

Enhancing Amphibious Flipper-Based Locomotion Through Terrain-Dependent Bayesian Optimization of CPG Control

Nnamdi C. Chikere  | Yasemin Ozkan-Aydin 

¹Department of Electrical Engineering, University of Notre Dame, Notre Dame, Indiana, IN 46556, USA |

Correspondence: Yasemin Ozkan-Aydin (yoalkanay@nd.edu)

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ABSTRACT

Sea turtles use flippers to move through both aquatic and terrestrial environments, despite the different mechanical demands imposed by fluid propulsion, rigid ground contact, granular yielding, rough terrain, and inclined surfaces. This multimodal locomotion capability motivates robotic systems that can exploit the same flipper morphology across heterogeneous environments, but it also creates a control challenge: a gait that performs well in one terrain may become inefficient or ineffective in another. In this study, we investigate terrain-dependent flipper locomotion using a six-actuator sea turtle-inspired robot controlled by a Hopf Central Pattern Generator (CPG). The controller parameterizes gait timing, oscillator amplitude, coupling, and group-level stroke amplitudes for the foreflippers, hindflippers, and hip joints. We first perform a simulation-based sensitivity analysis to identify how CPG parameters influence forward speed and cost of transport across rigid, sandy, rocky, inclined, and aquatic terrains under diagonal and synchronous gait coordination. We then use multi-objective Bayesian optimization to search for terrain- and gait-specific controllers that balance forward speed and energetic cost. The optimized controllers are transferred to hardware through a simulation-guided, hardware-calibrated workflow and evaluated on the physical robot across rigid, sand, rocks, inclines (downhill and uphill), and water testbeds. Hardware results show that diagonal coordination improves forward progression and electrical cost of transport across terrestrial, granular, rocky, and inclined terrains, while synchronous coordination is more effective in water. These results demonstrate that flipper-based amphibious locomotion benefits from terrain-dependent gait selection and parameter tuning rather than a single fixed coordination pattern. These findings provide insight into the viability of optimized CPG control for non-legged, flipper-driven locomotion and may inform the development of next-generation amphibious robots for environmental monitoring, exploration, and search-and-rescue operations in coastal and other heterogeneous terrains.

1 Introduction

Sea turtles provide a useful biological model for studying amphibious flipper-based locomotion because they use highly specialized foreflippers for aquatic propulsion while also interacting with terrestrial substrates during key life stages. Although adult sea turtles are primarily aquatic, they traverse beaches during nesting, while hatchlings crawl from nests to the ocean immediately after emergence [1, 2]. These land–water transitions expose the same flipper morphology to fundamentally different interaction mechanics. Terrestrial progression depends strongly on substrate contact and slip, whereas aquatic propulsion is governed by fluid-mediated thrust and the resulting body motion. Consequently, a gait that performs well in one environment may be inefficient or ineffective in another.

Central pattern generators (CPGs) provide a compact framework for generating rhythmic locomotor commands. In animals, CPGs are neural circuits capable of producing rhythmic motor patterns even in the absence of rhythmic sensory input [3]. Their activity can be modulated by sensory feedback and descending

commands to adjust frequency, duty ratio, amplitude, and coordination across different locomotor contexts [4]. This biological principle has motivated the development of robotic controllers based on low-dimensional oscillator models, including Hopf [5], Matsuoka [6], Rayleigh [7], Van der Pol [8], and Kuramoto-type oscillators [9]. When arranged in coupled networks, these oscillators can generate stable limit-cycle behavior and encode interlimb phase relationships, enabling rhythmic control in quadrupeds [10, 11], amphibious robots and snake-like robots [12, 13], and salamander-inspired systems [14, 15]. This combination of low-dimensional rhythmic control and explicit interlimb coordination is particularly suitable for flipper-driven locomotion.

Applying CPG control to amphibious flipper locomotion nevertheless presents challenges that differ from conventional legged systems. In legged robots, touchdown and liftoff provide distinct contact transitions that can be used to identify stance and swing phases and to synchronize feedback with the gait cycle. Flipper-driven locomotion does not always exhibit similarly well-defined

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transitions. On land, the flipper may remain in contact with the substrate over an extended portion of the stroke while slipping or deforming, whereas during swimming, the flipper interacts continuously with the surrounding fluid. Consequently, gait timing and parameter selection cannot rely solely on clearly separated contact events. The effect of a CPG parameter can therefore change substantially with the surrounding medium. For example, adjustments to oscillation frequency or coupling can alter progression and energetic cost differently on rigid ground than in sand or water.

Previous work on CPG-based robotics has addressed changing locomotor conditions by incorporating sensory feedback to modify oscillator parameters during operation and by using optimization to identify effective controller settings. Proprioceptive or exteroceptive measurements can be incorporated into oscillator networks to modify their rhythmic output during locomotion [16, 17, 18]. In legged and multi-legged systems, feedback from loading or joint motion has been used to improve robustness under perturbations and changing terrain [16, 19, 20]. Related CPG architectures have also been used in other bioinspired robots to coordinate locomotor transitions across different modes [21, 22, 18, 23]. In a complementary approach, optimization methods, including reinforcement learning, evolutionary algorithms, and Bayesian optimization, have been used to tune CPG parameters more systematically than manual trial-and-error approaches [24, 25]. Together, these studies indicate that rhythmic control can accommodate complex robot morphologies, but its parameters remain closely coupled to the mechanics of the robot and its interaction with the environment.

In our previous work, we introduced a sea turtle hatchling-inspired flippered robot and showed that terrestrial locomotion is strongly affected by both flipper mechanical properties and coordination strategy [26, 27]. These findings show that flippered morphologies can produce effective locomotion outside aquatic environments, while also emphasizing the strong dependence of performance on inter-flipper coordination. Extending this platform to amphibious and heterogeneous-terrain locomotion therefore calls for a control framework that can vary coordination patterns and adjust its parameter regime to the mechanical demands of each terrain, while explicitly accounting for the tradeoff between forward speed and energetic cost.

In this study, we investigate terrain-dependent amphibious locomotion using a sea turtle-inspired robot controlled by a Hopf-CPG network. The robot has two foreflippers with independently actuated stroke (fore-aft) and elevation (up-down) motions, together with two fore-aft single-DOF hindflippers mounted obliquely at approximately 45° relative to the body axis. The hindflippers provide posterior push-off and lateral stabilizing interactions during substrate contact while preserving the compact flipper arrangement needed for amphibious operation. The CPG defines the temporal coordination of these six actuated joints and allows their motion amplitudes to be adjusted by functional group. We compare diagonal and synchronous coordination as these patterns provide distinct biologically inspired coordination strategies for distributing propulsive effort across paired appendages. Diagonal or alternating limb coordination is common in terrestrial locomotion, where phase timing and duty factor are adjusted to regulate stability and progression across speeds and substrates [28]. In flippered animals, coordination is also medium-dependent: sea turtles use coordinated foreflipper strokes for swimming, while pinnipeds and other amphibious mammals can employ more asynchronous appendage motions depending on the task and environment [1, 29]. Prior robotic

studies likewise show that gait coordination interacts strongly with flipper compliance and substrate mechanics [30, 26]. These biological and robotic observations motivate the diagonal and synchronous phase templates used here, since tuning relative phase, stance-swing timing, and amplitude distribution allows a single flipper morphology to produce different locomotor behaviors across land, inclines, rocks, granular media, and water.

