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Simulation of Intelligent Energy Management and Autonomous Recovery for Lunar Rovers

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ABSTRACT :

Lunar rovers must survive extreme temperature swings and manage limited battery energy, because solar power disappears during the roughly fourteen-day lunar night. This paper presents a software-based academic simulation of intelligent energy management and autonomous recovery for lunar rovers. The system generates synthetic telemetry (battery level, electronics bay temperature, solar power and lunar phase) for lunar day, night and dawn, cleans the data, and uses a Decision Tree classifier to predict thermal risk as Low, Moderate, High or Critical.

A rule-based energy manager then decides the state of the camera, navigation and heater subsystems and selects an energy-saving mode, while an autonomous recovery engine checks five wake-up conditions and reports a readiness score. All modules are presented through an interactive Streamlit dashboard. The Decision Tree reached 99% accuracy on a 100-sample synthetic test set; because the risk label is derived from temperature thresholds, this reflects the synthetic labelling rule and not real-mission performance. The work is a simulation only and does not communicate with or control any real spacecraft, including Chandrayaan-3 or Pragyan.

Keywords: lunar rover, energy management, autonomous recovery, thermal risk, Decision Tree, Streamlit.

INTRODUCTION:

A solar-powered lunar rover receives energy only while the Sun is above the horizon. During the lunar night the battery cannot be recharged and electronics are exposed to temperatures near -180 °C, whereas at lunar noon overheating is a risk. Public reports on the Chandrayaan-3 mission describe the vehicles being placed in sleep mode with the aim of reviving them at the next sunrise, which illustrates how important night survival and safe wake-up are.

This project models the decision problem in software. A simulated telemetry stream is passed through data preprocessing, an AI thermal-risk model, an intelligent energy manager and an autonomous recovery engine, and the results are shown on a mission dashboard. The system is Chandrayaan-inspired only; all data are computer-generated.

OBJECTIVE:

- To simulate lunar day, night and dawn telemetry and clean it for analysis.
- To predict thermal risk with a Decision Tree classifier inside a scikit-learn Pipeline.
- To decide camera, navigation and heater states and an energy-saving mode from telemetry and predicted risk.
- To evaluate wake-up safety conditions and compute a recovery readiness score.
- To present all results in an interactive dashboard and verify the modules with automated tests.

LITERATURE SURVEY:

1. Larson and Wertz (1999) describe spacecraft power systems built from solar arrays, batteries and power distribution, and the use of power budgets and operating modes such as nominal, reduced-power and safe modes.

2. Gilmore (2002) documents spacecraft thermal control techniques, including insulation, radiators and heaters, which motivate cold-only heater use under limited battery energy.

3. Heiken et al. (1991) describe the lunar environment, including the wide surface temperature swing between lunar day and night.

4. Francis et al. (2017) report AEGIS, an autonomous targeting system on the Mars Science Laboratory rover, showing practical on-board autonomy in planetary exploration.

5. Hundman et al. (2018) studied spacecraft telemetry anomaly detection with LSTM networks and dynamic thresholds, demonstrating machine learning on telemetry data.

6. Breiman et al. (1984) and Quinlan (1986) introduced decision-tree learning, whose rule-like structure suits explainable, safety-related classification.

METHODOLOGY:

1. Lunar Environment Simulation and Telemetry Generation: 400 records are generated (Lunar Day 160, Night 180, Dawn 60) with phase-specific ranges for solar power, temperature and battery level; three duplicates and two missing values are added to the raw file to exercise cleaning.

2. Data Preprocessing: duplicates are removed, missing values are imputed with median or mode and values are clipped to physical limits, giving 400 clean records.

3. AI Thermal Risk Prediction: a Pipeline of StandardScaler, OneHotEncoder and a DecisionTreeClassifier (Gini, depth 5) is trained on 300 samples and tested on 100 (random_state 42).

4. Intelligent Energy Management: rules choose Safe Mode (battery below 20% or Critical risk), night hibernation, low-power conservation, solar recharge, thermal mitigation or nominal exploration. The heater is turned on only below -40 °C and is never on in hot conditions.

5. Autonomous Recovery Engine: five checks (battery at least 35%, solar at least 15 W, temperature between -60 °C and +70 °C, Lunar Day or Dawn, and risk Low or Moderate) give a readiness score and a status such as Safe Mode, Recovery Recommended or Normal Operation.

6. Mission Dashboard: a Streamlit application with preset scenarios, sliders, charts and dataset management.

EXISTING SYSTEM:

- Fixed-threshold modes treat temperature, battery and solar input independently, with no single risk indicator.
- Wake-up after the lunar night can depend on ground confirmation.
- Mission software is not open, so students cannot easily explore the reasoning behind decisions.
- There is no simple environment to test unusual telemetry combinations.

PROPOSED SYSTEM:

- Machine-learning thermal-risk prediction combined with explicit, testable rules.
- Explainable output: every decision and recovery check has a rationale and pass/fail value.
- Integrated pipeline from data generation to dashboard, reproducible with a fixed random seed.
- Advisory only: no commands are sent to any real hardware.

