# Learning Energy Efficient Trotting For Legged Robots

Athanasios Mastrogeorgiou, Aristotelis Papatheodorou, Konstantinos Koutsoukis,
Konstantinos Machairas, and Evangelos Papadopoulos

***Abstract*— Quadrupedal locomotion remains a complex control challenge, particularly when energy efficiency is considered. Recent advances in Deep Reinforcement Learning (DRL) offer a promising framework for automating the synthesis of low-level controllers from sensory input. In this work, we develop a DRL-based scheme for energy-efficient trotting on the Laelaps II quadruped, simulated in MuJoCo. A high-fidelity model of the robot is constructed, with emphasis on accurately capturing drivetrain dynamics. We design a reward function and action space that promote stable trotting while minimizing the Cost of Transport (CoT). The proposed method initially presented in [1] demonstrates improved energy efficiency during trotting on level terrain, replicating treadmill-like conditions at NTUA's Control Systems Lab.**

## I. INTRODUCTION

Quadrupedal locomotion demands rapid reflexes, coordinated leg control, precise force handling, and robust balance, traditionally requiring extensive manual tuning. Model-free DRL methods effectively learn locomotion directly from experience [2], yet often overlook energy efficiency [3], penalize joint accelerations without considering mechanical antagonism [4], and struggle with coordinated gait patterns like trotting due to increased data needs and invalid configurations [5]. This work investigates energy-efficient trotting for the quadruped Laelaps II [1], focusing on forward locomotion on level terrain with reduced energy consumption.

## II. METHODOLOGY

Initially a highly realistic MuJoCo representation of the Laelaps II quadruped (Fig. 1) was created, with all mechanical and electrical properties accurately reflecting the physical system. These properties were obtained from component datasheets and, where necessary, experimentally validated. To enable energy-efficient trotting, the robot's energy consumption was incorporated into the reward function. The total actuation energy $E_{tot}$ is defined as the sum of the mechanical actuation energy $E_{act}$ and the electrical losses $E_{el}$ computed via integration of the respective power expressions (1). Numerical integration was performed using the Simpson 1/3 rule over a given time interval $\Delta t = t_2 - t_1$ and timestep dt. The quantities $\tau_{m,i}$, $\dot{q}_{m,i}$, $R_{m,i}$, and $K_{T,i}$, denote the torque, angular velocity, winding resistance, and torque constant of the $i_{th}$, motor, respectively.

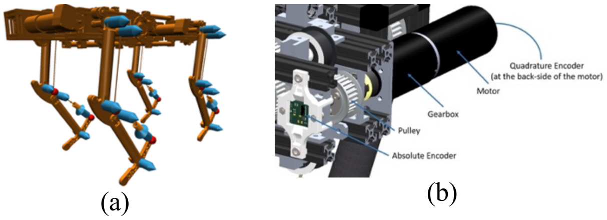

*Figure 1 Laelaps II, (a) MuJoCo model, (b) Drivetrain.*

$$E_{act} = \int_{t1}^{t2} \sum_{i=1}^{8} \left|\tau_{m,i}\dot{q}_{m,i}\right| dt, E_{act} = \int_{t1}^{t2} \sum_{i=1}^{8} \left[\left(\frac{\tau_{m,i}}{K_{T,i}}\right)^2 R_{m,i}\right] dt \ (1)$$

In the reward function (2), a simplified version of CoT is used since the robot's mass ($m$) and the gravity's acceleration ($g$) are constants. Furthermore, the reward in (2) accounts for the distance traversed from the beginning of the episode $\Delta x_{ep}$, not only the one in the current step. Finally, the total reward $rew_{tot}$ computed at each agent timestep, combines a positive term promoting forward progression, a penalty for lateral deviation from the desired trajectory, and an energy-related term based on the Cost of Transport (CoT).

$$rew_{en} = w_{en} \frac{E_{tot}}{\Delta x_{ep} + e} \ (2), rew_{tot} = rew_x - rew_y - rew_{en} \ (3)$$

## III. RESULTS

Similar approaches have also tried to reduce energy consumption by penalizing joint acceleration or the mechanical part of the actuation power during a gait, but not the drivetrain's total energy demands. After training and testing them on Laelaps II, our approach still achieved the lowest CoT , i.e., 1.89, (Fig. 2).

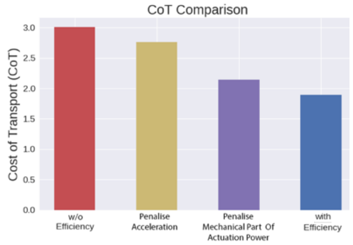

*Figure 2 Using the proposed reward function the lowest CoT was achieved.*

All authors are with the Athena Research Center, Greece, except A. Papatheodorou, who is with the ORI, University of Oxford, United Kingdom. This research work was supported by the project "Applied Research for Autonomous Robotic Systems" (MIS5200632) which is implemented within the framework of the National Recovery and Resilience Plan (NNRP) "Greece 2.0" (Measure: 16618- Basic and Applied Research) and is funded by the European Union-NextGenerationEU.

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