Our objective is to determine how CPG parameters and gait coordination should change across terrains. We first use Latin hypercube sampling in simulation to quantify the first-order sensitivity of locomotion performance to the controller parameters. The resulting sensitivity information is then used to reduce the search space for multi-objective Bayesian optimization, which identifies terrain- and gait-specific tradeoffs between forward progression and energetic cost. Finally, representative simulation-derived controllers are transferred to the physical robot and evaluated on rigid ground, sand, rocks, 10° uphill and downhill inclines, and water. The hardware experiments test whether the terrain-dependent gait preferences identified through the simulation-guided workflow remain meaningful on the physical platform.

The contributions of this work are threefold. First, we present a Hopf-CPG control framework for a six-actuator sea turtle-inspired robot that supports terrain-dependent diagonal and synchronous flipper coordination. Second, we combine sensitivity analysis and multi-objective Bayesian optimization to identify CPG parameter regimes that balance speed and cost of transport across terrestrial, inclined, granular, rocky, and aquatic environments. Third, we validate the resulting simulation-guided controllers on hardware and show that the dominant gait preference changes across environments, with diagonal coordination favored on land and inclines and synchronous coordination favored in water. By linking CPG parameterization, terrain interaction, and hardware performance, this work supports the development of amphibious robots for field settings where locomotion must transition between land, water, and deformable or irregular substrates.

2 Sea Turtle-Inspired Robot

The robot used in this study is a sea turtle-inspired amphibious platform developed to investigate locomotion across heterogeneous terrains, including rigid, granular, rocky, inclined, and aquatic environments. The body measures 21 cm in length, 18 cm in width, and 7 cm in height, with a total system mass of 1.18 kg. Figure 1 summarizes the robot morphology, flipper arrangement, actuation layout, and onboard electronics, while Fig. 2 and Supplementary Movie S4 show representative outdoor operation of the physical platform across terrestrial and aquatic settings. Additional views of the mechanical design, compliant flipper construction, electronics architecture, and amphibious operation are provided in Supplementary Movie S1.

The robot has four independently actuated flippers and six actuated degrees of freedom. Each foreflipper has two active degrees of freedom: a fore-aft stroke joint that provides the primary propulsive motion and an up-down hip joint that controls flipper elevation during recovery and terrain clearance. Each hindflipper has one active fore-aft degree of freedom and is mounted at an oblique angle of approximately 45° relative to the body axis. The six joints are driven by ST3215-HS servos.

The flippers use a compliant composite construction consisting of a rigid internal skeleton with passive distal joints encapsulated in silicone. This construction allows passive deformation during

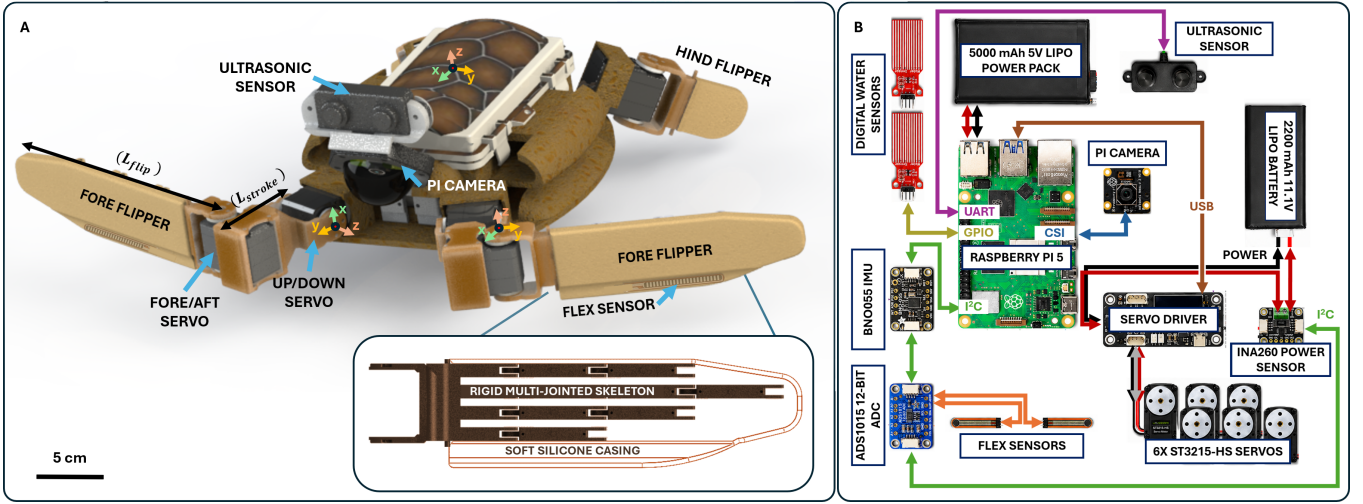


FIGURE 1 | Mechanical and electronic design of the sea turtle-inspired robot. (A) Mechanical layout of the robot, comprising two foreflippers and two hindflippers. Each foreflipper is actuated by two ST3215-HS servos to provide up-down and fore-aft motion, while each hindflipper is actuated by one fore-aft servo. This configuration gives two DOF per foreflipper, one DOF per hindflipper, and six servos in total. The anterior body carries an ultrasonic sensor for proximity feedback and a Raspberry Pi camera for visual sensing. Flex sensors embedded along the flippers measure bending during locomotion. The flipper inset shows a rigid multi-jointed ABS skeleton embedded within a compliant silicone shell for terrain interaction and thrust generation. **(B)** Electronics architecture centered on a Raspberry Pi 5, which coordinates onboard sensing and actuation. The servo driver commands the six servos and is powered by a 2200 mAh, 11.1 V LiPo battery, while the Raspberry Pi is powered separately by a 5000 mAh, 5 V LiPo power pack. An INA260 sensor measures actuator-side voltage and current for energy estimation. A BNO055 IMU provides inertial feedback, an ADS1015 12-bit ADC digitizes the flex-sensor outputs, and digital water-contact sensors detect aquatic immersion.

substrate and fluid interaction while maintaining sufficient proximal stiffness for force transmission. The chassis incorporates sealed electronics and passive buoyancy for aquatic operation. High-level control and data logging are performed onboard using a Raspberry Pi 5, with the servos commanded through a dedicated ESP32-based servo driver. Detailed descriptions of fabrication, flipper construction, waterproofing, electronics, sensing, power

architecture, and kinematics are provided in the Supplementary Information.

3 Robot Control Framework

The controller is based on a coupled Hopf central pattern generator (CPG) network that generates rhythmic commands for the robot's six actuated joints. Each actuator is assigned one oscillator, and phase-biased inter-oscillator coupling imposes the desired coordination relationships for synchronous, diagonal, and turning motions. Figure 3 summarizes the controller architecture and the principal parameters governing oscillation frequency, amplitude, and inter-joint coordination. The detailed controller implementation and gait-transition mechanism are provided in the Supplementary Information.

