

Data Driven, AIs and ML in Prognostic and Diagnostic of Electrical Machines and Batteries

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Outline



INTRODUCTION



CASE STUDIES



PLANS AND
VISION



QUESTIONS

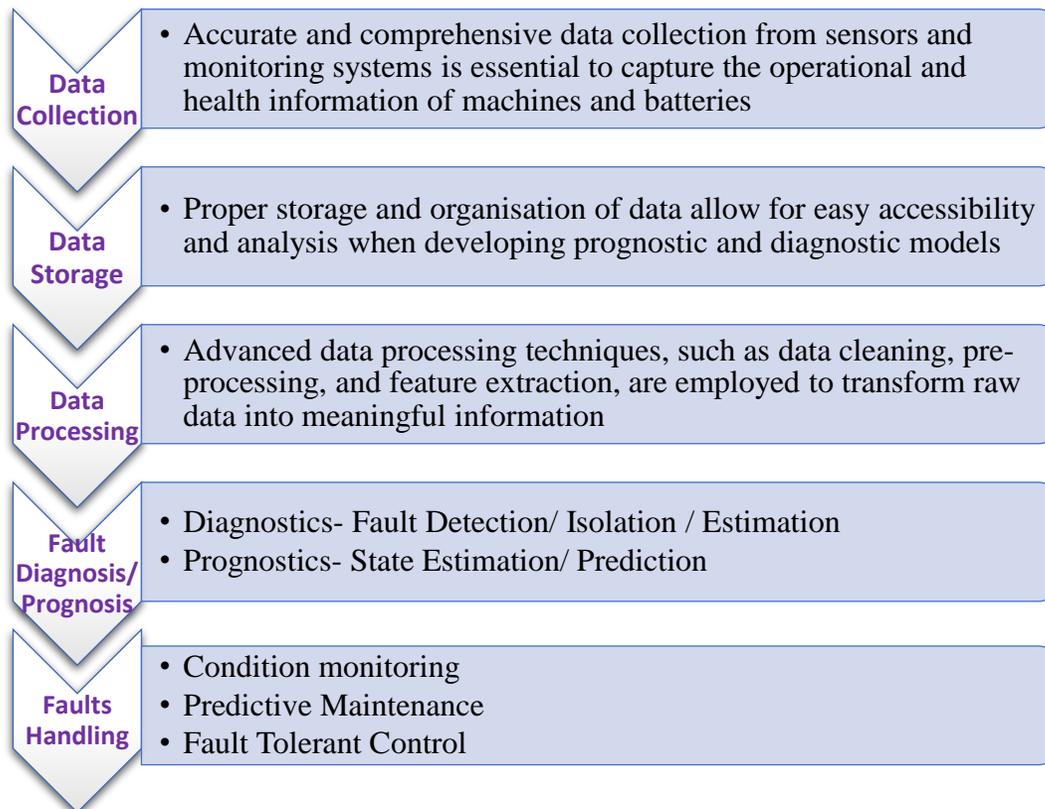
Prognostics and Diagnostics Overview



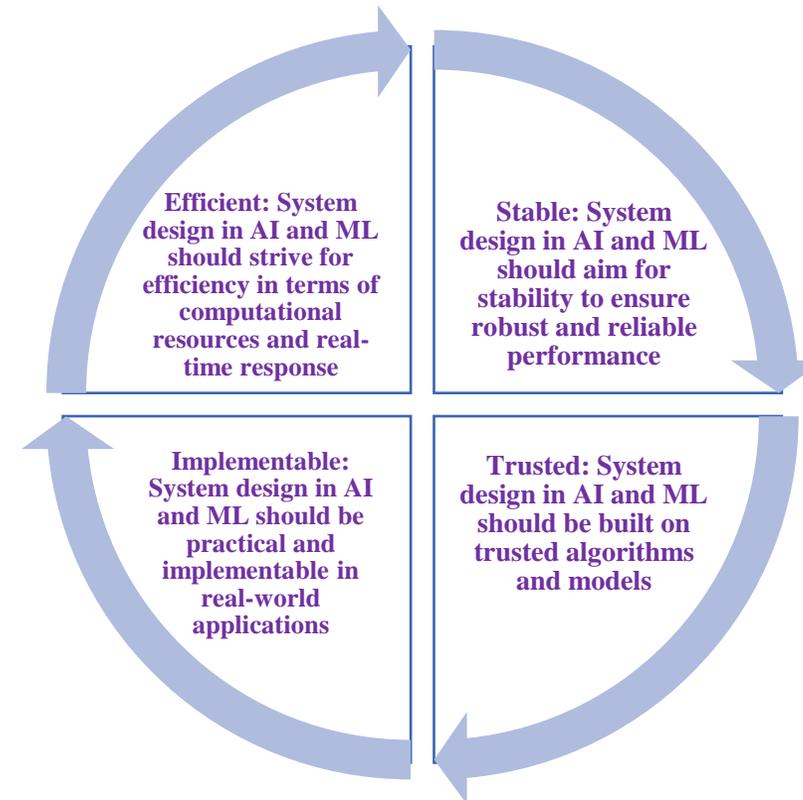
Diagnostics focuses on **d**etecting faults and anomalies to facilitate timely maintenance and repairs



Prognostics involves **p**redicting the remaining useful life and identifying potential failures



Data Driven General Fault Diagnosis/ Prognostic Procedure



Comprehensive Test/Validation is imperative

AIs & ML in PEMD



We asked AI 'where will AI benefit power electronics, machines and drives?'

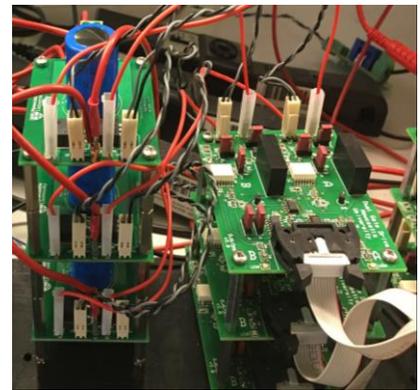
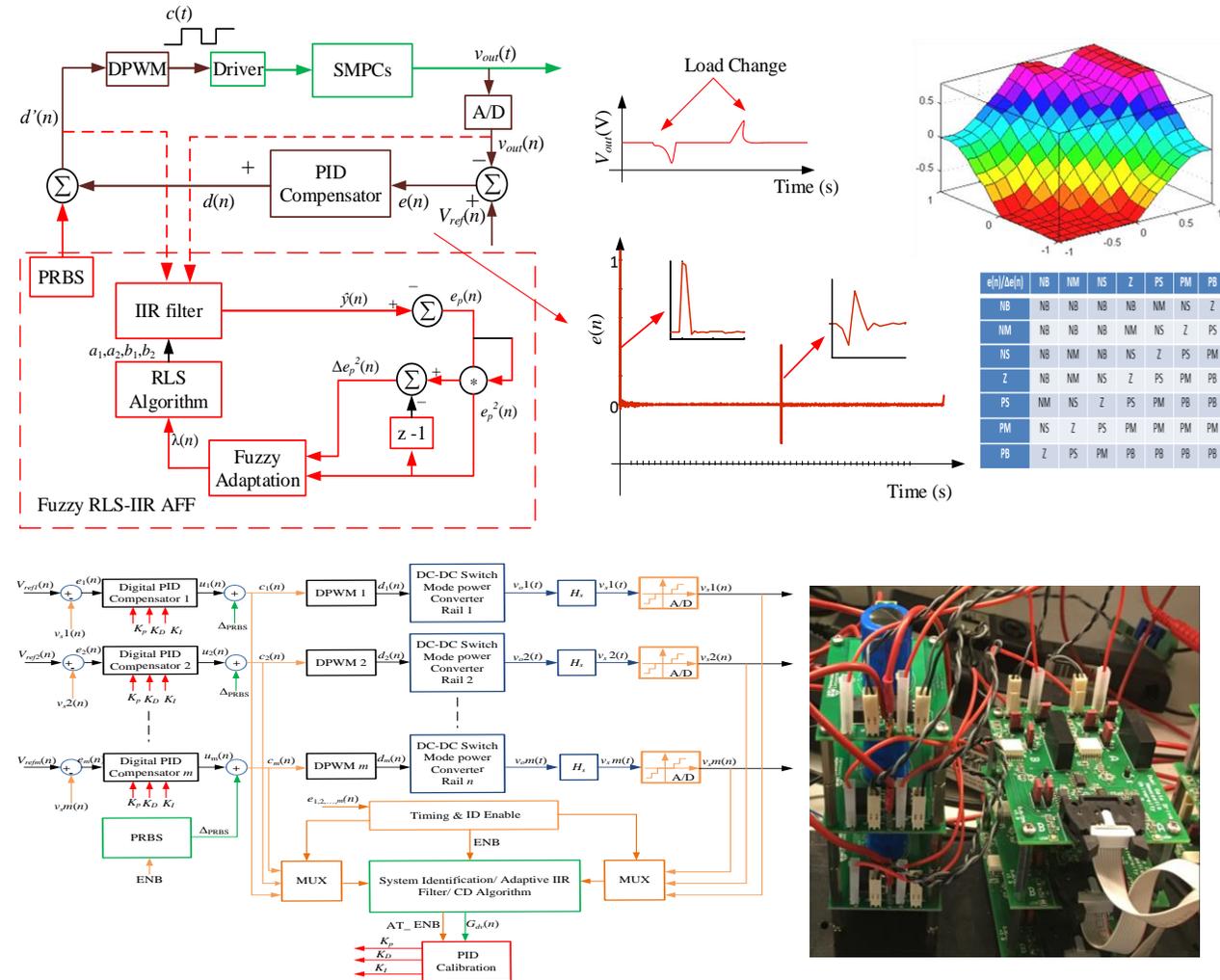
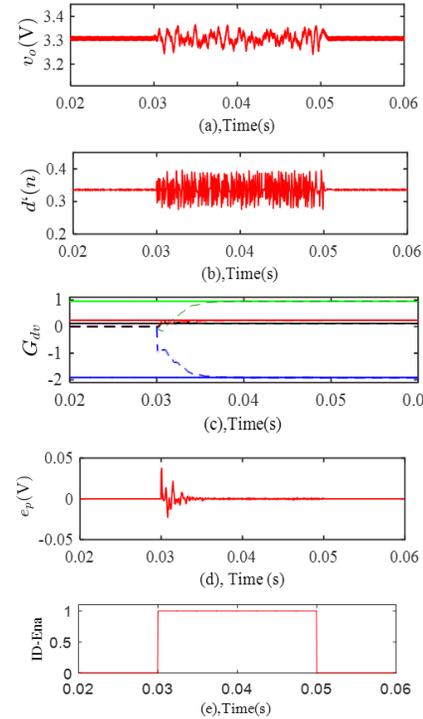
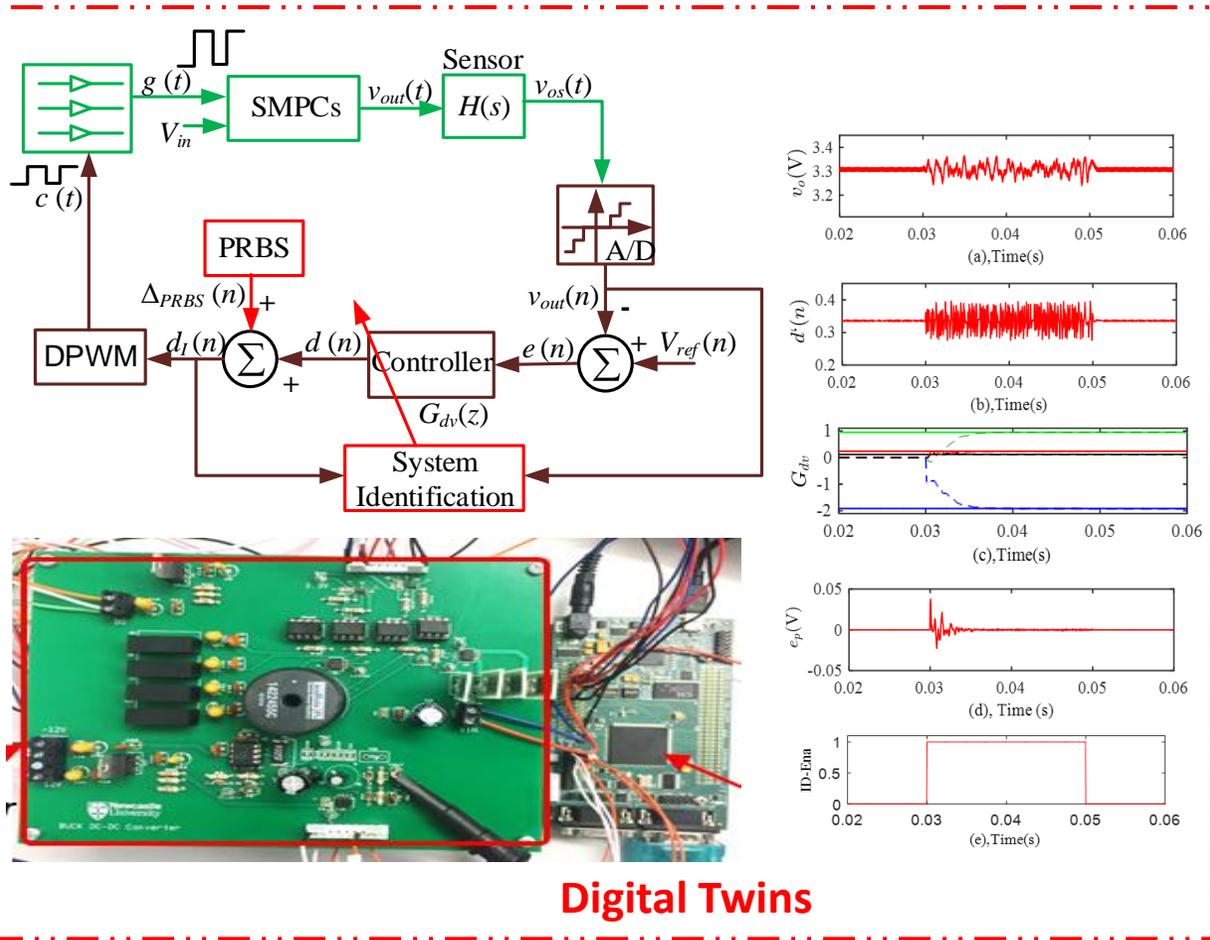
With AI being a common topic of discussion, we decided to ask AI "Where are the opportunities for using AI to benefit power electronics, machines and drives (PEMD)?"

