Energy Prediction on Sloping Ground for Quadruped Robots

Mohamed Ounally[1], Cyrille Pierre[1] and Johann Laconte[1]

***Abstract*— Energy management is a fundamental challenge for legged robots in outdoor environments. Endurance directly constrains mission success, while efficient resource use reduces ecological impact. This paper investigates how terrain slope and heading orientation influence the energetic cost of quadruped locomotion. We introduce a simple energy model that relies solely on standard onboard sensors, avoiding specialized instrumentation and is applicable in previously unexplored environments. The model is identified from field runs on a commercial quadruped and expressed as a compact function of slope angle and heading. Validation on natural terrain demonstrates near-linear power–slope relationships, elevated costs for lateral motion, and additive behavior across trajectory segments, enabling efficient path-level energy prediction.**

I. INTRODUCTION

Robots are increasingly deployed in demanding outdoor environments such as agriculture, mining, planetary exploration, and disaster response. In these domains, autonomy is limited not only by perception and decision-making capabilities but also by the ability to complete missions within available energy resources [1]. This challenge is particularly acute for mobile platforms operating across diverse terrains and conditions [2]. Ensuring sufficient endurance is therefore a prerequisite for reliable and effective operation in the field.

Energy awareness is essential for both practical and ecological reasons. On the one hand, efficient energy use extends mission duration and reduces the risk of premature task interruption. On the other, sustainable practices in sectors such as agriculture require machines that minimize unnecessary energy expenditure and reduce their environmental footprint. Robots must therefore plan motions that simultaneously optimize operational efficiency and respect ecological constraints.

Legged platforms offer unique advantages in natural and agricultural settings where wheeled or tracked vehicles may be less suitable. They can traverse irregular ground, adapt to varying terrain geometries, and operate in areas where heavy machines would damage vegetation or soil through compaction. These properties make quadrupeds and other legged systems attractive candidates for tasks that demand both mobility and low environmental impact [3], [4].

However, as seen in Figure 1, the energy requirements of legged locomotion are difficult to predict. Unlike wheeled vehicles, where motion costs can often be related to distance and slope, legged robots rely on complex multi-body dynamics, coordinated gaits, and repeated ground contacts. This makes it challenging to identify which locomotion strategies are energetically most favorable under specific terrain conditions.

[1]Université Clermont Auvergne, INRAE, UR TSCF, 63000, Clermont-Ferrand, France; `name.surname@inrae.fr`

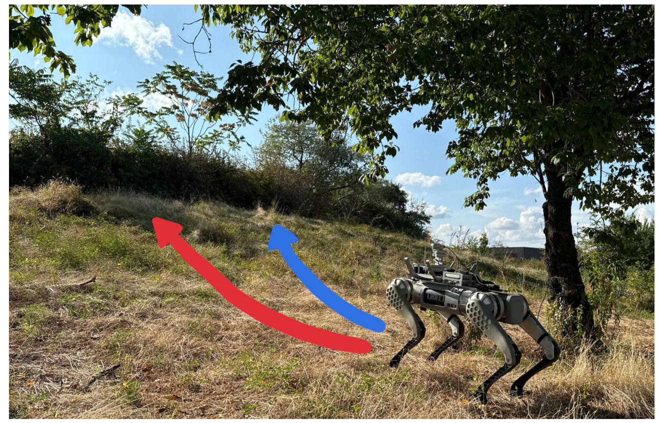

Fig. 1: For legged robots, the complexity of their dynamics makes energy consumption difficult to predict. The energy consumption of the two illustrated paths (blue: direct uphill, red: indirect detour) is not necessarily proportional to distance: on sloped terrain, longer but smoother trajectories can require less energy than shorter, steeper ones.

This work focuses on the influence of terrain slope on the energy consumption of quadruped robots. We analyze how heading direction relative to an incline affects overall energy use and how such knowledge can inform motion planning. By modeling these relationships from onboard measurements, we introduce a practical basis for energy-aware navigation strategies in real-world agricultural and outdoor environments. To this end, our contributions are

- A simple, generic and reproducible method to predict heading dependent energy maps for quadrupeds using only standard onboard sensors;
- A calibration procedure linking energy consumption to the robot's movements; and
- A field validation and demonstration of energy aware path planning on sloped terrain.