3.1 Coupled Hopf Oscillator Dynamics

For oscillator i with state (x_i, y_i) , the coupled Hopf dynamics used in the terrain-dependent sensitivity and optimization studies are

$$\dot{x}_i = \alpha (\mu - r_i^2) x_i - \omega_i y_i, \quad (1)$$

$$\dot{y}_i = \alpha (\mu - r_i^2) y_i + \omega_i x_i + \lambda_{cpl} C_i, \quad (2)$$

where $r_i^2 = x_i^2 + y_i^2$. The parameter $\alpha > 0$ determines the convergence rate to the limit cycle, $\mu > 0$ sets the squared limit-cycle radius, and ω_i denotes the instantaneous angular frequency. The uncoupled limit-cycle amplitude is therefore $\sqrt{\mu}$.

Inter-oscillator coordination is introduced through the phase-biased coupling signal

$$C_i = \sum_{j \neq i} [y_j \cos(\theta_{ij}) - x_j \sin(\theta_{ij})], \quad \theta_{ij} = 2\pi(\phi_i - \phi_j), \quad (3)$$

where ϕ_i and ϕ_j are the prescribed phase offsets of oscillators i and j , expressed as fractions of one oscillation cycle. The coupling strength λ_{cpl} is included among the CPG parameters examined in



FIGURE 2 | Outdoor mixed-terrain deployment of the sea turtle-inspired amphibious robot. The robot is shown in representative field environments, including vegetation-covered ground, shallow water, aquatic vegetation, and rocky shoreline substrate. The platform uses compliant flippers, waterproofed actuation, onboard electronics, and passive buoyancy to support amphibious locomotion.

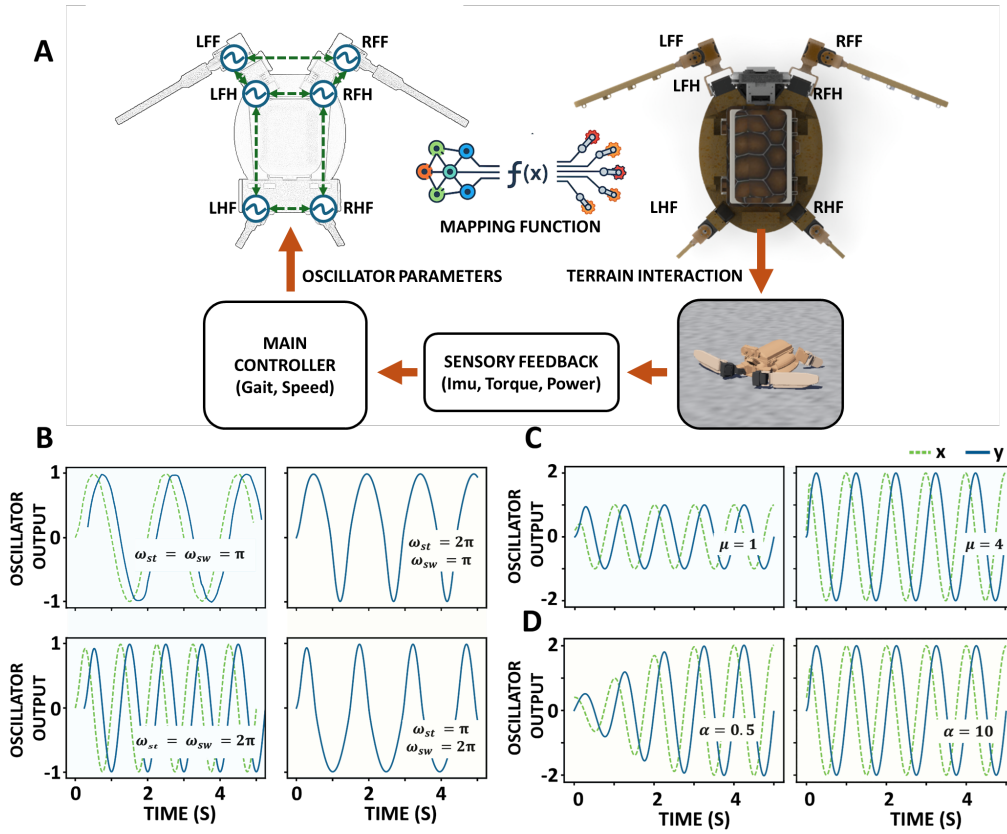


FIGURE 3 | Overview of the control framework and parameter effects. (A) Architecture of the Hopf CPG controller for the sea turtle-inspired robot. Oscillator parameters define joint coordination, which are mapped to joint commands through nonlinear functions. Terrain interaction generates proprioceptive sensory feedback (IMU, joint torque, power), which informs the main controller for adaptive gait and speed regulation. Abbreviations: LFF = left foreflipper, RFF = right foreflipper, LFH = left fore-hip, RFH = right fore-hip, LHF = left hindflipper, RHF = right hindflipper. (B) Effect of stance and swing frequency scheduling on oscillator output. Symmetric and asymmetric cases demonstrate how duty ratio varies with ω_{st} and ω_{sw} . (C) Influence of amplitude parameter μ on output magnitude. (D) Influence of convergence rate α on waveform stability and transient behavior. Together, these plots illustrate how oscillator parameters shape rhythm, amplitude, and duty ratio, forming the basis for adaptive locomotion.

the sensitivity analysis and optimization.

3.2 Frequency Scheduling and Duty Ratio

To introduce temporal asymmetry within the flipper cycle, the instantaneous oscillator frequency is scheduled as a function of the oscillator state:

$$\omega_i(y_i) = \frac{\omega_{st}}{1 + \exp(-ay_i)} + \frac{\omega_{sw}}{1 + \exp(ay_i)}, \quad (4)$$

where ω_{st} and ω_{sw} are the stance- and swing-associated angular frequencies, respectively, and $a > 0$ controls the sharpness of the transition between the two frequency regimes. For the oscillator-state convention used in the simulation, $y_i > 0$ gives $\omega_i \rightarrow \omega_{st}$, whereas $y_i < 0$ gives $\omega_i \rightarrow \omega_{sw}$. The relative values of ω_{st} and ω_{sw} therefore regulate temporal asymmetry within the oscillation cycle. This formulation is inspired by the σ -Hopf oscillator [31].

3.3 Output Mapping and Saturation

The oscillator state is mapped to the commanded joint position as

$$q_i = o_i + A_i^{\text{eff}} \tanh(x_i), \quad (5)$$

where o_i is the neutral joint position and A_i^{eff} is the effective joint amplitude.

The hyperbolic tangent provides a smooth bounded output, after which the command is constrained to the allowable joint range. Separate group-level amplitude scaling factors A_{fore} , A_{hind} , and A_{hip} modify the foreflipper, hindflipper, and hip joint amplitudes, respectively. These three scaling factors are included among the parameters examined through sensitivity analysis and optimization.

