MDM2 – Case Study: Intelligent Systems in Production
One-Page Proposal

Team	Group 6
Members	Kishan cheeramath Dalmy John Tomson Roy Adithye Mathew
Project Title	Predictive maintenance on Turbofan Engines
GitHub Repository URL	https://github.com/Intelligentcasestudy/Group6
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Industrial Application (target domain/use-case)	
Keywords (3–6)	Predictive Maintenance, Remaining Useful Life (RUL), Deep Learning, LSTM (Long Short-Term Memory)
Submission Date (YYYY-MM-DD)	19-10-2025
Gant Chart	The gantt chart is provided below

1) Problem Statement & Measurable Outcomes (3–4 sentences)	The project aims to build a predictive maintenance framework that estimates the Remaining Useful Life (RUL) of turbofan engines using multivariate sensor data from the NASA CMAPSS dataset. The problem centers on accurately forecasting engine degradation trajectories to enable proactive maintenance decisions. Success will be measured by the model's predictive accuracy (using RMSE and MAE) and its ability to detect faults early. A production-ready LSTM model should achieve a statistically significant improvement in prediction accuracy compared to baseline regression models.
2) Motivation & Industrial Relevance (2–3 sentences)	Accurate RUL prediction is vital in aerospace and manufacturing industries, where unplanned equipment downtime leads to substantial costs and safety risks. Predictive maintenance powered by deep learning enables condition-based interventions, extending equipment lifespan and optimizing maintenance resources. This aligns with Industry 4.0 initiatives that emphasize data-driven decision-making and smart asset management
3) Related Work Snapshot (2–3 key references)	1. **Saxena & Goebel (2008)** – Introduced the NASA CMAPSS Turbofan Engine dataset, a benchmark for prognostics research in engine degradation modeling. http://boschsoftwaretechnologies.com/media/documents/downloads/2023/remaining_useful_life_with_industry4-0_a_bosch_pov.pdf 2. **De Vita & Bruneo (2019)** – Demonstrated LSTM networks' effectiveness for predictive maintenance in smart industrial systems. 3. **Wu et al. (2024)** – Provided a comprehensive survey of deep learning-based RUL prediction methods, identifying LSTM, CNN, and hybrid models as state-of-the-art approaches for data-driven prognostics.

4) Method & Feasibility (≤6 sentences)	The project employs an **LSTM-based deep learning architecture** to model time-dependent degradation patterns in engine sensor data. After exploratory data analysis and feature engineering, temporal features will be normalized and labeled for supervised training. The LSTM model will be trained and validated using sequence-to-point prediction windows to estimate RUL. Model performance will be evaluated using RMSE, MAE, and R^2 metrics. The use of publicly available NASA CMAPSS data and cloud-based computing (e.g., Colab, TensorFlow) ensures both technical and economic feasibility. The approach can be scaled and adapted for deployment in industrial IoT environments.
5) Milestones & Timeline (short table/list)	List milestones aligned with course phases (P1–P5) with target dates.
6) Risks & Ethics (1–2 sentences)	Key risks include model overfitting due to limited failure examples and potential data bias from simulated datasets. Ethical considerations involve ensuring model transparency, data privacy, and responsible AI deployment in safety-critical aerospace systems.

Phase 1 rubric (15%): Team & GitHub (2%), On-time (2%), Topic & Proposal (5%) — Industrial Application, Problem+Outcomes, Feasibility+Timeline; Presentation (6%).