The remainder of this paper is organized as follows. Section II reviews existing approaches to energy modeling, from wheeled to legged robots, and identifies the gap concerning heading-dependent costs in path planning. Section III introduces the proposed framework, including the notation, motion model, and the methods used to construct and learn energy maps as well as to evaluate candidate paths. Section IV presents field experiments that validate the modeling assumptions and illustrate the impact on path optimization.

II. RELATED WORK

Energy-aware navigation has evolved along two largely separate paths: physics-based models for wheeled platforms and stability-focused approaches for legged systems. This split has created a critical gap in demanding outdoor environments where both energy efficiency and locomotion versatility are essential for mission success [1].

Early mobile robotics treated energy consumption as proportional to distance traveled, a reasonable approximation on flat terrain where rolling resistance dominates [5]. However, this equivalence breaks down dramatically when robots encounter slopes. Gravitational work introduces fundamental asymmetries that depend on both terrain inclination and motion direction relative to the gradient [1]. Classical energy models for wheeled vehicles decompose power into rolling resistance, aerodynamic drag, and gravitational components [6]. This immediately reveals that heading direction relative to slope matters as much as slope magnitude itself. The insight led to anisotropic cost fields where energy becomes a function of both position and heading direction [7]. Planners can now exploit directional asymmetries for substantial energy savings. Such approaches demonstrate that even moderate slopes create opportunities for optimization through careful heading selection [8].

The fact that optimal paths depend on motion direction motivated sophisticated geometric approaches [7]. These frameworks treat cost as an explicit function of both configuration and velocity direction [9]. Fast marching methods and Hamilton-Jacobi formulations further enable efficient computation of direction-dependent optimal paths [10]. However, these mathematical tools remain largely disconnected from empirical energy measurements on legged platforms. This limits their applicability to real-world quadruped navigation [11].

Research on quadruped energetics has pursued a fundamentally different path, emphasizing gait optimization, mechanical efficiency, and cost of transport analysis primarily on level ground [12]. Studies establish clear relationships between speed, coordinated gaits, and energy consumption for various legged platforms [13]. They provide insights into actuator efficiency and the role of leg compliance in reducing metabolic cost. Modern quadrupeds such as ANYmal have demonstrated robust rough-terrain locomotion with reasonable energetic cost [4]. This pushes the analysis toward real-world conditions while maintaining focus on stability and traversability. However, energy considerations typically appear as learned penalties or uniform scalars applied to flat-ground costs rather than as primary variables that guide global path selection. Energy remains secondary to traversability [14].

Recent advances in perceptive locomotion have enabled quadrupeds to navigate complex outdoor terrain with impressive robustness [15]. These systems use vision and proprioception to select footholds and avoid obstacles. They excel at local navigation and real-time adaptation to terrain features, yet global route choice remains driven by geometric heuristics rather than empirically grounded energy models [14]. Agricultural applications further highlight this gap, where robots must balance task completion with energy efficiency across varied terrain geometries [16]. They lack the tools to predict how different paths will affect battery consumption.

Unlike wheeled vehicles that may recover energy through regenerative braking during descent, quadrupeds must actively control their limbs throughout the gait cycle [13]. This makes downhill motion energetically nontrivial. The fundamental difference suggests that energy-optimal paths for legged robots may involve complex heading strategies rather than simple elevation minimization. Evidence from planetary analogue experiments confirms that heading direction relative to slope can reverse energetic preferences [1]. Indirect traverses can be competitive with direct climbs under certain conditions.

Recent work has begun to address energy prediction for ground robots on uneven terrain, demonstrating that slope direction significantly affects consumption for wheeled platforms [17]. However, transfer to legged systems requires new measurements and validation because multi-body dynamics, coordinated gaits, and ground contacts fundamentally alter the energy budget compared to wheels.

Many existing energy models assume access to joint torque sensors, detailed terrain geometry, or sophisticated mechanical models that complicate field deployment on commercial platforms [18]. While such signals provide rich information for research validation, practical autonomy requires approaches that leverage ubiquitous sensors such as battery management systems, odometry, and inertial measurement units [19]. Battery electrical power serves as a conservative proxy for mechanical work and directly relates to mission duration. This makes it attractive for energy-aware planning despite being less precise than torque-based estimates. As such, we propose a generic and easy-to-calibrate energy model that relies only on standard battery measurements.