3.4 Gait Specification via Phase Templates

The CPG network uses prescribed phase templates to define inter-joint coordination. Let

$$\mathcal{J} = \{\text{LFF}, \text{RFF}, \text{LHF}, \text{RHF}, \text{LFH}, \text{RFH}\}$$

denote the six actuated degrees of freedom. A gait g is represented by a phase vector $\phi^g \in [0, 1)^{|\mathcal{J}|}$, whose entries specify the desired relative oscillator phases as fractions of one cycle. The synchronous and diagonal templates used in the terrain-dependent sensitivity and optimization studies are

$$\phi^{\text{syn}} = (0, 0, 0, 0, 0.75, 0.75), \quad (6)$$

$$\phi^{\text{diag}} = (0, 0.5, 0.5, 0, 0.75, 0.25). \quad (7)$$

The synchronous gait coordinates the left and right foreflippers in phase and likewise coordinates the hindflippers, whereas

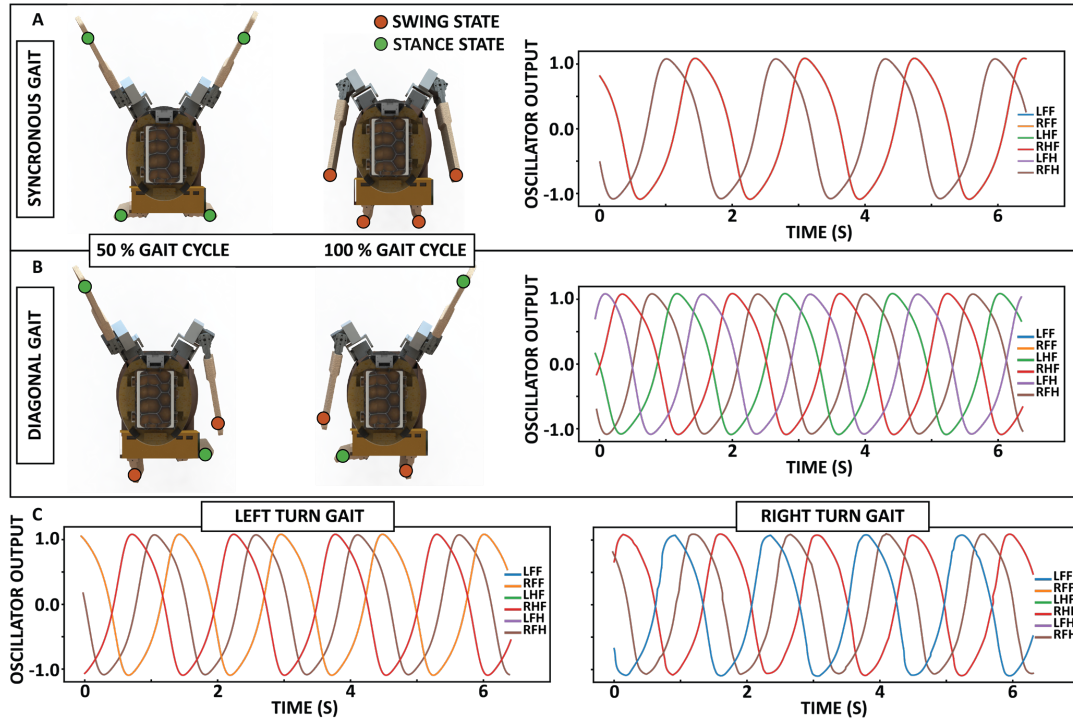


FIGURE 4 | Gait coordination patterns generated by the CPG controller. Representative snapshots and oscillator outputs for different gait formulations. A. *Synchronous gait*, where both foreflippers move in phase to generate thrust, while hindflippers provide stabilization. Oscillator traces show left and right foreflippers synchronized in stance and swing. B. *Diagonal gait*, where contralateral fore- and hindflippers are coordinated with a π phase difference, producing alternating strokes. Snapshots illustrate 50% and 100% gait cycle states. C. Turning gaits: (Left) *Left turn* achieved by advancing the right flippers relative to the left; (Right) *Right turn* achieved by advancing the left flippers relative to the right. Oscillator traces confirm the asymmetric phase offsets driving curved trajectories. LFF = left foreflipper, RFF = right foreflipper, LHF = left hindflipper, RHF = right hindflipper, LFH = left fore-hip, RFH = right fore-hip.

the diagonal gait introduces half-cycle staggering between contralateral fore- and hindflippers. Figure 4 also illustrates turning motions supported by the same controller architecture. The corresponding turning phase templates and the transient coupling strategy used during outdoor gait-switching demonstrations are provided in the Supplementary Information.

4 Parameter Sensitivity Analysis

To identify which CPG parameters most strongly govern locomotor performance and to define an efficient search space for subsequent optimization, we conducted a structured Latin Hypercube Sampling (LHS) study and computed first-order Pearson R^2 sensitivity values between each sampled parameter and the two primary objectives: forward speed and CoT. Figure 5A–D summarizes these sensitivities across level and inclined terrain-gait conditions. All simulations were performed in Webots [32] across eight level terrain-gait combinations (Fig. 5E), consisting of rigid, aquatic, sand, and rocky terrains under synchronous and diagonal gaits, and eight inclined conditions, consisting of $\pm 10^\circ$ and $\pm 20^\circ$ slopes under both gaits. This yielded 16 terrain-gait conditions in total.

The Webots environments were constructed as comparative terrain models rather than as full-fidelity replicas of the corresponding physical testbeds. Rigid and inclined conditions were represented by frictional rigid surfaces, with the inclined surfaces set to $\pm 10^\circ$ and $\pm 20^\circ$. The sand condition was implemented as an uneven height-field surface with compliant and frictional contact properties rather than a discrete-particle granular model, while the rocky condition used discrete rigid obstacles distributed over a rigid ground surface. Aquatic locomotion

was represented using a Webots Fluid volume together with link-specific *ImmersionProperties* applied to the body and flippers. The fluid density and dynamic viscosity were not separately adjusted and therefore retained the Webots water defaults of 1000 kg m^{-3} and 0.001 Pa s , respectively, while link-specific drag coefficients were specified to represent direction-dependent hydrodynamic resistance. Detailed terrain dimensions, contact properties, and hydrodynamic coefficients are provided in the Supplementary Information.

The simulations were used primarily as controlled comparative environments for identifying parameter sensitivity, speed-efficiency tradeoffs, and candidate terrain-dependent gait preferences, rather than for predicting absolute hardware performance. In particular, the sand and water models do not explicitly reproduce grain-scale rearrangement, spatially varying substrate properties, or the complete fluid-structure interaction of the physical robot. The subsequent hardware experiments therefore evaluate whether the qualitative gait preferences and performance trends identified in simulation remain meaningful on the physical platform, rather than testing for direct numerical agreement between simulated and measured performance. The LHS bounds were selected from preliminary simulation sweeps, actuator and joint-limit constraints, and controller-stability considerations. The goal was to cover a broad range of physically plausible CPG behaviors while excluding parameter values that produced immediate joint saturation, unrealistically high flipper speeds, persistent loss of limit-cycle convergence, or visually non-locomotory motions across most terrains. Frequency bounds were chosen to span slow, traction-oriented strokes and faster recovery/propulsive cycles without exceeding the practical actuation bandwidth used in the robot model.