The response from ChatGPT [<https://openai.com>], for which we would like your feedback, was as follows.

There are numerous opportunities for utilizing AI to benefit power electronics, machines, and drives (PEMD) and here are some areas where AI can make a significant impact:

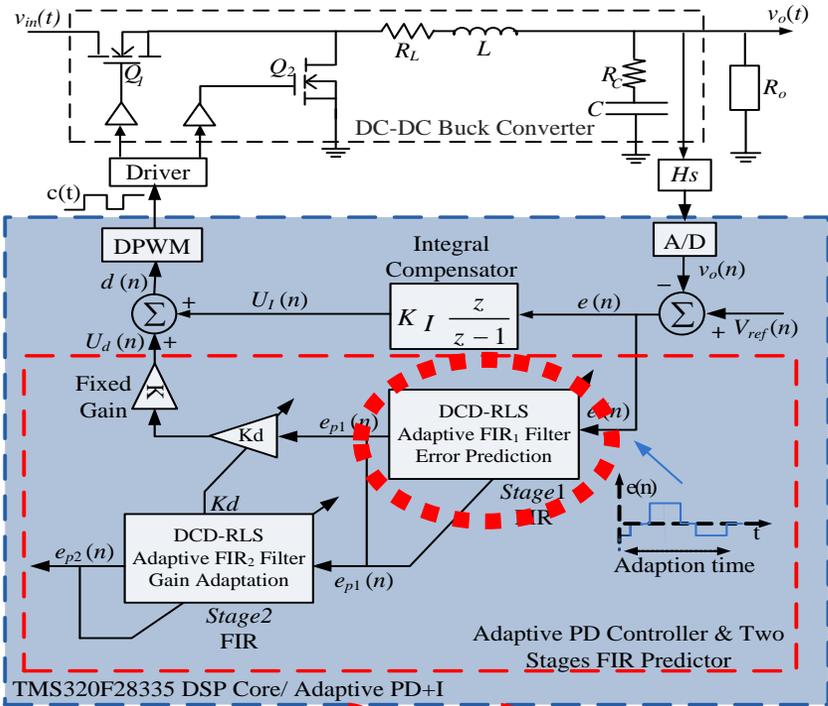
1. **Fault Diagnosis and Prognostics:** AI techniques such as machine learning and deep learning can be employed to develop advanced fault diagnosis and prognostic systems for PEMD. By analysing data from sensors, AI algorithms can detect and predict faults in power electronics components, machines, and drives, allowing for proactive maintenance and minimizing downtime.
2. **Energy Optimization:** AI can optimize the energy consumption and efficiency of PEMD systems. By analysing real-time data from sensors and actuators, AI algorithms can adjust control parameters and optimize the operation of power converters, motor drives, and other components to minimize energy losses and improve overall system efficiency.
3. **Condition Monitoring and Predictive Maintenance:** AI can enable condition monitoring and predictive maintenance in PEMD systems. By continuously monitoring operational parameters and analysing historical data, AI algorithms can detect early signs of component degradation or failure, allowing for timely maintenance interventions and reducing the risk of unplanned downtime.
4. **Control and Optimization:** AI-based control techniques can enhance the performance and capabilities of PEMD systems. Reinforcement learning algorithms can learn optimal control policies
5. **Power Quality Improvement:** AI can contribute to improving power quality in PEMD systems. By analysing voltage and current waveforms, AI algorithms can identify and mitigate power quality issues, such as harmonics, voltage sags, or flicker, through active control strategies and optimized filtering techniques.
6. **Intelligent Energy Management:** AI can be used to develop intelligent energy management systems for PEMD applications. By considering multiple factors such as load demand, energy storage, renewable energy availability, and grid conditions, AI algorithms can optimize the allocation and utilization of energy resources, ensuring reliable and efficient operation.
7. **Virtual Prototyping and Design Optimization:** AI-based simulation and optimization techniques can accelerate the design and development of PEMD systems. By using AI models and algorithms, designers can simulate and optimize different configurations, topologies, and control strategies, reducing the time and cost associated with physical prototyping.
8. **Smart Grid Integration:** AI can facilitate the integration of PEMD systems with smart grids. By analysing real-time grid data and considering demand response, energy pricing, and grid stability, AI algorithms can enable optimal coordination and control of PEMD systems, enhancing the reliability and efficiency of grid operations.