III. THEORY

This section establishes the mathematical foundation for energy prediction on sloped terrain. We begin with notation and coordinate systems, describe the robot motion model, and present the theoretical tools for constructing energy models from empirical measurements.

A. Notations and Assumptions

Let α denote the local slope angle of the terrain, defined with respect to the horizontal plane. The robot's heading relative to the slope direction is denoted by γ, where $\gamma = 0^\circ$ corresponds to the robot facing directly uphill, $\gamma = 180^\circ$ to facing directly downhill, and $\gamma = 90^\circ$ to facing perpendicular to the slope. We assume that the robot evolves in a locally planar environment. As such, the generalized velocity (twist) of the robot is noted as $\boldsymbol{\varpi}^\wedge \in \mathfrak{se}(2)$, of which $\boldsymbol{\varpi} \in \mathbb{R}^3$ is the coordinates of the twist [20]. Figure 2 depicts a summary of the notations.

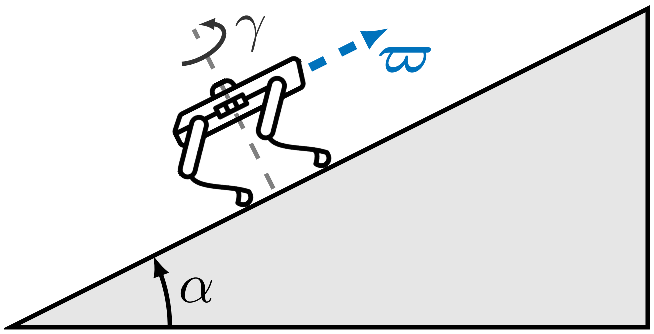

Fig. 2: Coordinate system on a sloped terrain. The robot moves with velocity $\varpi(t)$ on a slope of angle α, oriented with a heading γ with respect to the slope direction.

The coordinate system assumes terrain can be locally approximated as planar over length scales relevant for energy measurement. Real terrain exhibits complex three-dimensional structure, but this simplification captures the first-order effects that dominate energy consumption on moderate slopes.

B. Energy of a given path

Having established the coordinate system and geometric relationships, we now formalize the energy computation for robot trajectories. We define the robot's path $\mathcal{P}$ as a function from time to the Special Euclidean group $SE(2)$ as

$$\mathcal{P} : \mathbb{R} \to SE(2), \tag{1}$$

where $\mathcal{P}(t) \in SE(2)$ represents the robot's pose (position and orientation) at time t. The associated body velocity $\varpi(t)^\wedge \in \mathfrak{se}(2)$ is

$$\varpi(t)^\wedge = \mathcal{P}(t)^{-1} \frac{d}{dt} \mathcal{P}(t). \tag{2}$$

From this, the energy required to follow a given path from $t = 0$ to $t = t_{\text{goal}}$ is given by the integral of the instantaneous power, as

$$E = \int_0^{t_{\text{goal}}} \langle \boldsymbol{f}(t)^\wedge \mid \varpi(t)^\wedge \rangle \, dt, \tag{3}$$

where $\boldsymbol{f}(t)^\wedge \in \mathfrak{se}^*(2)$ is the generalized force (wrench) applied at pose $\mathcal{P}(t)$, and $\varpi(t)^\wedge \in \mathfrak{se}(2)$ is the generalized velocity. The above equation simplifies to

$$E = \int_0^{t_{\text{goal}}} \boldsymbol{f}(t)^T \varpi(t) \, dt, \tag{4}$$

thereby simply being the inner product between two real 3×1 vectors.

The overall difficulty is the complexity of the wrench $\boldsymbol{f}$ as it often depends on a variety of unknown and unobservable variables. In the following, we make the assumption that the force is only dependent on the terrain slope and the relative pose of the robot, so that

$$\boldsymbol{f} = \alpha, \gamma : \mathbb{R}^2 \mapsto \mathfrak{se}^*(2), \tag{5}$$

where $\alpha \in [0, \pi/2)$ is the slope inclination and $\gamma \in [0, \pi]$ is the heading angle as defined previously. Note that γ can be restricted to $[0, \pi]$ due to symmetry considerations (the energy cost of approaching a slope at an angle γ is the same as approaching at an angle $2\pi - \gamma$).