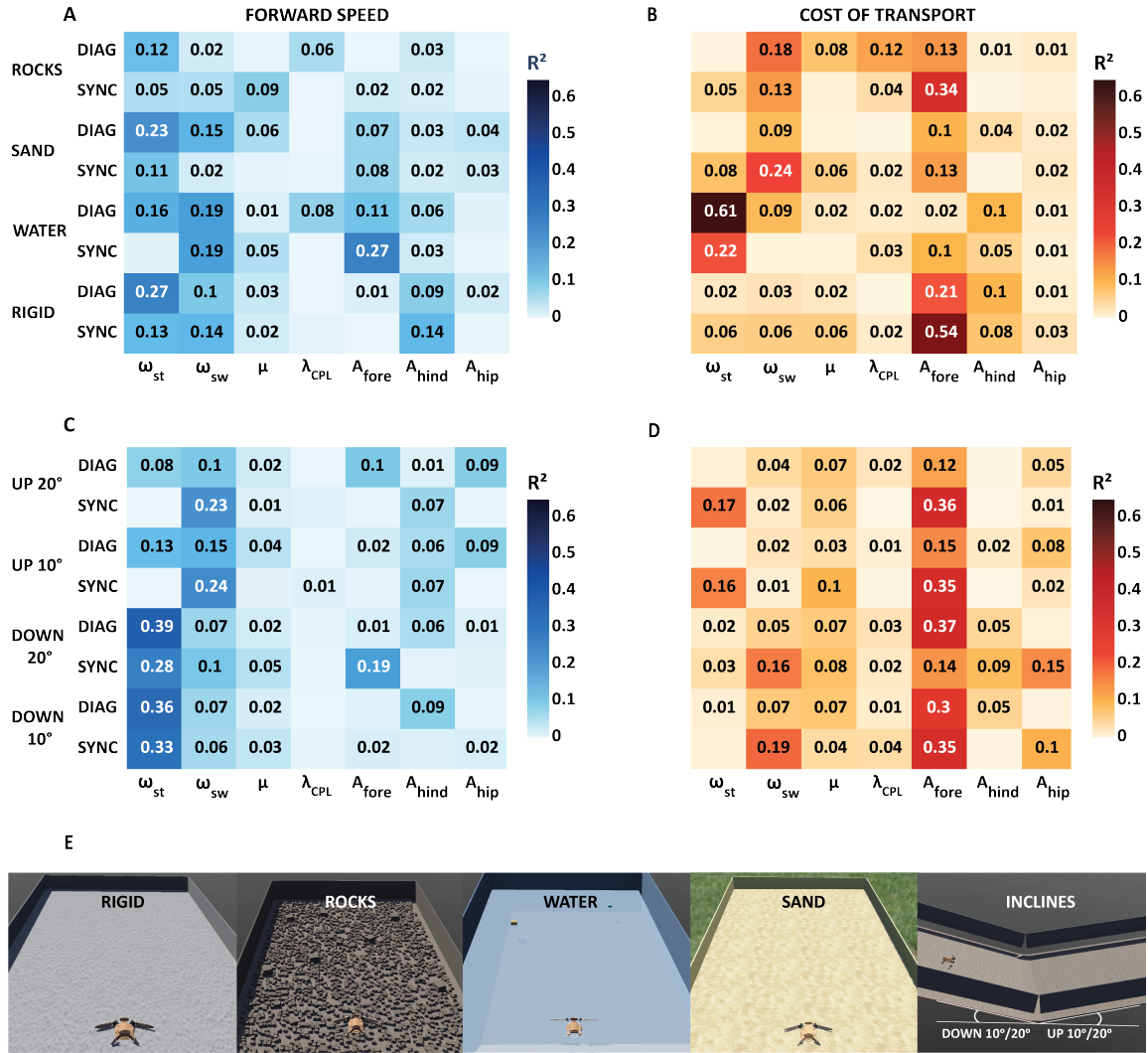


FIGURE 5 | First-order sensitivity of CPG parameters across simulated terrain and gait conditions. Pearson R^2 coefficients quantify the linear association between each sampled CPG parameter and two locomotion metrics: forward speed and mechanical cost of transport (CoT). Panels **A** and **B** show the sensitivity maps for forward speed and CoT, respectively, across level-terrain conditions, including rigid, rocky, aquatic, and sandy substrates under diagonal (DIAG) and synchronous (SYNC) gaits. Panels **C** and **D** show the corresponding sensitivity maps for inclined terrains at 10° and 20° in both downhill and uphill directions. Panel **E** shows representative renderings of the simulated rigid, rocky, aquatic, sandy, and inclined environments. The rigid terrain is geometrically flat, with no surface-height noise applied. Each terrain-gait condition was evaluated using $n = 150$ Latin Hypercube Sampling (LHS) trials, and trials with forward speed below 0.005 m s^{-1} were excluded as non-locomoting cases. Cell values below 0.01 are omitted for readability.

Amplitude-related bounds were selected so that the resulting mapped joint commands remained within the software-enforced joint limits while still allowing sufficiently large foreflipper, hindflipper, and hip excursions to interact with sand, rocks, slopes, and water. The coupling range was chosen to include weakly coupled oscillators, where phase relationships can remain compliant, and more strongly coupled regimes, where the network rapidly enforces the desired gait template. These ranges were intentionally kept wider than the final optimized operating values to enable the sensitivity analysis to reveal parameter relevance across a broad feasible design space rather than only near a hand-tuned controller.

Each condition comprised 150 independent trials sampled via LHS over the seven-dimensional CPG parameter space: stance frequency $\omega_{st} \in [0.5, 5.0]$, swing frequency

$\omega_{sw} \in [0.5, 5.0]$, limit-cycle amplitude $\mu \in [0.3, 2.0]$, coupling strength $\lambda_{cpl} \in [0.1, 1.5]$, and three group-level amplitude gain scales: $A_{fore} \in [0.5, 1.8]$ for the foreflipper fore-aft stroke, $A_{hind} \in [0.4, 1.5]$ for the hindflipper fore-aft stroke, and $A_{hip} \in [0.3, 1.3]$ for the foreflipper up-down hip elevation. Here, ω_{st} and ω_{sw} are the frequency parameters used by the CPG frequency scheduler, while the amplitude gains scale the nominal joint-space stroke amplitudes before joint-limit clamping. Each trial lasted 20 s; trials in which forward speed fell below 0.005 m s^{-1} were classified as non-locomoting and excluded from the sensitivity calculation.

