Predicting the Remaining Useful Life of Jet Turbofan Engines Using Depth-Continuous Neural ODEs

Project Proposal

MAT292H, PRA0102
University of Toronto

Mani Majd, 1011082427

Alison Lei, 1011121929

Jia Qi Huang, 1011078316

Kelly Hong, 1010469734

October 3, 2025

1 Project Motivation and Goal

The health state of turbofan jet engines is critical for ensuring commercial aircraft's flight safety [1]. An important metric for assessing the engine's health state is Remaining Useful Life (RUL), an indication of the remaining length of time for which the engine can safely operate before it needs to be repaired or replaced [2]. Accurate predictions of the RUL are important as they allow early identification of problems in the engine before catastrophic failures, and can improve maintenance planning and reduce unplanned downtimes [1, 3].

Current methods for RUL predictions primarily involve applications of deep learning—a machine learning method that utilizes multilayer neural networks—to learn patterns in engine sensory data [1, 3, 4, 5]. Although these models were shown to be able to capture complex and noisy patterns in the sensor data, they operate on a discrete number of layers, which may fall short in modeling the time-dependent and therefore continuous engine dynamics. This motivates the use of neural ordinary differential equations (neural ODEs), which model the transformation of data in the neural network as depth-continuous differential equations [6, 7], and have already shown successes in predicting the RUL of systems such as lithium batteries [8, 9, 10]. Thus, the proposed goal of this work is to extend the application of neural ODEs to predicting the RUL of turbofan engines, and to evaluate their performance against existing deep learning approaches. We hypothesize that neural ODEs can match, or potentially surpass, the effectiveness of existing approaches.

2 Technical Background

2.1 Multilayer Neural Networks

Multilayer neural networks are a class of machine learning models made up of multiple hidden layers connected by weighted links [11]. During training, these weights are adjusted such that the network's output is as accurate as possible [12]. For a network consisting of T layers, an input given to the network evolves according to the following equation:

$$\mathbf{h}_{t+1} = \mathbf{h}_t + f(\mathbf{h}_t, \theta_t) \tag{1}$$

where $\mathbf{h}_t$ is the state of the input at the tth layer for discrete $t \in \{0, 1, \cdots, T\}$, θ_t are the weights of the tth layer, and $f(\mathbf{h}_t, \theta_t)$ describes how the state transforms from layer t to layer $t+1$. The output of the network is given by the state at the final layer, $\mathbf{h}_T$ [7]. A graphical representation of multilayer neural networks is given in Figure 1a. This architecture forms the basis of existing top-performing RUL prediction methods, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) [1, 3, 4], which could all be conveniently implemented using Python's *PyTorch* library [13].

2.2 Neural ODEs

The neural ODE can be understood as a multilayer neural network that takes infinitesimally small steps in depth t, with an effectively infinite number of layers [7]. It models state transformations as a continuous process governed by an ordinary differential equation of the general form:

$$\frac{d\mathbf{h}(t)}{dt} = f(\mathbf{h}(t), t, \theta) \tag{2}$$

Here, $t \in [0, T]$ represents depth within the neural network, $\mathbf{h}(t)$ describes the state of the input at depth t, and $f(\mathbf{h}(t), t, \theta)$ models the continuous network layers, with θ corresponding to the layer's weights [6, 7]. The output of a neural ODE is the value of the state function at the final depth T, or $\mathbf{h}(T)$, which can be found by performing a numerical integration of Equation 2 using Python's *torchdiffeq* library [7]. The continuous nature of neural ODE makes it suitable for modeling time-continuous systems [14], and hence is a promising approach for time-series turbofan engine sensory data. Figure 1b provides a graphical illustration of neural ODEs alongside a comparison with multilayer neural networks.