AIs & ML in PEMD

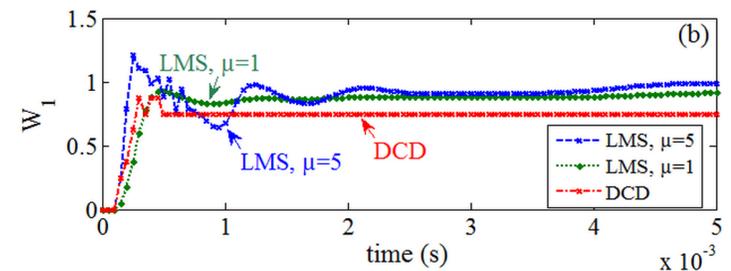
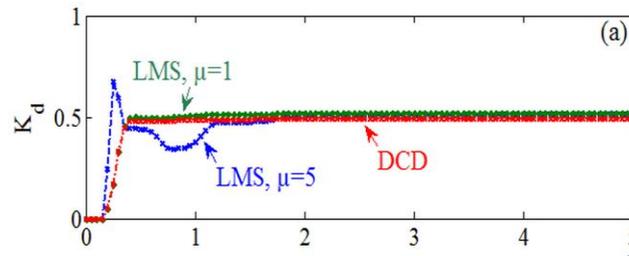
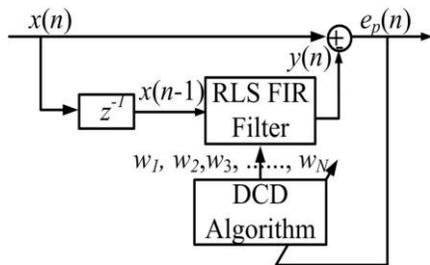
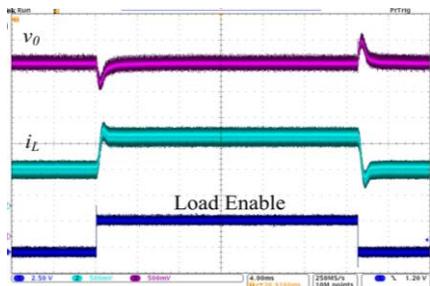
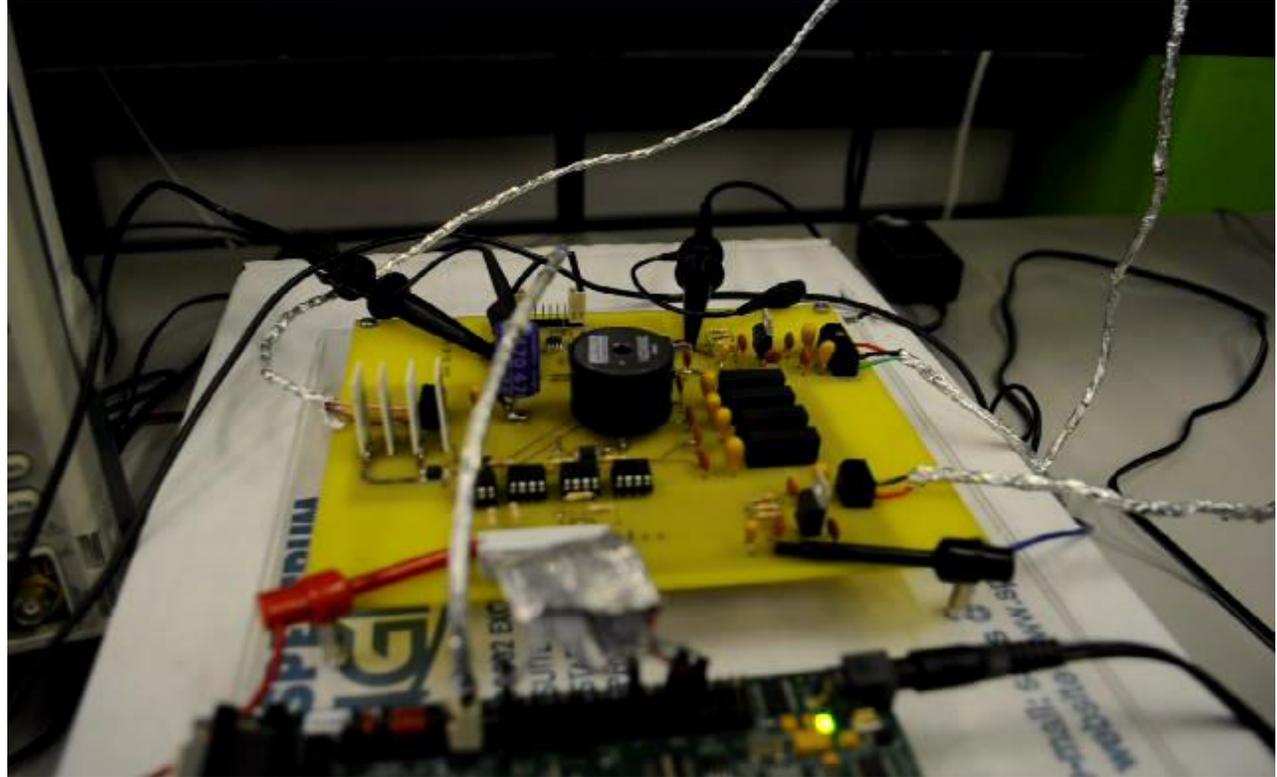


- [] M. Al-greer, M. Ahmeid, M. Armstrong, D. Giaouris, "Advances on System Identification Techniques for DC-DC Switch Mode Power Converter Applications.", *IEEE Transactions on Power Electronics*, vol. 34, pp. 6973 – 6990, July. 2019.
- [] M. Algreer, M. Armstrong, and D. Giaouris, "Active On-Line System Identification of Switch Mode DC-DC Power Converter Based on Efficient Recursive DCD-IIR Adaptive Filter," *IEEE Transactions on Power Electronics*, vol. 27, pp. 4425-4435, 2012.
- [] M. Algreer, M. Armstrong, and D. Giaouris, "Adaptive PD+I Control of a Switch-Mode DC-DC Power Converter Using a Recursive FIR Predictor," *IEEE Transactions on Industry Applications*, vol. 47, pp. 2135-2144, 2011.
- [] Jin Xu, M. Armstrong, M. Al-greer, "Centralised System Identification of Multi-Rail Power Converter Systems using an Iterative Decimation Approach", *IEEE Transactions on Circuits & Systems*, vol. 68, pp. 3520-3533, May 2021.
- [] M. Al-greer, M. Armstrong, V. Pickert, "Selecting an Appropriate Fuzzy PID Structure for Power Electronic Applications.", *IET Journal of Engineering*, 2019.
- [] M. Ahmeid, M. Armstrong, M. Al-Greer, and S. Gadoue, "Computationally Efficient Self-Tuning Controller for DC-DC Switch Mode Power Converters Based on Partial Update Kalman Filter." *IEEE Transactions on Power Electronics*, vol. PP, pp. 1-1, 2017.
- [] M. Ahmeid, M. Armstrong, S. Gadoue, M. Algreer, P. Missailidis, "Real-Time Parameter Estimation DC-DC Converters Using a Self-tuned Kalman Filter", *IEEE Transactions on Power Electronics*, vol.32, pp. 5666 - 5674, July. 2017.
- [] M. Al-greer, M. Armstrong, Jin Xu, "Coordinate Descent Auto-Tuning Architecture for Multi Rail DC-DC Switch Mode Power Converters," in Proc. 19th IEEE Workshop on Control and Modeling for Power Electronics, *IEEE COMPEL 2018*, Padova, Italy.
- [] Jin Xu, M. Armstrong, M. Al-greer, "Computational Burden Reduction in Real-Time System Identification of Multi-Rail Power Converter by Re-using Covariance Matrix Approximation" in *2020 IEEE Applied Power Electronics Conference and Exposition (APEC), 2020*.

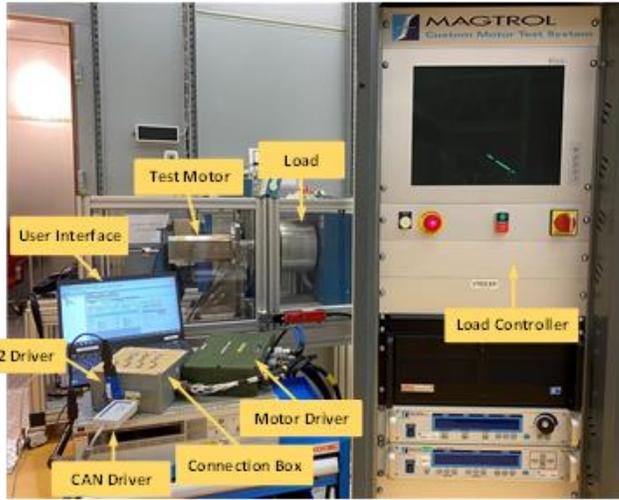
AIs & ML in PEMD



$$G_{pd}(z) = K_d(1 + w_1 z^{-1})$$

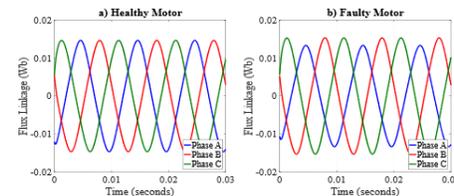
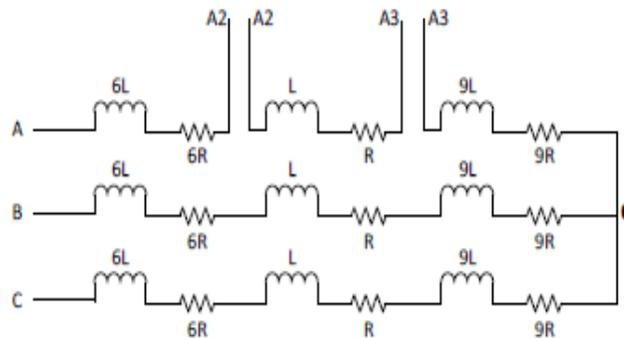


Condition Monitoring and Fault Detections of PMSM



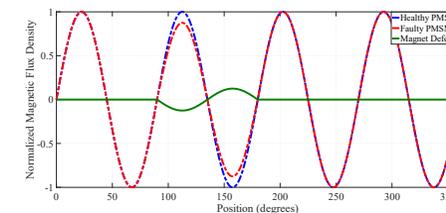
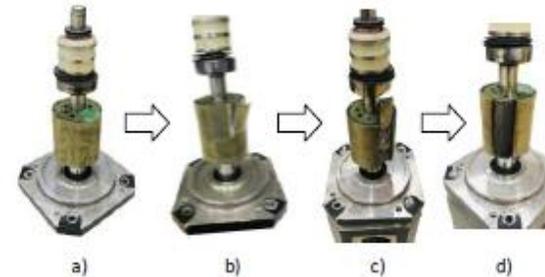
Stator Inter-turn Short Circuit Faults

- The stator winding of a PMSM is a distributed winding consisting of 16 series turns stranded by eight conductors. One of the 16 turns was connected to the test terminal for the experiment.



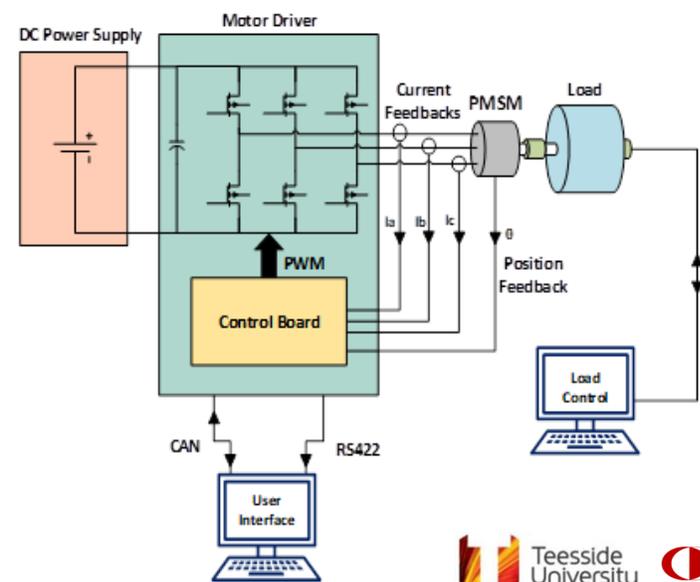
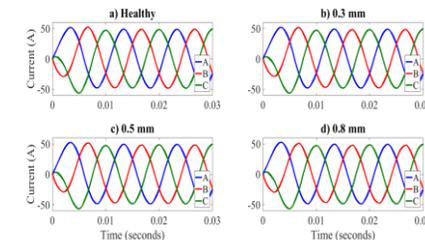
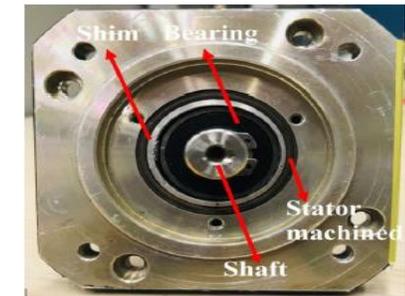
Non-Uniform Demagnetisation Faults

- Non-uniform demagnetisation was achieved using a test motor. For this purpose, one magnet is separated from the rotor and excessive heat is applied until it demagnetises.