Performance Metrics. Two locomotion objectives were computed from each valid trial. Forward speed v was obtained from center-of-mass (COM) displacement along the principal travel axis divided by elapsed time. Mechanical power was computed as

the instantaneous sum of the actuator torque-velocity products,

$$P(t) = \sum_{i=1}^N |\tau_i(t) \dot{q}_i(t)|, \quad (8)$$

and integrated over the trial duration T to yield total energy consumption:

$$E = \int_0^T P(t) dt. \quad (9)$$

Energetic efficiency was characterized by the mechanical cost of transport (CoT),

$$\text{CoT}_{\text{mech}} = \frac{E}{m g |\Delta x_{\text{fwd}}|}, \quad (10)$$

where m is robot mass, g is gravitational acceleration, and $|\Delta x_{\text{fwd}}|$ is the COM forward displacement. Trials in which $\dot{v}_x < 0.005 \text{ m s}^{-1}$ or $\text{CoT}_{\text{mech}} > 500$ were classified as non-locomoting and excluded from both sensitivity analysis and Gaussian process (GP) surrogate initialization. Lateral deviation from the intended heading was recorded as a secondary validity criterion; trials exceeding the terrain-specific deviation threshold were excluded alongside the speed filter.

Sensitivity Measure. For each parameter-objective pair, the Pearson coefficient of determination R^2 was computed across all valid trials within a condition. Because LHS provides broad, space-filling coverage rather than controlled marginal variation, the resulting R^2 captures the first-order linear association between a single parameter and an output, while the remaining parameters vary throughout their full ranges. A threshold of $R^2 > 0.10$ on either objective was used to classify a parameter as *free* (included in Bayesian optimization); $0.02 \leq R^2 < 0.10$ as *borderline* (included if biologically motivated); and $R^2 < 0.02$ on both objectives as *fixed* (held at its swept median during optimization).

4.1 Results of Parameter Sensitivity Analysis

The full R^2 matrices for all 16 conditions are shown in Fig. 5. Four consistent patterns emerge across terrains and gaits.

1) Coupling strength is universally negligible. The inter-oscillator coupling parameter λ_{cpl} produced $R^2 < 0.06$ on both forward speed and CoT in every one of the 16 conditions (panels A–D), with a median R^2 of 0.004 across all condition-objective pairs. This result indicates that, within the swept range [0.1, 1.5], variations in coupling strength do not meaningfully alter either propulsion or energetic cost once stable oscillator lock is achieved. λ_{cpl} is therefore fixed at its swept median in all subsequent optimization runs, reducing the effective search space by one dimension.

2) Foreflipper fore-aft stroke amplitude is the dominant cost-of-transport regulator. The foreflipper fore-aft amplitude gain scale A_{fore} returned the highest CoT R^2 in 14 of 16 conditions (panels B and D), with peak values of $R^2 = 0.54$ (flat synchronous), $R^2 = 0.35$ (rocks synchronous), $R^2 = 0.35$ (down-10° synchronous), and $R^2 = 0.36$ (up-10° and up-20° synchronous). Notably, A_{fore} contributes almost nothing to forward speed variation ($R^2 \leq 0.03$) on flat terrain and all swim conditions; the same parameter that most strongly predicts energetic cost is largely orthogonal to propulsion. This dissociation is consistent with the biomechanics of real sea turtles. In *Caretta caretta*, anterior limb stroke amplitude modulates thrust magnitude and therefore energy per cycle, rather than cycle frequency alone [1].

3) Stance frequency governs speed on level and downhill terrain; swing frequency governs speed uphill. On flat and downhill surfaces (panels A and C, lower rows), stance frequency ω_{st} is the leading speed predictor: $R^2 = 0.27$ (flat diagonal), $R^2 = 0.33$ – 0.39 (downhill synchronous and diagonal at

both grades). The relationship reverses on uphill terrain: for both +10° and +20° synchronous conditions the dominant speed parameter shifts to swing frequency ($R^2 = 0.24$ and $R^2 = 0.23$ respectively), with stance frequency dropping to $R^2 \approx 0.00$. This inversion reflects a fundamental mechanical difference between assisted and resistive locomotion: on downhill slopes, gravitational acceleration aids the push-off phase, so cycle rate (stance frequency) drives speed; on uphill slopes, the limiting factor is the recovery (swing) phase, whose duration directly determines how quickly the limb can be repositioned for the next power stroke. The diagonal gait shows a similar but attenuated version of this pattern, retaining modest stance-frequency sensitivity ($R^2 = 0.13$) even at +10° uphill.

4) Limit-cycle amplitude shows terrain-dependent relevance. The oscillator amplitude parameter μ exhibits $R^2 < 0.05$ on both objectives for flat, swim, and sand conditions, where its effect is absorbed by the amplitude gain scales: since net joint displacement scales with both μ and $A_{\text{fore/hind/hip}}$, varying μ alone produces a response already explained by the gain parameters in a linear regression over LHS samples. On rocky terrain and inclined surfaces, however, μ rises to borderline relevance ($R^2 = 0.09$ for rocks-synchronous speed; $R^2 = 0.10$ and 0.08 for down-20° CoT), consistent with the secondary role of μ in setting the oscillator convergence rate, that is the speed at which the limit cycle recovers after a mechanical perturbation such as a flipper striking a rock or the robot negotiating a slope transition. Accordingly, μ is fixed at its median for flat, swim, and sand optimization runs (reducing those problems to five dimensions) but retained as a free variable for rocky and inclined terrain (six dimensions).

4.2 Optimization Search Space

The sensitivity analysis directly determines the Bayesian optimization search space for each terrain group. For level terrains (flat, swim, sand) λ_{cpl} and μ are fixed at their per-terrain filtered medians, yielding a five-dimensional problem over $[\omega_{\text{st}}, \omega_{\text{sw}}, A_{\text{fore}}, A_{\text{hind}}, A_{\text{hip}}]$. For rocky and inclined terrains, only λ_{cpl} is fixed, leaving a six-dimensional search space that additionally includes μ . The strong nonlinear interdependence among the remaining free parameters, evidenced by the heterogeneous R^2 patterns across gait and terrain conditions, makes reliable manual tuning difficult and directly motivates the adoption of sample-efficient Gaussian-process-based multi-objective Bayesian optimization, described in Section 5.

5 Multi-Objective Bayesian Optimization (MOBO) of CPG Parameters

Manual tuning of CPG parameters is labor-intensive, bias-prone, and unable to reveal trade-offs between competing objectives. From the sensitivity analysis in Section 4, locomotor performance is shaped by a subset of parameters, including the stance and swing frequencies, oscillator radius, coupling strength, and amplitude gains, whose interactions are strongly nonlinear and terrain-dependent. We therefore adopt *multi-objective* Bayesian optimization (MOBO) [33] to simultaneously maximize forward speed and energy efficiency across eight terrain conditions and two gait classes, producing a set of Pareto-optimal controllers for each condition rather than a single scalar optimum.