Note that since the wrenches are independent of the robot's internal dynamics, a useful linearity property holds. If a velocity $\alpha\varpi_1$ (respectively ϖ_2) produces an instantaneous energy consumption of $P_1 dt$ (respectively $P_2 dt$), then any linear combination of these two motions results in an energy consumption of $(\alpha P_1 + P_2) dt$.

Although these assumptions are quite strong, they still offer a good approximation and make calibration more straightforward, since it reduces to fitting a simple low-dimensional function that can even be handled with linear models.

Under our terrain-only assumption, the wrench depends on local slope and attack angle:

$$\boldsymbol{f}(\alpha, \gamma) = \begin{bmatrix} f_x(\alpha, \gamma) \\ f_y(\alpha, \gamma) \\ \tau(\alpha, \gamma) \end{bmatrix}. \tag{6}$$

At each instant, the body velocity is known and defined by Equation 2. The wrench components Equation 6 are determined experimentally. With both quantities available, the path energy E follows directly from Equation 4. In summary, the energy prediction reduces to identifying the wrench components, thus closing the framework with a compact and practical formulation for path-level estimation.

IV. EXPERIMENTS

This section outlines an outdoor protocol to estimate, from onboard signals only, the components of the applied wrench and to assemble a dataset for future energy-aware navigation.

A. Experimental Setup

We use a Unitree B1 with its stock sensor suite, shown in Figure 1: a battery monitor (voltage and current), an IMU that provides orientation, and legged odometry that yields pose and body-frame velocities. The experiments take place outdoors on a mix of a controlled ramp and natural grassy terrain. Slopes range roughly from $5°$ to $20°$. The robot travels along straight segments at constant speed of $0.3\,\mathrm{m\,s^{-1}}$, using its default walking gait.

B. Data Preprocessing

The data stream is continuous and minimal: IMU orientation, odometry with body-frame velocities, and battery voltage–current pairs. Very low-speed samples are discarded to avoid division artifacts. To limit noise and spikes, we apply a light median-type outlier filter and a short exponential moving average on both power and velocities. We also enforce a simple consistency bound between electrical and mechanical power to reject clearly inconsistent points. The slope inclination α and the heading direction γ are extracted from the IMU gravity vector.

C. Calibration and Evaluation Protocol

We follow the approach in Section III. Our goal is to recover the applied wrench from onboard signals only. Over short time windows, we compute the electrical power from the battery readings and read body-frame velocities from the odometry. This gives the in-plane forces and the yaw torque without external sensors.

To make the estimation robust, we run a grid of tests that covers both terrain and motion. Slopes range from mild to steeper values on a ramp and on natural grass. Headings include uphill, downhill, cross-slope in both directions, and several intermediate angles. Speed is kept close to a constant value along each segment, and we repeat each condition several times to check repeatability.

The outcome is a dataset of short-window wrench estimates indexed by slope and heading, together with simple quality checks (repeatability across runs, basic power consistency, and removal of obvious outliers). This dataset is the basis we use to describe how the wrench varies with terrain and direction.

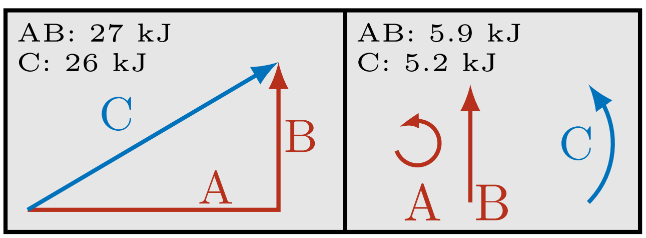

Fig. 3: Energy superposition : measured energy of composite paths compared with the sum of their parts. Close agreement supports the additivity assumption used by the model.

D. Superposition and Path Equivalences

The model treats energy as the line integral of a local per-distance cost; therefore, energies add when path segments are concatenated. We test this superposition in two settings, both shown in Figure 3. On the left, the robot executes a two-segment path (A then B) and we compare its total to a single straight segment C that connects the same endpoints; the relative difference is about 4%. On the right, we produce the same pose change either by “in-place yaw then straight” (A then B) or by a smooth circular arc C; again the relative difference is about 13%. Across repeats, the differences stay within the natural variability of the measurements. These results are consistent with the per-distance formulation and support linear accumulation of energy along simple motion primitives.