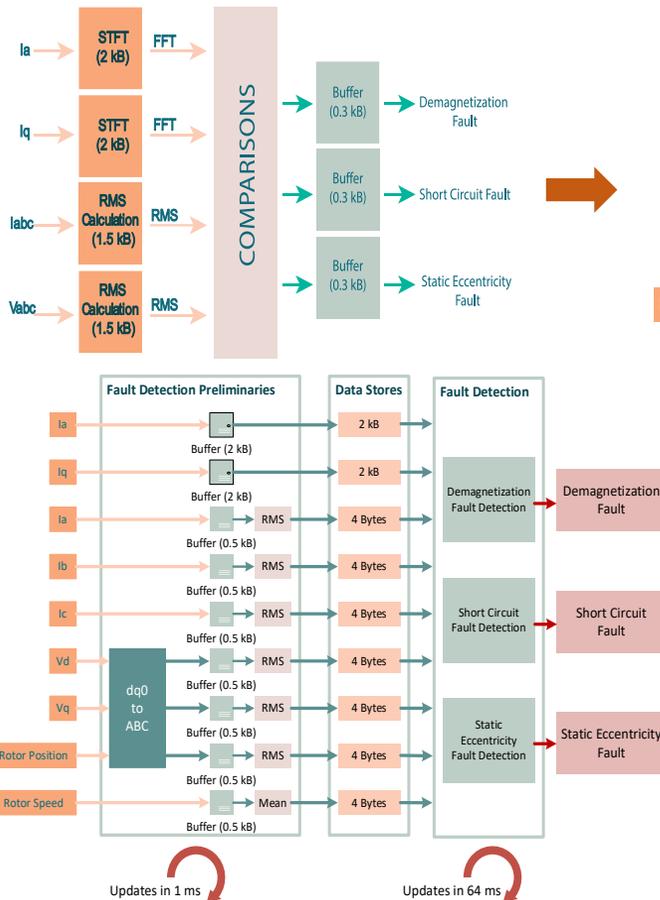
Static Eccentricity Faults

- The inner part of the motor cage was machined 0.5 mm from one side, and a shim was placed on the other side. When the air gap was 1.8 mm, the displacement of 0.5 mm corresponds to 28% SEF.

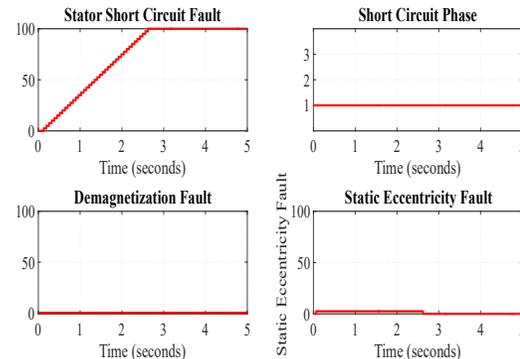
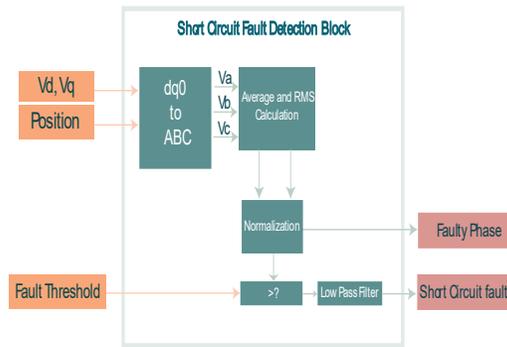


Condition Monitoring and Fault Detections of PMSM

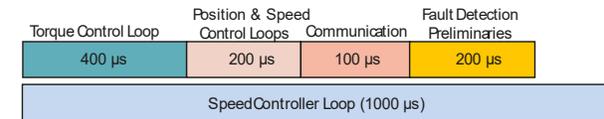
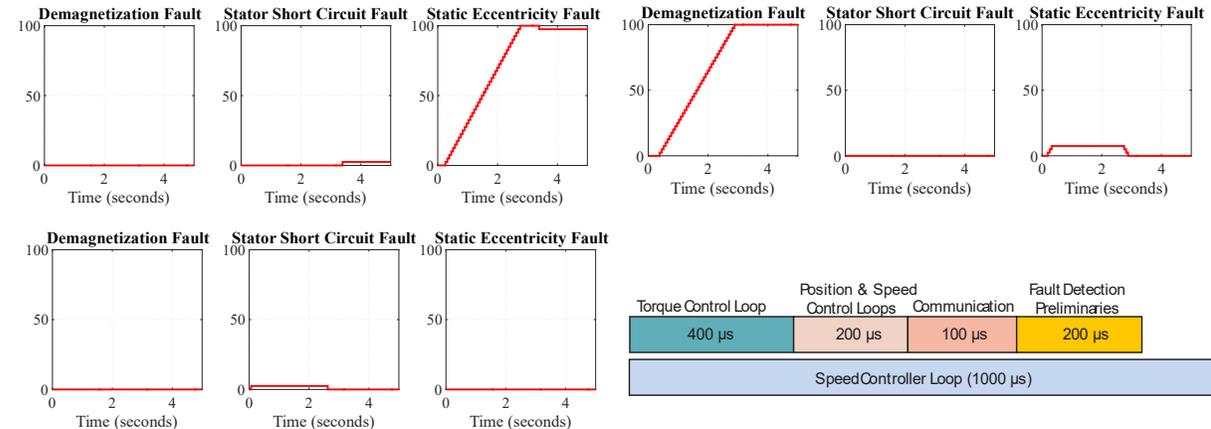
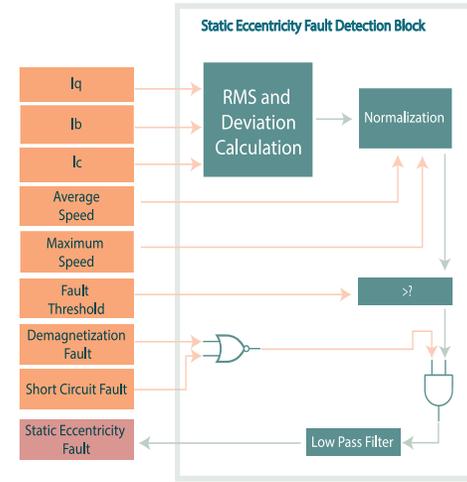
Memory requirement for data storage of the fault detection algorithm



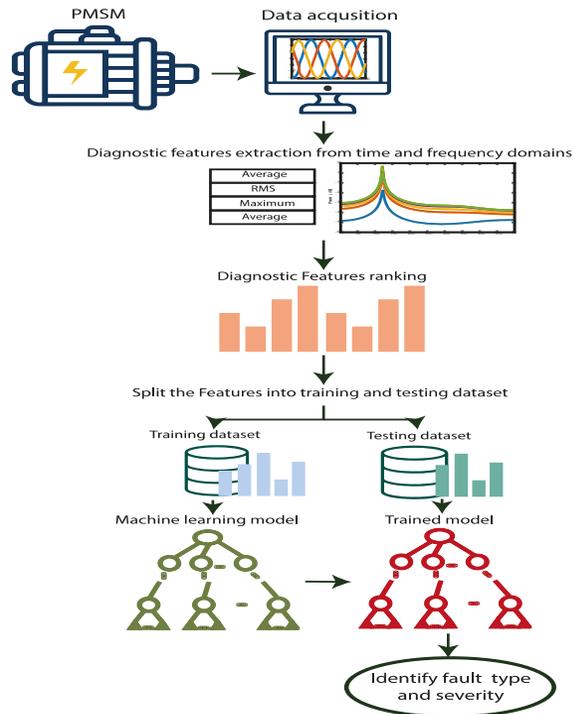
Content of the short circuit fault detection block



Content of the static eccentricity fault detection block



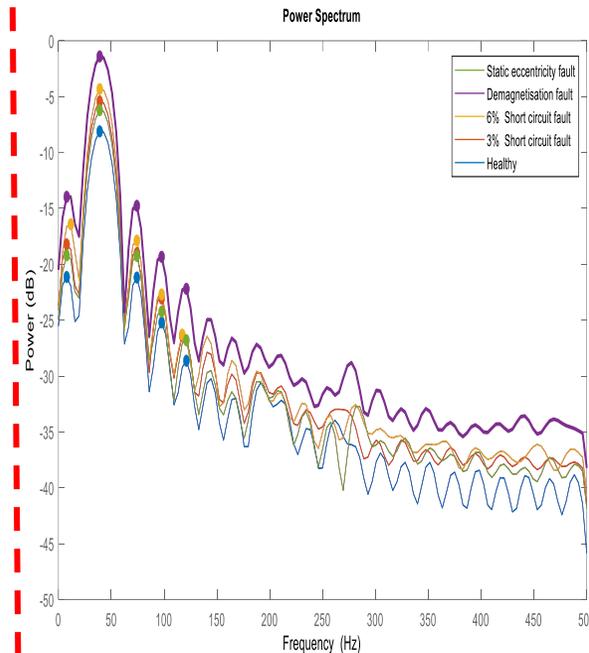
Condition Monitoring and Fault Detections of PMSM



