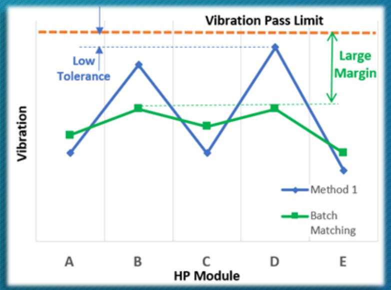


2. Drawing Spec VS ML Model
(Improve HP Build Yield)



3. Batch Matching
(Improve Engine Test Yield)





Best Combination with the largest margin to vibration reject at Test.

4. Faster Approval of out of Specification Measurement
(Improve HP Build and Engine Test Yield)

Chief Design Engineer

Project Road Map (Operations)

1 → 2 → 3 → 4 → 6

Phase 1

- Demo ML Project to improve parameter control in HP module build based of historical data.

1 Month

Phase 2

- Trial the ML model to the actual HP module build.
- Monitor the improvement of Test result. Sample n=2 0
- Fine tune the implementation of new method.

3 Months

Phase 3

- If Phase 2 is successful, implement the to the other 2 IP modules Compressor and Turbine.
- Trial again as not the identical build.

3 Month

Phase 4

- Connect the equipment to MES on one cell
- Use the ML in MES to feedback to production.

1 Month

Phase 6

- Improve with AI to the system.

1 Month

Technology Roadmap

Strategic

30 months

Smart inventory forecasting and quality monitoring system

12 months

Deployment of AI-proven ML system to other modules

6 months

System integration to centralized MES

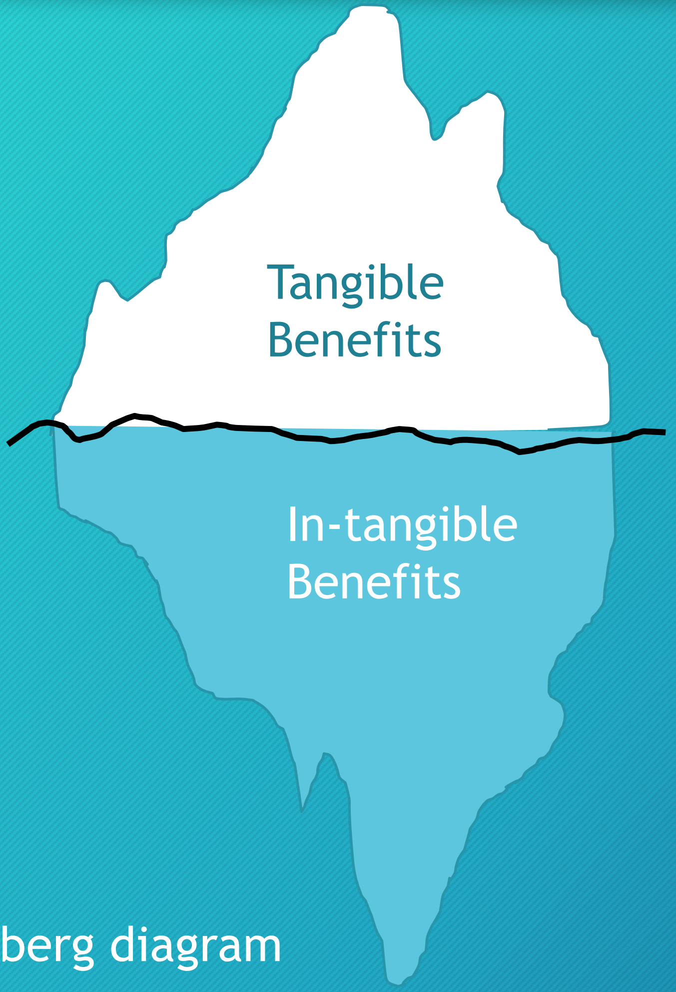
9 months

Deployment of ML enabled engine build platform

Operational

time

Technology Business Benefits



Iceberg diagram

- Increase on RFT from 80% to 91%
- Reduce number of engine rework by 50%
- On-time delivery with zero penalty
- Reduce OT hours by 50%
- Productivity increases by 20%
- Zero human intervention on data capturing

- Increase digital awareness and culture
- Upskill workforce
- Improve accountability
- Training of ML model on the fly
- Increase workforce confidence
- Safe engine flying

Cost-Benefit Analysis (Projected ROI)

Payback benefits calculator $'s

Capital Expenditure

Spend	Remarks/Justification	2020	2021	2022	2023	2024	2025	2026	2027
Connectivity setup for MES with Machine	4 processes + OEM configuration	$200,000							
Firewall Changes		$5,800							
Security Certs		$4,000							
Programme Integrator		$7,500							
Total CAPEX		**$217,300**							