5.1 Problem Formulation

5.1.1 Parameter vector

The full search space is the seven-dimensional vector

$$\mathbf{x} = (\omega_{\text{st}}, \omega_{\text{sw}}, \mu, \lambda_{\text{cpl}}, A_{\text{fore}}, A_{\text{hind}}, A_{\text{hip}}), \quad (11)$$

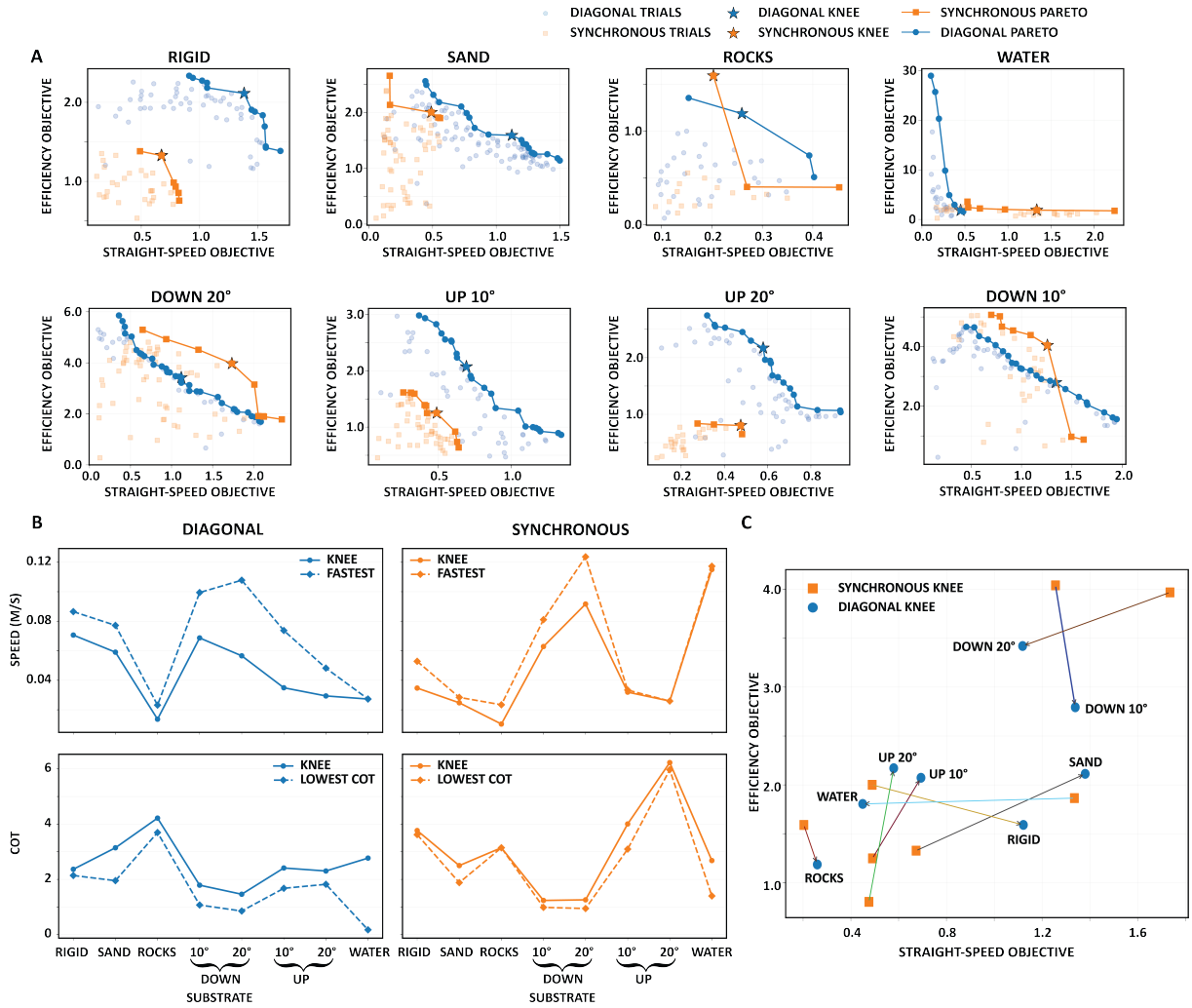


FIGURE 6 | Multi-objective Bayesian optimization of gait parameters across terrains. (A) Pareto fronts for diagonal and synchronous gaits in the two-objective space defined by the straight-speed objective and the CoT-based efficiency objective. The vertical axis is an efficiency objective, with higher values corresponding to lower Cost of Transport. Transparent points show valid controller evaluations, connected markers show the non-dominated Pareto set, and stars indicate the representative Pareto solution used for terrain-gait comparison. For water, the representative solution was selected from Pareto points with a forward speed at least 75% of the maximum Pareto speed, before applying the closest-to-ideal criterion, thereby avoiding the selection of near-stationary, low-energy motions. (B) Gait-centric performance envelopes showing representative knee solutions and the corresponding speed- or CoT-prioritized Pareto solutions. Diagonal coordination provides stronger, balanced performance on rigid substrates, sand, uphill inclines, and rocks, while synchronous coordination performs best in water and downhill terrain. (C) Objective-space shift between synchronous and diagonal representative solutions. Arrows point from synchronous to diagonal gait for each terrain; rightward movement indicates increased straight-speed objective, and upward movement indicates improved energy efficiency, corresponding to lower CoT.

where $\omega_{st}, \omega_{sw} \in \mathbb{R}_{>0}$ are the stance and swing angular frequencies (rad s^{-1}), $\mu > 0$ is the Hopf oscillator radius (limit-cycle amplitude), λ_{cpl} is the uniform inter-oscillator coupling gain, and $A_{fore}, A_{hind}, A_{hip}$ are group-level amplitude scale factors applied to the foreflippers, hindflippers, and hip joints respectively. Informed by the sensitivity analysis, two parameters are *fixed* at their Latin hypercube median in conditions where they exert negligible influence on performance: μ and λ_{cpl} are held fixed on flat, sand, and water substrates (5-D free space); for rocky terrain, A_{hip} is held fixed and λ_{cpl} is freed to allow terrain-adaptive coupling (6-D free space); for all inclined conditions, λ_{cpl} is held fixed and μ is freed to modulate limit-cycle amplitude against gravity (6-D free space). The global bounds on all parameters are listed in Table 1.

TABLE 1 | Parameter search bounds for MOBO. The effective search dimension per terrain-gait combination is given in Table 2.

Symbol	Description	Lower	Upper
ω_{st}	Stance frequency	0.5	5.0
ω_{sw}	Swing frequency	0.5	5.0
μ	Oscillator radius	0.3	2.0
λ_{cpl}	Coupling strength	0.1	1.5
A_{fore}	Foreflip. amplitude	0.5	1.8
A_{hind}	Hindflip. amplitude	0.4	1.5
A_{hip}	Hip amplitude	0.3	1.3

5.1.2 Objective functions

Two scalar objectives are defined and simultaneously maximized.