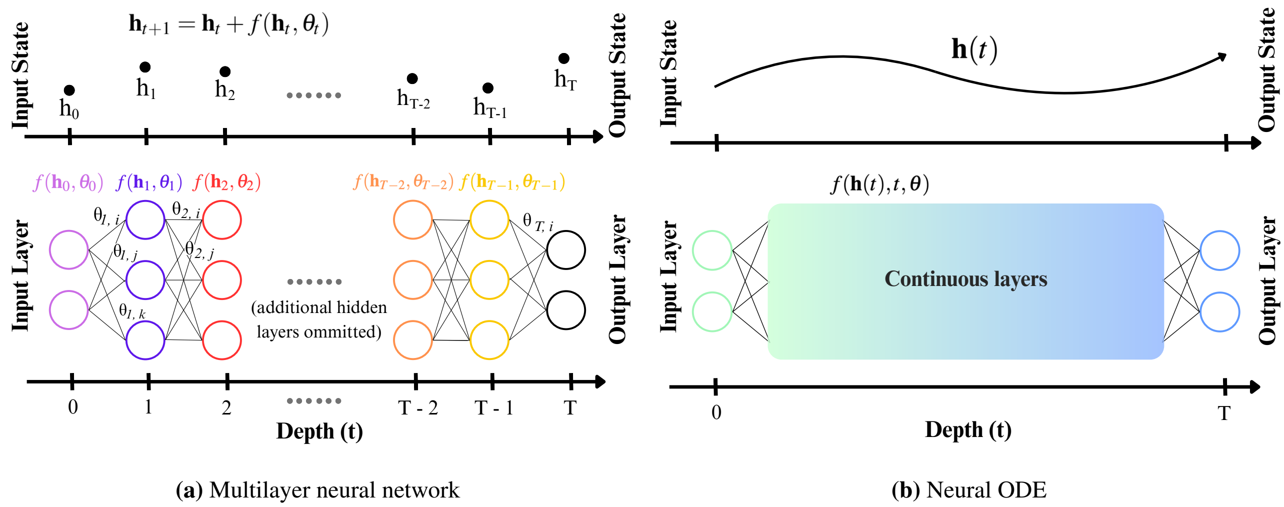

Figure 1: Graphical representations of multilayer neural networks (panel a) and neural ODEs (panel b). The top panels illustrate how states transform within each network, and the bottom panels showcase network structures. While state transformation and layers are discrete in multilayer neural networks, neural ODEs model them to be continuous.

3 Objectives

The objectives of this project are to: 1) develop and train neural ODEs on turbofan sensor data, 2) assess the RUL predictive accuracies of neural ODEs, 3) implement existing top-performing RUL prediction methods such as Long Short-Term Memory (LSTM) networks [1, 3, 4], and 4) evaluate the performance of neural ODEs against these existing models.

4 Potential Dataset

A crucial aspect of the proposed project is the availability of jet engine sensory data. NASA's open-source CMAPSS Jet Engine Simulation Dataset is a reputable and widely recognized dataset for turbofan engine RUL prediction [1, 3, 4, 15]. It provides time-series measurements of multiple internal sensors of turbofan engines over their operational cycles, with ground-truth RUL labeled for both model training and testing [15]. The CMAPSS dataset hence allows for model training and direct evaluation of model prediction accuracies, and is therefore well-suited for the proposed work.

5 Project Milestones and Proposed Timeline

Expected project milestones and their proposed timeline are outlined below in Table 1.

Milestone	**Estimated Timeline**
Detailed review of relevant literature on neural ODEs and turbofan RUL prediction	Week of Oct. 6
CMAPSS dataset familiarization, preprocessing and parsing for model training	Week of Oct. 13
Implementation and training of neural ODE for RUL prediction using *PyTorch*	Week of Oct. 27
Implementation of existing deep learning RUL prediction methods using *PyTorch*	Week of Nov. 3
Evaluation of models	Week of Nov. 10
Draft of final report	Week of Nov. 24

Table 1: Project Schedule Overview

Overall, the proposed project aims to explore the performance of neural ODEs in predicting the RUL of turbofan engines, motivated by their strengths in modeling time-continuous systems and the importance of ensuring aircraft safety.