Operating Expenditure

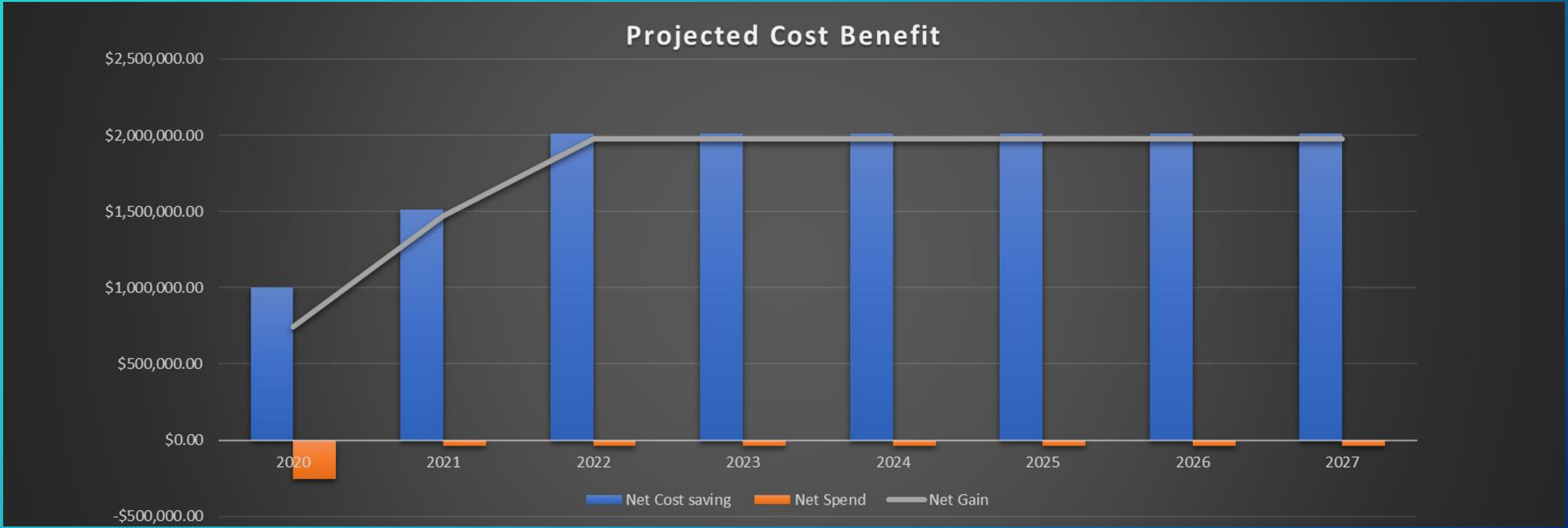
Spend	Remarks/Justification	2020	2021	2022	2023	2024	2025	2026	2027
Platform Licence (Annual)	ML Platform licence fee _ support cost	$30,000.00	$30,000.00	$30,000.00	$30,000.00	$30,000.00	$30,000.00	$30,000.00	$30,000.00
IT Support Cost (Annual)		$9,000.00	$9,000.00	$9,000.00	$9,000.00	$9,000.00	$9,000.00	$9,000.00	$9,000.00
Annual OPEX		**$39,000**	**$39,000**	**$39,000**	**$39,000**	**$39,000**	**$39,000**	**$39,000**	**$39,000**

		1st process	2nd process	3rd process					
Expected savings	**Remarks/Justification**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**	**2026**	**2027**
Engine delivery penalty	$100,000 per engine rework. Total year target 200 engines, and 80% RFT (tgt 91%)	$1,000,000	$1,500,000	$2,000,000	$2,000,000	$2,000,000	$2,000,000	$2,000,000	$2,000,000
Labour overtime	current total 800 hours, cost rate of $25	$2,500	$10,000	$15,000	$15,000	$15,000	$15,000	$15,000	$15,000
Annual expected savings		**$1,002,500**	**$1,510,000**	**$2,015,000**	**$2,015,000**	**$2,015,000**	**$2,015,000**	**$2,015,000**	**$2,015,000**
Total		**$14,602,500**							

Return on Investment

	2020	2021	2022	2023	2024	2025	2026	2027
Net Cost saving	$1,002,500.00	$1,510,000.00	$2,015,000.00	$2,015,000.00	$2,015,000.00	$2,015,000.00	$2,015,000.00	$2,015,000.00
Net Spend	-$256,300.00	-$39,000.00	-$39,000.00	-$39,000.00	-$39,000.00	-$39,000.00	-$39,000.00	-$39,000.00
Net Gain	**$746,200.00**	**$1,471,000.00**	**$1,976,000.00**	**$1,976,000.00**	**$1,976,000.00**	**$1,976,000.00**	**$1,976,000.00**	**$1,976,000.00**

Cost-Benefit Analysis (Projected ROI)



Risk Management

Risk Assessment on ML Technology implementation											
No	Category	Risk	Desc	Cause	Likelihood	impact	Score	mitigration	Likelihood	impact	Score
1	Connectivity	Cannot establish streaming of data into MES	Infrastructure not ready for machine-to-MES connection	Not designed in original design architectural	4	9	36	Engaged IT to survey existing network infrastructure	1	9	9
								Work with OEM to open connectivity	1	9	9
2	Data	Bad quality data in the batch of historical sets	Incorrect data collection and documentation	Manual collection of data and manual input	7	9	63	Digital threads, connectivity, remove human intervention	1	9	9
		Not enough data to do analytic	Sample size of data collected is low	Data not easily extracted from the non-connected systems	6	9	54	Connect the system and establish database for streaming and storing of data	3	9	27
		Data cannot be analysis and model cannot be developed	Data collection not influential	Sample size is low	4	9	36	Extend data collection on more engines	4	9	36
			Data collection not influential	Dimension data collected in current process the influential	3	9	27	Engine design / CFD on other parameters requirements	1	9	9
3	Resource	Data cannot be analysis and model cannot be developed	Lack of internal expertise	Internal skill set is not on data science	4	9	36	Outsource	1	9	9
					4	9	36	Upskill personnel / hire personnel with expertise	1	9	9
			Data collection not influential	Sample size is low	4	9	36	Extend data collection on more engines	4	9	36
			Data collection not influential	Dimension data collected in current process the influential	3	9	27	Engine design / CFD on other parameters requirements	1	9	9

Conclusion

- Business utilizing Industry 4.0 are constantly evolving at a rapid pace benefitting from cost reduction and scalability while developing proactive solutions in preventive maintenance
- The Engine Assembly business model is viable in possible defining a new way in solving problems which are time-consuming and inefficient to improve product quality to maintain competitive edge
- Digital transformation will bring the engine business towards data-powered business model, data-driven product preservation, data-managed product lifecycle and data-committed for environment