E. Power to slope trends

Figure 4 shows measured electrical power as a function of slope angle α for two hill directions: uphill and downhill. Each panel reports scatter points and a linear fit for two body-frame directions of travel (red: v_x forward, blue: v_y lateral).

The uphill panel shows power increasing with slope α, as the gravity component grows. The downhill panel shows the opposite: power decreases with α, but only slightly. The robot does not regenerate on descent, so power stays positive; leg mechanics and footstep control keep it above zero.

In both panels, lateral travel (i.e., side-stepping relative to the body) costs more than forward travel. This systematic gap is consistent with legged locomotion: side-stepping uses less efficient gait patterns, induces extra load transfers, and requires more corrective foot placement; hence, higher power is required for the same slope.

Taken together, these linear trends are the data basis for the heading-aware cost in Section III-B. Uphill and downhill lines have opposite slopes, as expected from gravity. The gap between forward and lateral motion shows that effort depends on direction. In practice, forward alignment is preferable, while long sideways segments should be avoided. To complete the calibration, we will add runs at intermediate headings to fill the (slope, heading) map used for planning.

V. CONCLUSION

We presented a simple energy model for legged locomotion on sloped terrain and demonstrated how it can be identified using standard onboard measurements. A compact function learned from field runs, captures the dominant energetic trends observed in outdoor experiments. Superposition tests further confirm that energy expenditures combine additively across trajectory segments, enabling path-level predictions through integration. Collectively, these results provide practical insights for energy-aware planning in legged robotics.

Future work will close the loop: we will deploy a lidar-based slope estimation with online evaluation of the energy model for adaptive path planning and control. We also plan to broaden the model, including different velocities and gait models, and evaluate on diverse ground conditions and robots.

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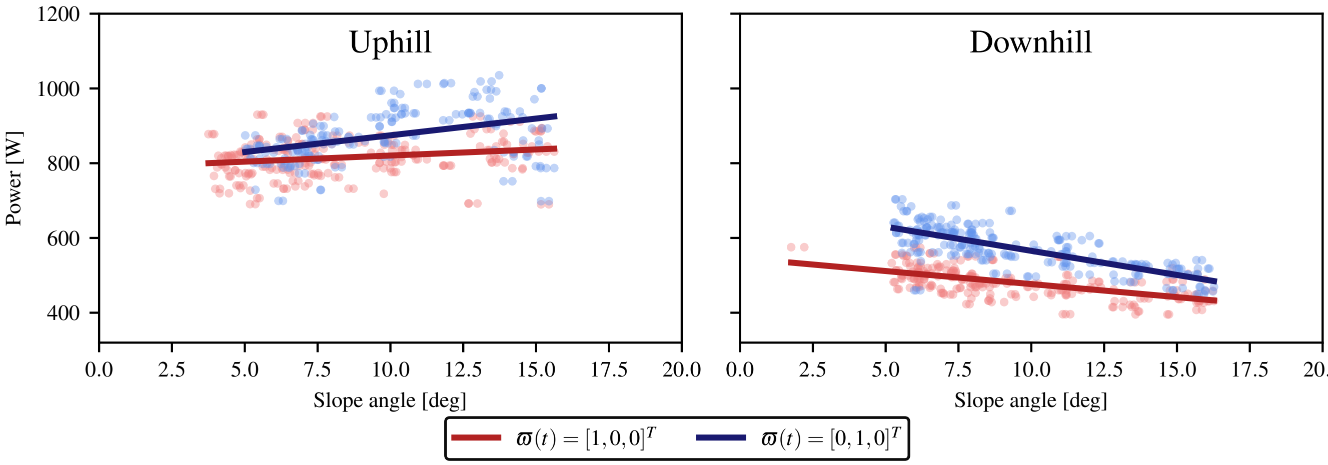

Fig. 4: Measured power as a function of slope angle (α) for uphill (left) and downhill (right) runs. Red and blue points correspond to two velocity headings, $\varpi(t) = [1, 0, 0]^T$ (forward) and $\varpi(t) = [0, 1, 0]^T$ (lateral). Linear fits highlight opposite trends: power increases with slope when climbing, while it decreases moderately when descending. These empirical relations form the basis of the heading-aware per-distance cost used in prediction and planning.

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