References

[1] S. Sanami and A. G. Aghdam. "Aero-engines anomaly detection using an unsupervised fisher autoencoder." Accessed: 2025-10-01, arXiv.org. [Online]. Available: https://arxiv.org/abs/2502.05428

[2] A. Baru and R. Johnson. "Three ways to estimate remaining useful life for predictive maintenance." Accessed: 2025-10-01, MathWorks. [Online]. Available: https://www.mathworks.com/company/technical-articles/three-ways-to-estimate-remaining-useful-life-for-predictive-maintenance.html

[3] A. Peringal, M. B. Mohiuddin, and A. Hassan. "Remaining useful life prediction for aircraft engines using lstm." Accessed: 2025-10-01, arXiv.org. [Online]. Available: https://arxiv.org/abs/2401.07590

[4] Z. Zhai, J. Wen, F. Wang, Z. Zhao, Y. Guo, and X. Chen, "Remaining useful life prediction of aero-engine based on transformer with tendency retainment," in *2022 International Conference on Sensing, Measurement & Data Analytics in the era of Artificial Intelligence (ICSMD)*, IEEE, Nov. 2022, p. 10 058 242. DOI: 10.1109/icsmd57530.2022.10058242 [Online]. Available: https://doi.org/10.1109/icsmd57530.2022.10058242

[5] I. H. Sarker, "Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions," *SN Computer Science*, vol. 2, no. 6, pp. 1–21, Aug. 2021. DOI: 10.1007/s42979-021-00815-1 [Online]. Available: https://doi.org/10.1007/s42979-021-00815-1

[6] G. Xiao. "Neural ordinary differential equations (neural odes): Rethinking architecture." Accessed: Oct. 01, 2025. [Online]. Available: https://medium.com/@justygwen/neural-ordinary-differential-equations-neural-odes-rethinking-architecture-272a72100ebc

[7] R. T. Q. Chen, Y. Rubanova, J. Bettencourt, and D. Duvenaud, "Neural ordinary differential equations," in *Advances in Neural Information Processing Systems (NeurIPS)*, Accessed: Oct. 01, 2025, Jun. 2018. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2018/file/69386f6bb1dfed68692a24c8686939b9-Paper.pdf

[8] K. Tran, T. Le, B. Huynh, H.-C. Trinh, and V.-R. Nguyen, *End-to-end framework for predicting the remaining useful life of lithium-ion batteries*, arXiv preprint, Accessed: Oct. 01, 2025, 2025. DOI: https://doi.org/10.48550/arXiv.2505.16664 [Online]. Available: https://arxiv.org/abs/2505.16664

[9] M. Yadav, P. Malhotra, L. Vig, K. Sriram, and G. Shroff, *Ode - augmented training improves anomaly detection in sensor data from machines*, arXiv preprint, Accessed: Oct. 01, 2025, 2016. DOI: https://doi.org/10.48550/arXiv.1605.01534 [Online]. Available: https://arxiv.org/abs/1605.01534

[10] T. Hu, Z. Mo, and Z. Zhang, "Neural ode powered model for bearing remaining useful life predictions with intra- and inter-domain shifts," *Advanced Engineering Informatics*, vol. 64, p. 103 077, Jan. 2025. DOI: 10.1016/j.aei.2024.103077

[11] M. Gardner and S. Dorling, "Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences," *Atmospheric Environment*, vol. 32, no. 14, pp. 2627–2636, 1998, ISSN: 1352-2310. DOI: https://doi.org/10.1016/S1352-2310(97)00447-0 [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1352231097004470

[12] S. H. Han, K. W. Kim, S. Kim, and Y. C. Youn, "Artificial neural network: Understanding the basic concepts without mathematics," *Dementia and Neurocognitive Disorders*, vol. 17, no. 3, pp. 83–89, Sep. 2018, Epub 2018 Dec 13. DOI: `10.12779/dnd.2018.17.3.83`

[13] PyTorch, *Pytorch*, `https://pytorch.org/`, Accessed: 2025-10-02, 2023.

[14] M. Biloš, J. Sommer, S. S. Rangapuram, T. Januschowski, and S. Günnemann, "Neural flows: Efficient alternative to neural odes," *arXiv preprint arXiv:2110.13040*, 2021. DOI: `10.48550/arXiv.2110.13040` [Online]. Available: `https://arxiv.org/abs/2110.13040`

[15] A. Saxena, K. Goebel, D. Simon, and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," in *Proceedings of the 1st International Conference on Prognostics and Health Management (PHM08)*, Denver, CO, Oct. 2008.