Time-domain diagnostic features

Health indicators	Mathematical expression
Mean	$\frac{1}{K} \sum_{n=1}^K i_n$
RMS	$\sqrt{\frac{1}{K} \sum_{n=1}^K i_n ^2}$
Standard Deviation	$\sqrt{\frac{\sum_{n=1}^K (i_n - \text{mean}(i))^2}{K - 1}}$
Shape Factor	$\frac{\text{RMS}}{\text{Mean}}$
Peak Value	The maximum absolute value of the stator current
Impulse Indicator	$\frac{\text{Peak value}}{\text{Mean}}$
Crest Factor	$\frac{ \text{Peak} }{\text{RMS}}$
Kurtosis	$\frac{1}{K - 1} \frac{\sum_{n=1}^K (x_n - \text{mean}(i))^4}{(\text{Standard Deviation})^4}$
Skewness	$\frac{1}{K - 1} \frac{\sum_{n=1}^K (x_n - \text{mean}(x))^3}{(\text{Standard Deviation})^3}$

Frequency-domain diagnostic features

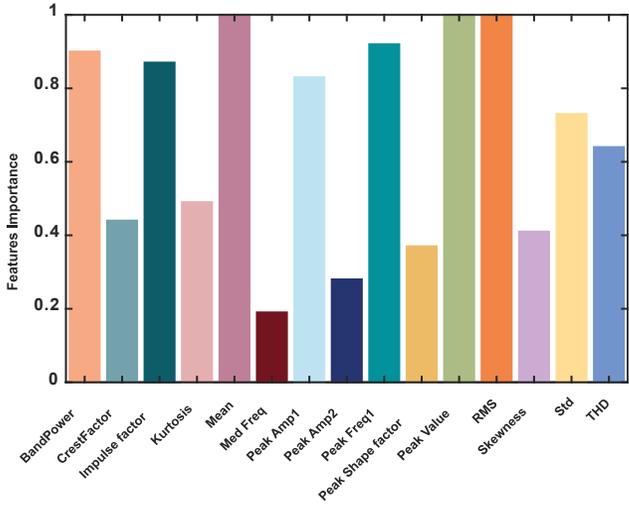


Ensemble Subspace Discriminant Tree (ESDT)

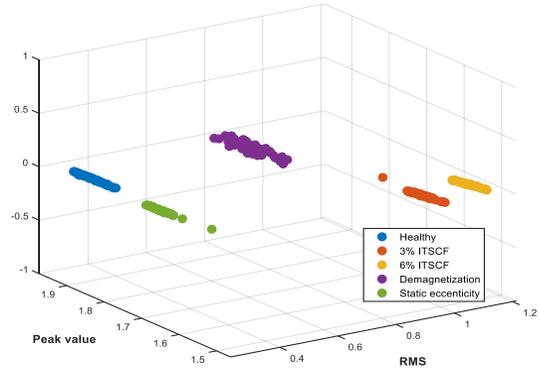
ESDT Algorithm

1. **Input:** a set of diagnostic features $\chi = \{x^{(1)}, x^{(2)}, \dots, x^{(d)}\}$.
2. **Parameters:** Number of subspaces K , number of features per subspace n , weight coefficient α , features quality measure $qual_m(x^c)$.
3. **Output:** feature subspace S .
4. For $i = 1$ to k , do
5. $S_i \rightarrow \emptyset$
6. End for
7. Repeat
8. For $i = 1$ to k , do
9. For $c = 1$ to k , do
10. If $x^c \notin S_i$ then
11. $f_{score}(x^c) \rightarrow \alpha \times qual_m(x^c) + (1 - \alpha) \times div_m(S, S_i, x^c)$
12. End if
13. End for
14. $x_{best} \rightarrow \text{argmax}_x f_{score}(x^c)$
15. $S_i \rightarrow S_i \cup x_{best}$
16. End for
17. Until every subspace consists of n features
18. Return S

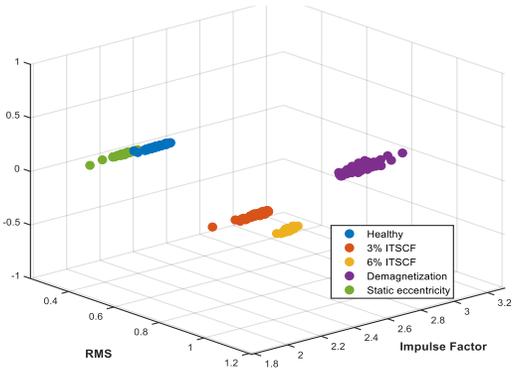
Condition Monitoring and Fault Detections of PMSM



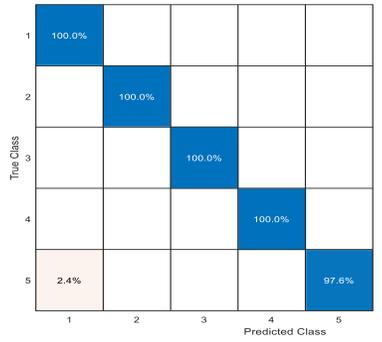
Features ranking results



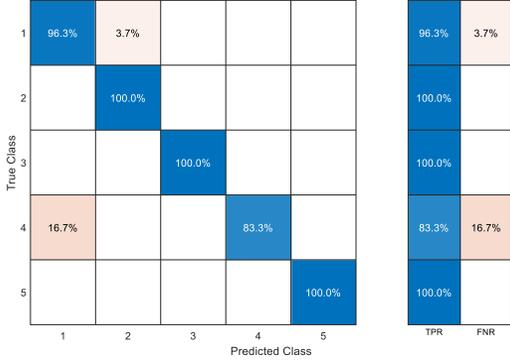
The extracted features for PMSM with 0.8Nm and running at 1800 rpm



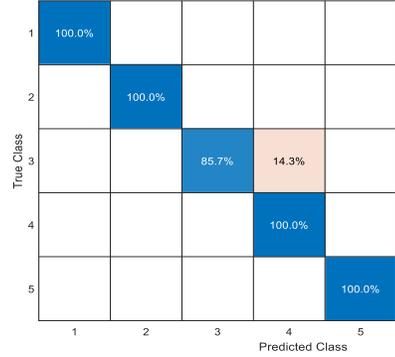
The extracted features for PMSM with 0.8Nm and running at 2400 rpm



PMSM loaded with 0.8 Nm and running at 1800 rpm

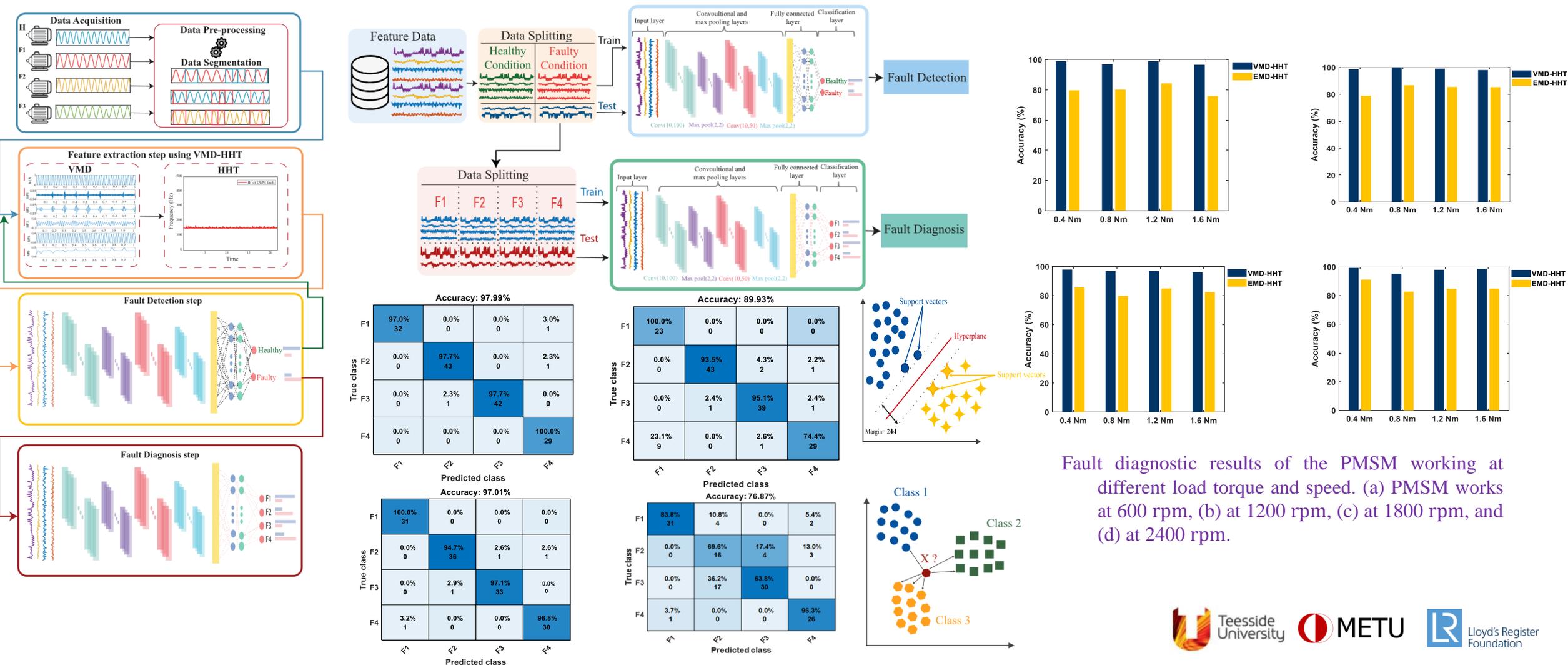


PMSM loaded with 1.2 Nm and running at 2400 rpm



Confusion matrix of the trained model: (1) Healthy class. (2) 3% short circuit. (3) 6% short circuit. (4) Demagnetisation fault. (5) Static eccentricity.

