**(Academic Year:2024-25) Phase 1 Project Review 1**

**on**

**Project Title** : **Improving Sustainability in Product Lifecycles Using Reinforcement Learning for Better Decision Making**

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# Problem statement

Improving Sustainability in Product Lifecycles Using Reinforcement Learning for Better Decision Making

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# Introduction

The project focuses on improving the sustainability of product lifecycles by using Reinforcement Learning (RL), a type of artificial intelligence that learns from decisions and their outcomes. The goal is to make better choices throughout a product's lifecycle—from design and manufacturing to recycling—by applying RL to optimize processes, reduce waste, and minimize environmental impact. This approach helps businesses make more sustainable decisions while improving efficiency and lowering costs.

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Literature Survey

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| **Year and Title** | **Algorithm** | **Result** | **Limitations / Drawbacks** |
| Sustainable Decision Making in Product Lifecycle: A Deep Reinforcement Learning Approach - 2022 | Actor-Critic Method | This study used an actor-critic method to make real-time decisions in product lifecycle management, balancing sustainability and profitability. The approach led to a 10% improvement in both cost savings and environmental performance. | The model faced difficulty in transferring learned policies to new product categories, limiting its adaptability. Additionally, the computational demands were high, which could hinder scalability. |
| Reinforcement Learning for Sustainable Resource Allocation in Manufacturing- 2023 | Multi-agent Reinforcement Learning(MARL) | This research employed MARL to optimize resource allocation in manufacturing, reducing material waste by 18% and energy consumption by 12%. Multiple agents learned collaboratively to improve overall sustainability. | MARL added complexity to the learning process, making convergence slow and requiring careful coordination between agents. The system also struggled in highly dynamic environments where resource availability fluctuated frequently. |
| Reinforcement Learning in Eco-friendly Manufacturing-2021 | Proximal Policy Optimization (PPO) | The algorithm successfully reduced energy consumption by 25% compared to traditional methods. | The study focused only on energy optimization and not other aspects of sustainability, such as waste reduction. |

# Motivation

The motivation for this project is to make products more environmentally friendly throughout their lifecycle. Using Reinforcement Learning (RL), businesses can improve decision-making to reduce waste, save energy, and promote recycling, all while lowering costs. This project aims to use AI to help create more sustainable and efficient products, benefiting both the environment and the economy. 6

# Objectives

# Improve Sustainability: Find ways to make products more eco-friendly at every stage, from design to recycling.

# Reduce Environmental Impact: Minimize resource use, emissions, and waste throughout a product’s lifecycle.

# Enhance Efficiency: Increase the overall efficiency of product development and manufacturing, while lowering costs.

# Scope

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1. **Applying Reinforcement Learning**: Using AI to optimize decisions across product design, manufacturing, and recycling.
2. **Improving Sustainability:** Reducing energy use, waste, and environmental impact at all stages of a product's lifecycle.
3. **Supporting Businesses**: Helping companies make cost-effective, eco-friendly decisions.
4. **Focusing on Real-World Applications:** Testing and implementing RL solutions in industries like manufacturing and supply chain management to improve sustainability practices.

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# Resource requirement

* **Deployment Platform :**Access to cloud platforms (e.g., AWS, Google Cloud) for handling large datasets and computations.
* **Software:**Reinforcement learning libraries (e.g., TensorFlow, PyTorch, OpenAI Gym).

Simulation tools for testing product lifecycle scenarios.

Data analysis tools (e.g., Python, MATLAB) for evaluating results.

* **Data:**Product lifecycle data, including information on design, manufacturing, energy usage, and waste.

Environmental impact data for training the model.

**System Overview**

The system collects data from different stages of the product lifecycle, like design and manufacturing. It then uses Reinforcement Learning (RL) to make decisions that reduce waste, save energy, and improve sustainability. The system learns from feedback to make better choices over time and provides businesses with recommendations for more eco-friendly practices.



**Architecture**

**1. Data Layer:**Collects and stores data from sensors and databases related to product lifecycles.

**2.** **Processing Layer:**Cleans and organizes data, extracting relevant features for analysis.

**3**. **Reinforcement Learning Layer**:Implements RL algorithms to learn optimal sustainability decisions through simulations.

**4. Decision-Making Layer:** Generates recommendations and applies learned policies in real-time during product design and manufacturing.

**5. User Interface:** Provides a dashboard for displaying sustainability metrics and actionable insights.

# DFD

**Expected Outcomes**

* **Better Decision-Making:** Improved methods for businesses to make eco-friendly choices throughout a product's lifecycle.
* **Increased Efficiency:** More efficient manufacturing processes that save time and resources.
* **Reduced Environmental Impact:** Lower energy use, waste, and emissions associated with product design, production, and disposal.

# References

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