SYSTEM REQUIREMENTS:

Hardware: ordinary computer with a dual-core processor, 4 GB RAM (8 GB recommended) and a standard display; no GPU needed.

Software: Windows, Linux or macOS; Python 3.9 or later; streamlit, pandas, numpy, scikit-learn, matplotlib and joblib; any modern web browser.

PROCESSING:

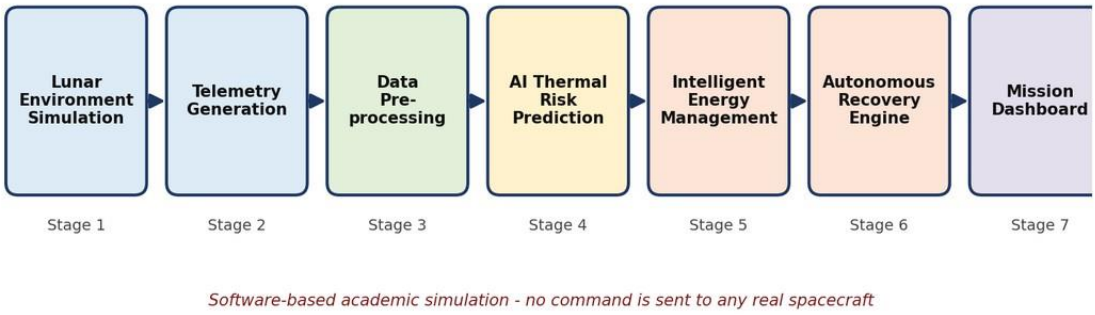


Figure 1: End-to-End System Workflow

MODULES:

- Lunar Environment Simulation (data_simulation.py): generates labelled telemetry.
- Data Preprocessing (data_preprocessing.py): validates and cleans data.
- AI Thermal Risk Model (train_model.py): trains, evaluates and saves the Decision Tree pipeline.
- Energy Management (energy_management.py): camera, navigation, heater and mode decisions.
- Autonomous Recovery Engine (recovery_engine.py): wake-up checks and readiness score.
- Dashboard (app.py): Streamlit mission-control interface.
- Testing (test_simulation.py): seven automated unit tests.

RESULTS AND OUTPUT SCREENSHOTS:

Seven automated unit tests passed. For the default dashboard input (battery 65%, bay temperature 35 °C, solar 55 W, Lunar Day) the system predicts Low thermal risk and the recovery engine reports Normal Operation with 100% readiness. The Decision Tree reached 99% test accuracy (one Moderate sample predicted as Low); temperature was the only feature with non-zero importance, because the label is defined from temperature.

Telemetry Visualizations:

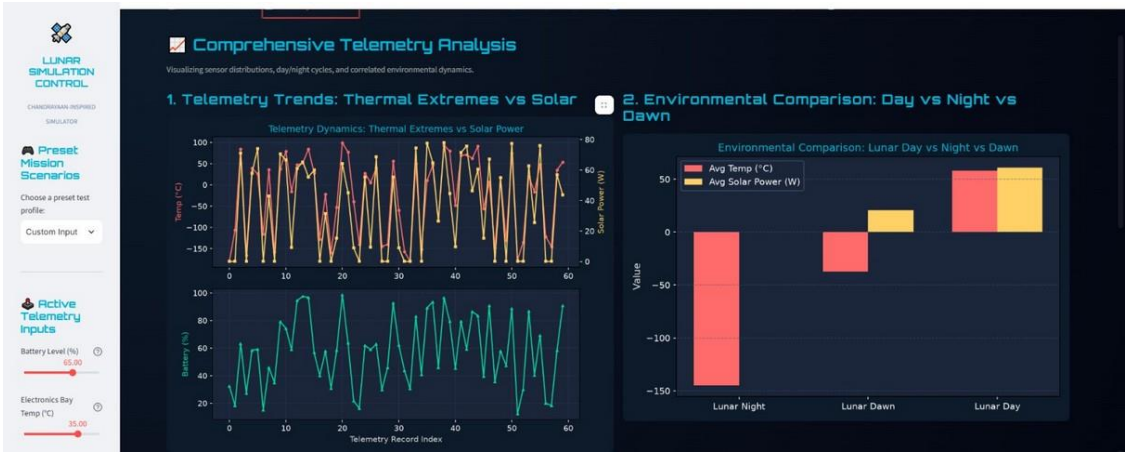


Figure 2: Comprehensive Telemetry Analysis

Dataset Management:

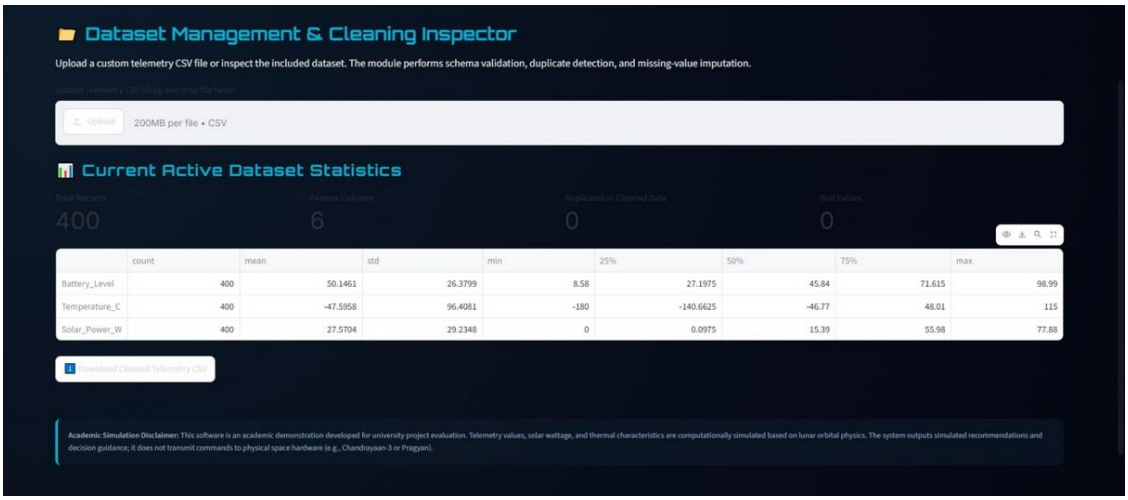


Figure 3: Dataset Management and Cleaning Inspector (400 records, 0 duplicates, 0 nulls)

Autonomous Recovery Engine:

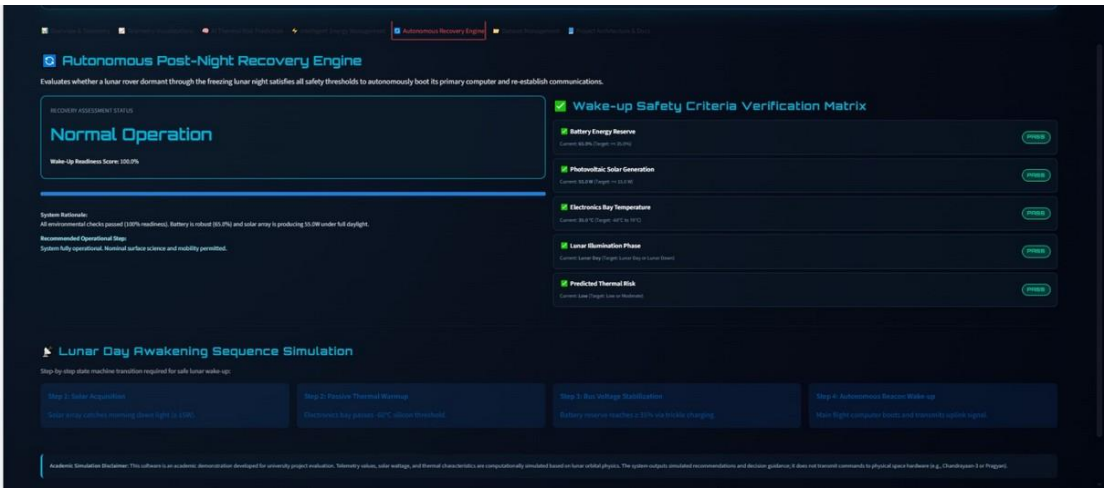


Figure 4: Autonomous Post-Night Recovery Engine

Model Evaluation:

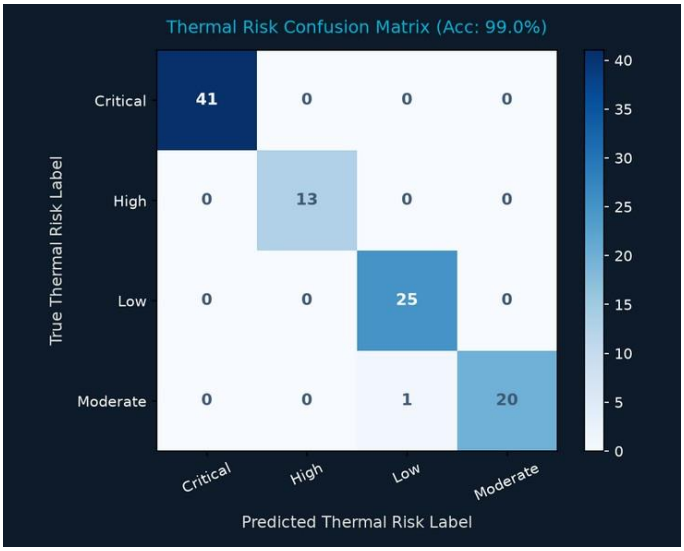


Figure 5: Confusion Matrix on the Synthetic Test Set

CONCLUSION:

The simulation shows how a machine-learning thermal-risk model and transparent rules can be combined for rover energy management and wake-up decisions, with every decision explained on the dashboard. The 99% accuracy reflects the synthetic labelling rule and should not be generalised to real telemetry.

Future work includes time-series simulation of a full lunar cycle, a physics-based thermal model, comparison with other learning models and validation on public planetary telemetry. The software is an academic simulation only and has no connection with ISRO, NASA or any real spacecraft.

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