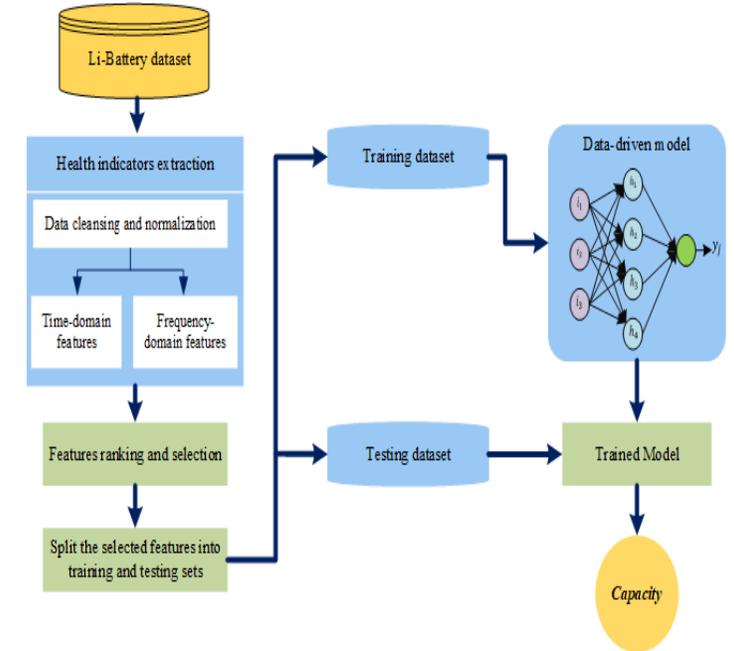
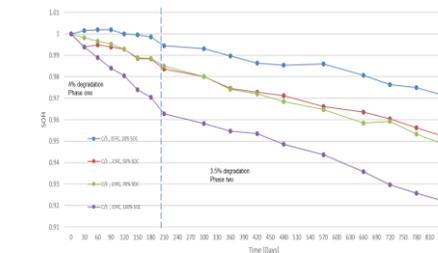
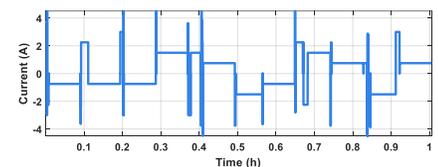
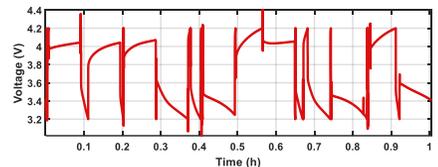
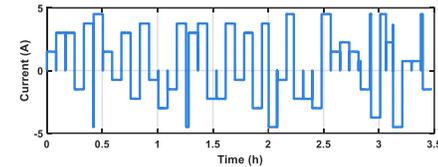
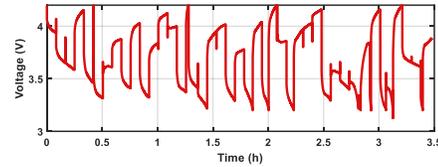
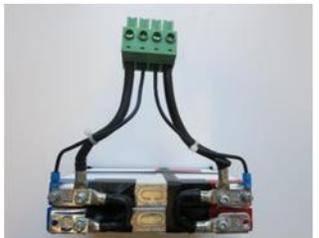
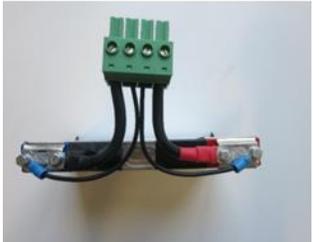
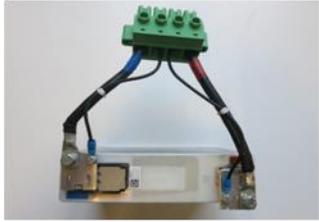
Condition Monitoring and Fault Detections of PMSM



Fault diagnostic results of the PMSM working at different load torque and speed. (a) PMSM works at 600 rpm, (b) at 1200 rpm, (c) at 1800 rpm, and (d) at 2400 rpm.



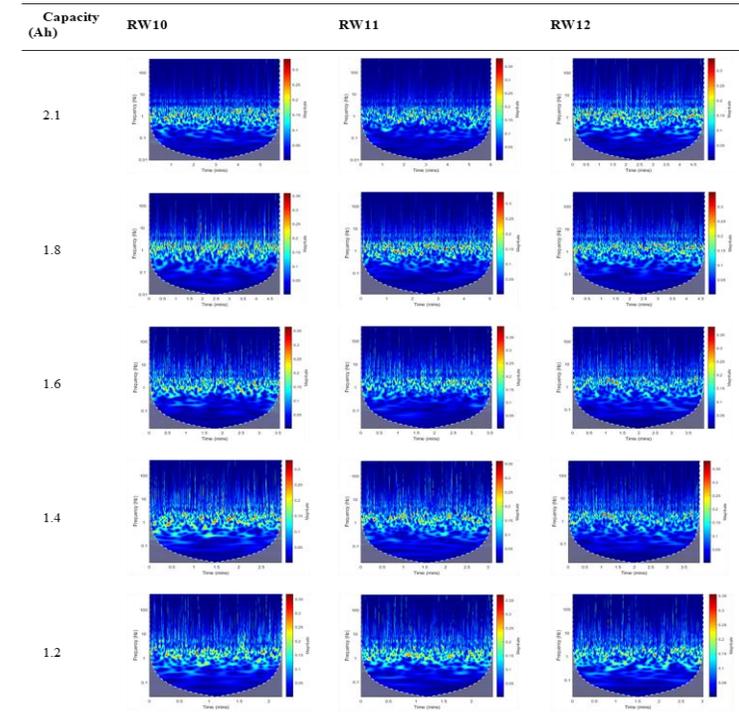
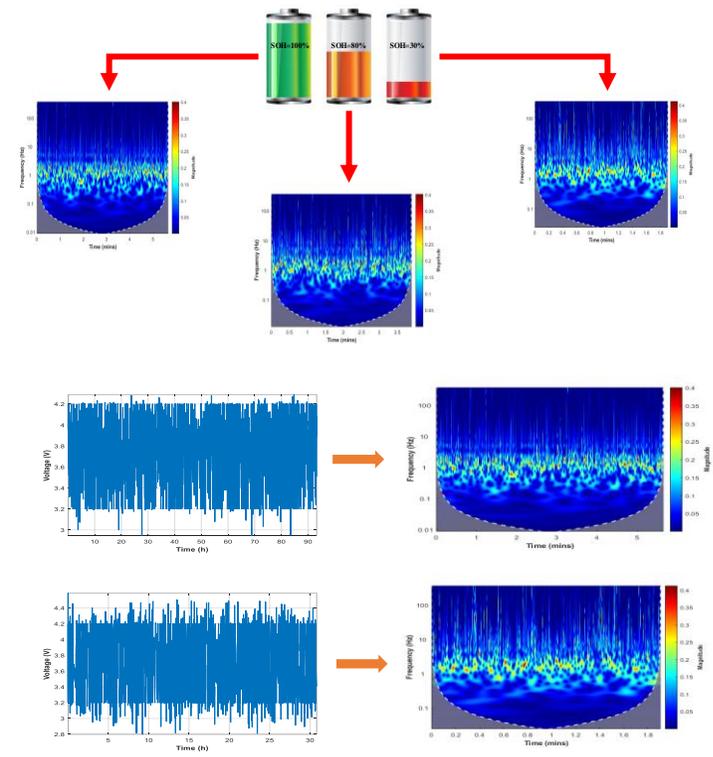
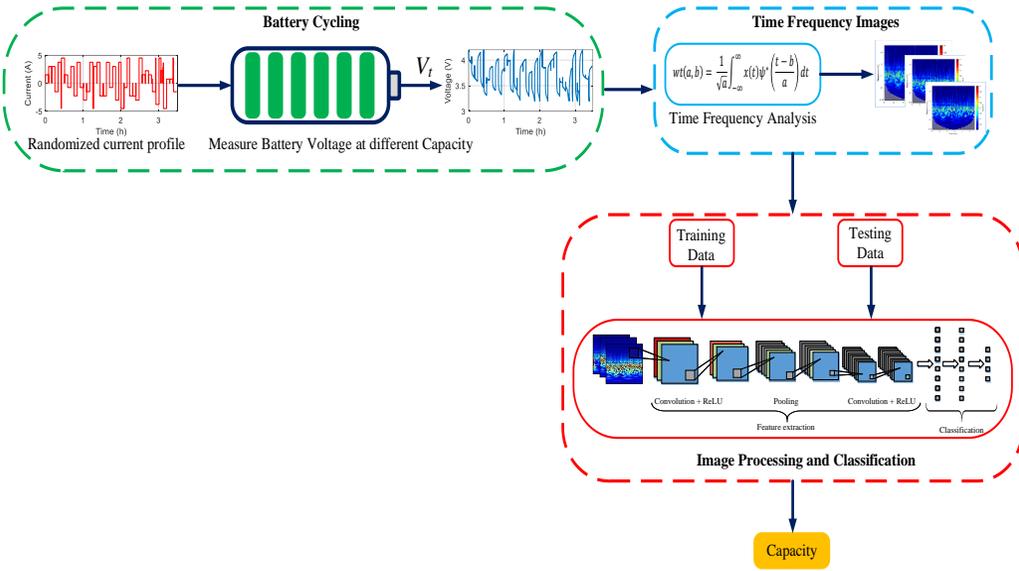
Prognostics & Diagnostics of Batteries



LiBs Experiential Calendar and Cycle Aging Analysis Based on Different Manufacturers

- [] Ma'D El-Dalahmeh, J. Lillystone, **M. Al-greer**, Mo'Ath El-Dalahmeh, "State of Health Estimation of Lithium-ion Batteries Based on Data-Driven Techniques", in *56th IEEE International Universities Power Engineering Conference, UPEC*, 2021.
- [] Ma'D El-Dalahmeh, P. Thummarapally, **M. Al-greer**, Mo'Ath El-Dalahem, "Lithium-ion Battery Capacity Prediction based on Time and Frequency Domains Diagnostics Features", in *56th IEEE International Universities Power Engineering Conference, UPEC*, 2021.
- [] A. Gailani, R. Mokidm M. El-Dalahmeh, **M. Al-greer**, "Analysis of Lithium-ion Battery Cells Degradation Based on Different Manufacturers, under review in 55th IEEE International Universities Power Engineering Conference, UPEC 2020.

Prognostics & Diagnostics of Batteries

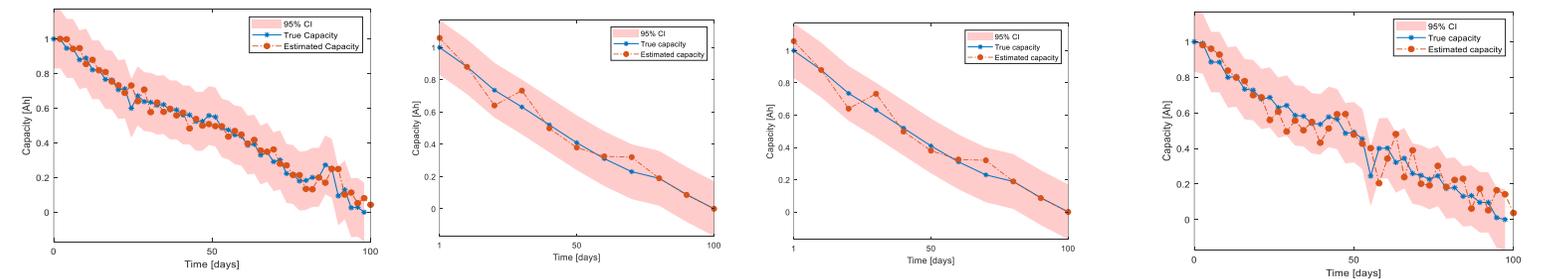


Capacity estimation accuracy for each battery cell using AlexNet

	RW9		RW10		RW11		RW12	
Optimiser	SGDM	Adam	SGDM	ADAM	SGDM	ADAM	SGDM	ADAM
Accuracy	95.0673%	95.69%	91.96%	94.20%	93.39%	94.27%	90.25%	91.5%

SoH estimation accuracy for each battery cell using the VGG-16 model

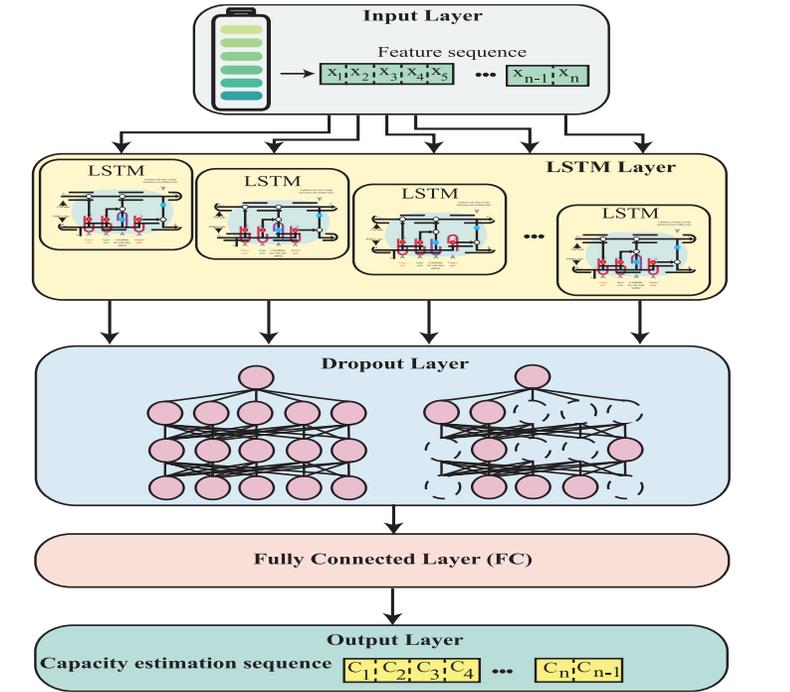
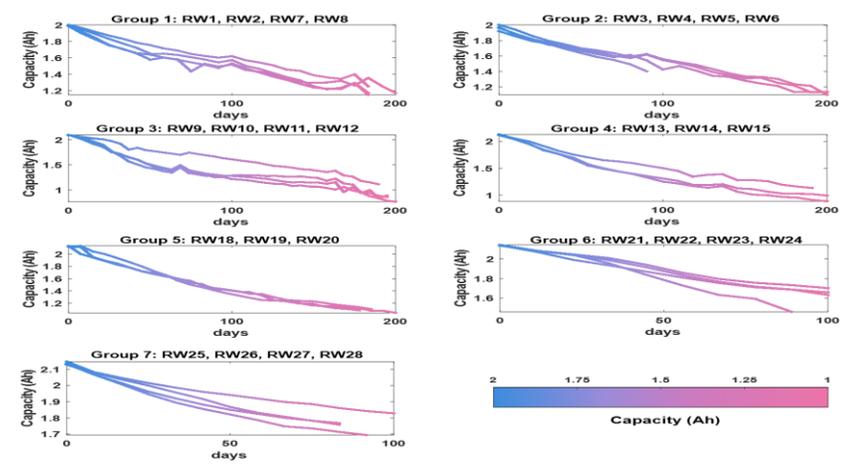
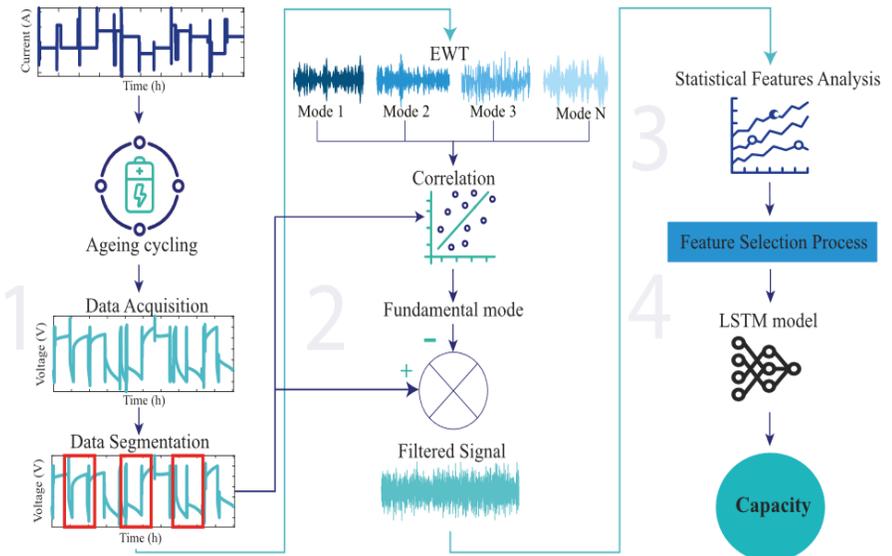
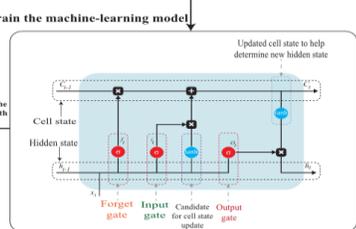
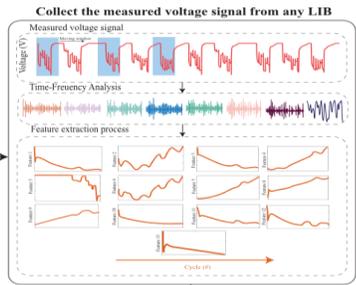
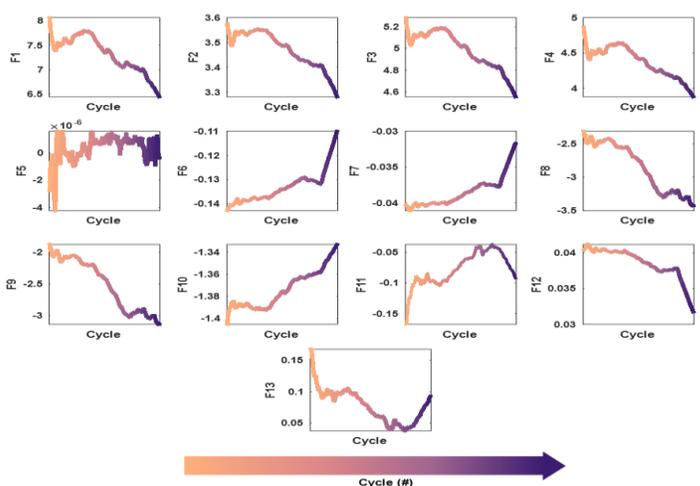
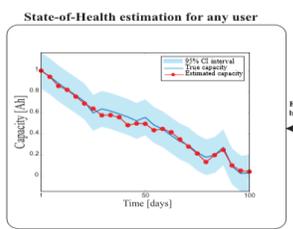
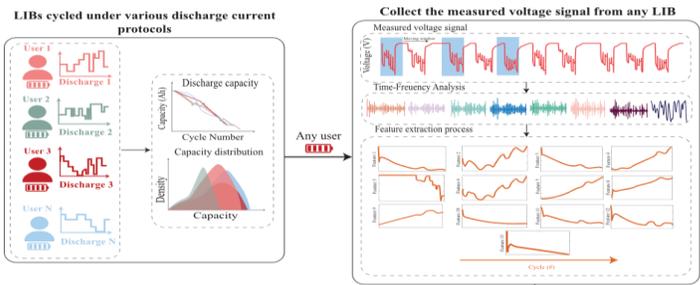
	RW9		RW10		RW11		RW12	
Optimiser	SGDM	ADAM	SGDM	ADAM	SGDM	ADAM	SGDM	ADAM
Accuracy	95.52%	95.52%	95.09%	95.60%	94.29%	94.92%	92.25%	95.5%



[1] Ma'D El-Dalameh, M. Al-greer, Mo'Ath El-Dalahem, M.Short, "Time Frequency Image Analysis and Transfer learning for Capacity Estimation of Lithium-ion Battery.," Energies, 2020, 13(20), 5447.



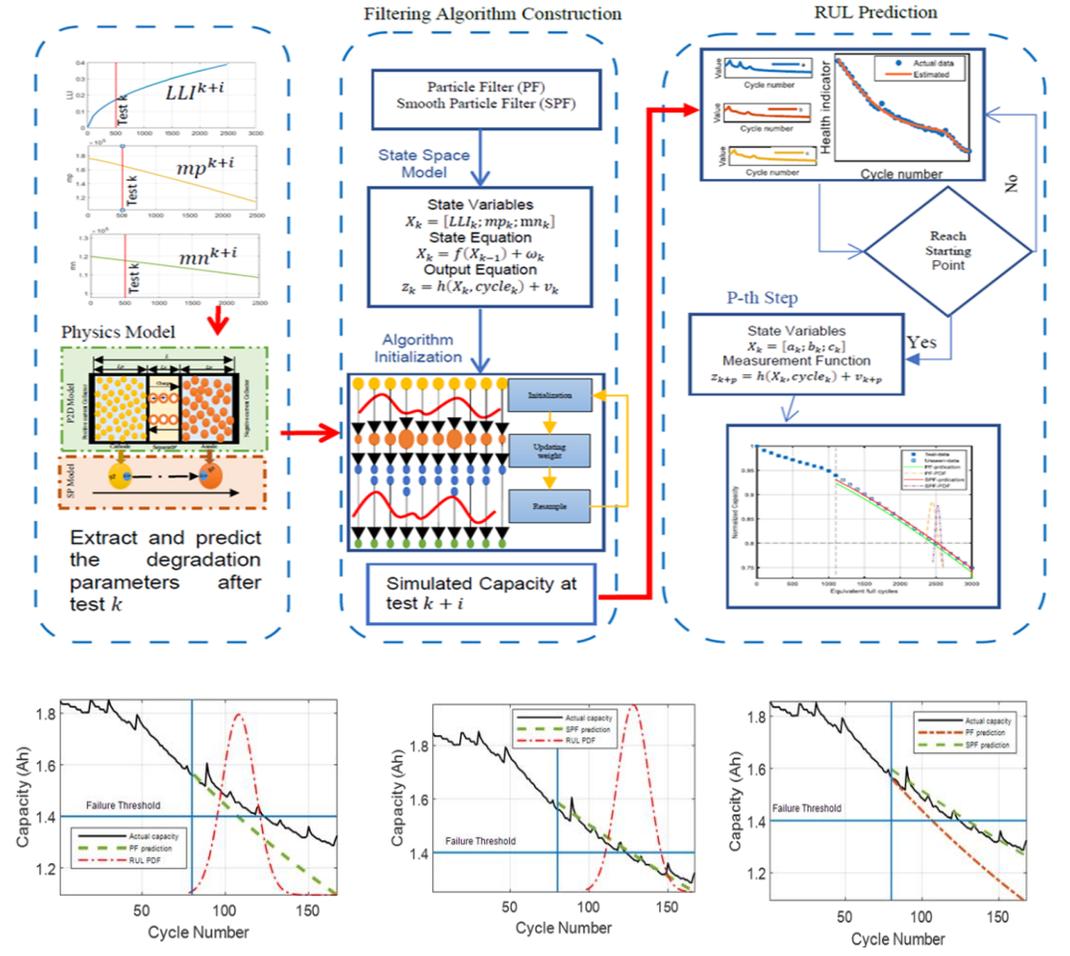
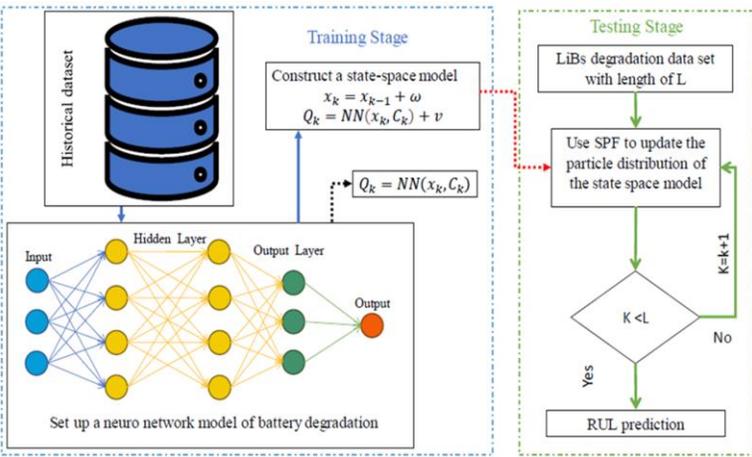
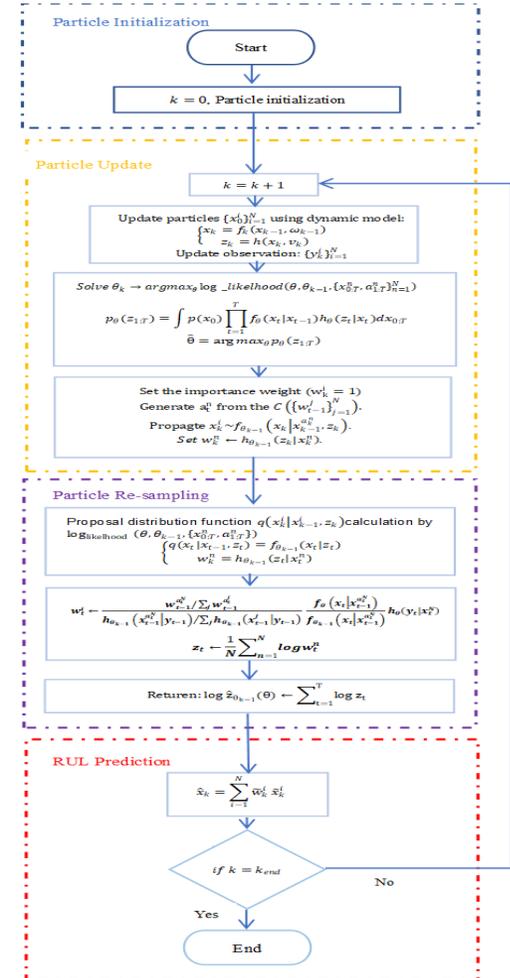
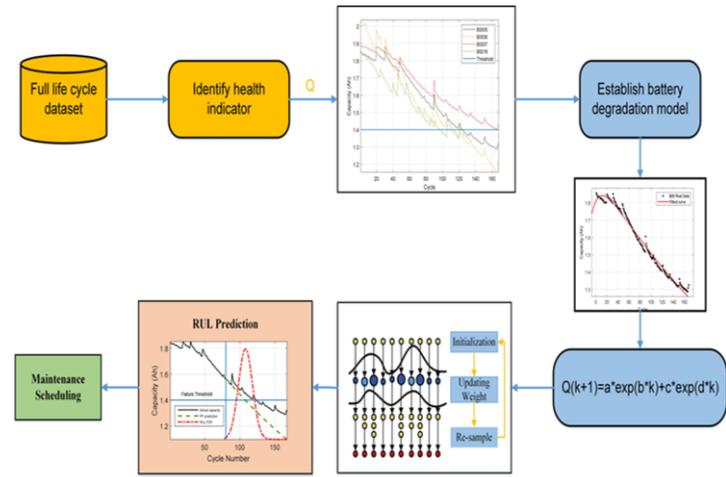
Prognostics & Diagnostics of Batteries



	RW1	RW4	RW9	RW14	RW19	RW22	RW25	W5	W9	Average
RMSE (%)	2.06	1.67	1.96	2.036	2.30	1.51	1.76	0.89	0.91	1.61%
AE (%)	3.87	3.56	7.39	3.82	4.34	2.69	3.72	1.62	1.50	3.61%

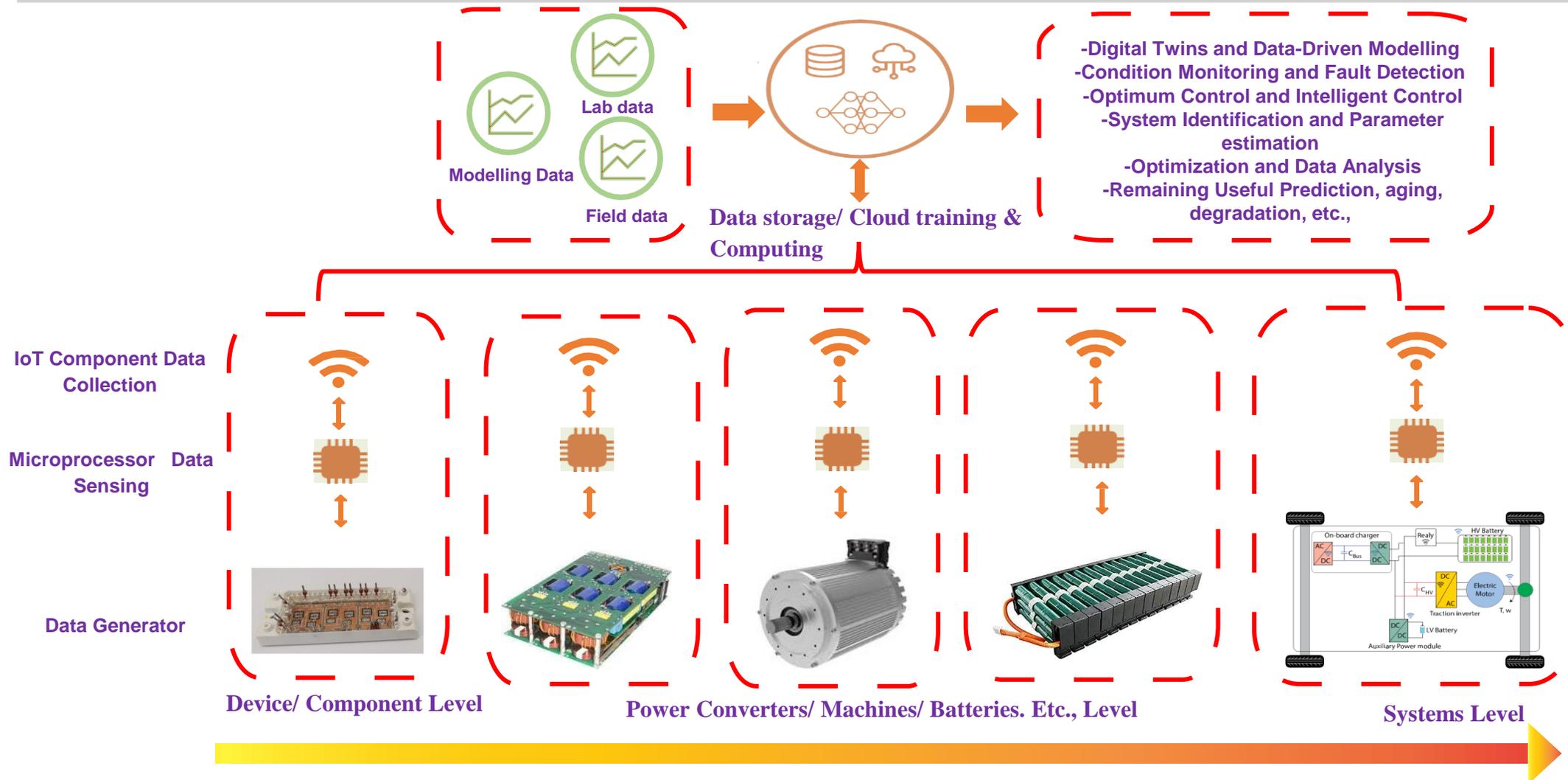
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Plans and Vision



Thanks!

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