Objective 1 — Straight-line speed. The first objective rewards signed forward velocity while penalizing trajectory curvature and lateral wandering. Let $\bar{v}_x$ denote the mean signed forward COM velocity over the 20 s evaluation window, after a 3 s CPG warm-up. Path straightness is quantified by the RMS perpendicular deviation from the straight line joining the initial and final COM positions. Let $\mathbf{p}_k = (x_k, y_k)$ denote the planar COM position at sample k , and define the unit vector

$$\mathbf{u} = \frac{\mathbf{p}_N - \mathbf{p}_1}{\|\mathbf{p}_N - \mathbf{p}_1\|}. \quad (12)$$

The lateral deviation is then

$$\delta_{\text{lat}} = \sqrt{\frac{1}{N} \sum_{k=1}^N [-(x_k - x_1)u_y + (y_k - y_1)u_x]^2}. \quad (13)$$

The straight-line speed objective is defined as

$$J_{\text{speed}}(\mathbf{x}) = \frac{\max(\bar{v}_x(\mathbf{x}), 0)}{\bar{v}_{\text{ref}}} \frac{1}{1 + \left(\frac{\delta_{\text{lat}}(\mathbf{x})}{\Delta_{\text{lat}}}\right)^2}, \quad (14)$$

where $\bar{v}_{\text{ref}} = 0.05 \text{ m s}^{-1}$ is a reference speed and $\Delta_{\text{lat}} = 0.10 \text{ m}$ sets the lateral-deviation penalty scale. This objective preserves high-speed solutions while reducing the score of trajectories that achieve forward progress through substantial lateral wandering.

TABLE 2 | Effective search dimensionality and fixed parameters per terrain class.

Terrain class	Free dim. d	Fixed parameters
Flat, sand, water	5	$\mu, \lambda_{\text{cpl}}$
Inclined ($\pm 10^\circ, \pm 20^\circ$)	6	λ_{cpl}
Rocks	6	A_{hip}

Objective 2 — Energy efficiency. The cost of transport is computed as

$$\text{CoT}(\mathbf{x}) = \frac{E_{\text{tot}}}{mg|\Delta x_{\text{fwd}}|}, \quad (15)$$

where E_{tot} is the time integral of joint mechanical power, $m = 1.18 \text{ kg}$ is the robot mass, $g = 9.81 \text{ m s}^{-2}$, and $|\Delta x_{\text{fwd}}|$ is the magnitude of forward displacement over the evaluation window. Because MOBO is formulated as a maximization problem, energy economy is represented using the inverse-CoT objective

$$J_{\text{eff}}(\mathbf{x}) = \frac{\Lambda_{\text{CoT}}}{\text{CoT}(\mathbf{x}) + \varepsilon}, \quad \Lambda_{\text{CoT}} = 5.0, \quad \varepsilon = 10^{-6}. \quad (16)$$

Thus, larger J_{eff} values correspond to lower CoT. The resulting two-objective problem is

$$\max_{\mathbf{x} \in \mathcal{X}} \mathbf{J}(\mathbf{x}) = \max_{\mathbf{x} \in \mathcal{X}} (J_{\text{speed}}(\mathbf{x}), J_{\text{eff}}(\mathbf{x})). \quad (17)$$

Together, the MOBO vector objective is

$$\mathbf{J}(\mathbf{x}) = (J_{\text{speed}}(\mathbf{x}), J_{\text{eff}}(\mathbf{x})) \in \mathbb{R}^2, \quad (18)$$

and the optimizer seeks to enlarge the dominated volume of $\mathbb{R}^2$ bounded above by $\mathbf{J}$.

Webots [32] was used as the physics-based simulation environment to evaluate each candidate CPG parameter set, and the resulting speed, displacement, lateral deviation, and actuator-energy metrics were returned to the optimizer after each trial.

For each terrain-gait condition, the evaluated parameter-objective pairs were used to update the Gaussian-process surrogate models, select new candidates through hypervolume-improvement-based acquisition optimization, and maintain the nondominated solutions as the estimated speed-CoT Pareto set. Detailed software and optimization implementation settings are provided in the Supplementary Information.

5.2 Gaussian-Process Surrogate and Hypervolume Tracking

For each terrain-gait condition, separate single-task Gaussian processes (GPs) were fit to the two objectives, straight-line speed and inverse CoT. Each Gaussian process (GP) used a Matérn-5/2 automatic relevance determination (ARD) kernel. Letting $\mathbf{x}_{1:n}$ and $\mathbf{y}_{1:n}^{(k)}$ denote the k -th objective observations up to trial n , the GP posterior is:

$$p(f^{(k)} | \mathbf{x}_{1:n}, \mathbf{y}_{1:n}^{(k)}) = \mathcal{GP}(\mu_n^{(k)}(\cdot), \sigma_n^{(k)2}(\cdot)), \quad (19)$$

with hyperparameters fitted by maximizing the exact marginal log-likelihood at each iteration. Each objective is standardized before fitting; predictions are de-standardized for Pareto book-keeping.

The Pareto front is tracked analytically after every observation. The hypervolume indicator $\text{HV}(\mathcal{P}_n; \mathbf{r})$ measures the volume of the objective space dominated by the current Pareto set $\mathcal{P}_n$ and bounded by the reference point $\mathbf{r}$:

$$\text{HV}(\mathcal{P}_n; \mathbf{r}) = \lambda_2 \left(\bigcup_{\mathbf{y} \in \mathcal{P}_n} [\mathbf{r}, \mathbf{y}] \right), \quad (20)$$

where λ_2 is the Lebesgue measure in $\mathbb{R}^2$. Convergence is declared when the relative hypervolume improvement over a trailing window W of 15 BO trials falls below 0.5%:

$$\frac{\max_{i \in W} \text{HV}_i - \min_{i \in W} \text{HV}_i}{\max(\max_{i \in W} \text{HV}_i, 10^{-9})} < 0.005, \quad (21)$$

with the convergence test enabled only after a minimum of 40 BO trials. All 16 terrain-gait sessions satisfied this criterion.

5.3 Acquisition Function and Warm-Start

Acquisition function. The next candidate is selected by maximizing the *q-Log Noisy Expected Hypervolume Improvement* (qLogNEHVI) acquisition function [34, 35]:

$$\alpha_{\text{NEHVI}}(\mathbf{x}) = \log \mathbb{E}[\text{HV}(\mathcal{P}_n \cup \{\mathbf{J}(\mathbf{x})\}; \mathbf{r}) - \text{HV}(\mathcal{P}_n; \mathbf{r})]^+, \quad (22)$$

where the expectation is taken with respect to the joint GP posterior. The log transformation improves numerical stability when the improvement probability is small, exactly analogous to the single-objective LogEI upgrade over EI. In all optimization sessions reported here, candidate selection used the hypervolume-improvement-based MOBO workflow described above. Acquisition optimization uses 16 restarts, each with 768 raw samples, over the d -dimensional unit hypercube.

Latin hypercube warm-start. Each session is seeded with observations generated during the Latin hypercube sampling (LHS) sweep described in Section 4. For each terrain-gait pair, the filtered LHS results (valid trials with $\bar{v}_x > 0.005$ and $\text{CoT} < 500$) are loaded as prior observations; their median values supply the fixed-parameter constants listed in Table 2. This warm-start ensures

TABLE 3 | MOBO Knee-point and Representative Pareto-point parameters and performance metrics for all terrain-gait combinations. d denotes the effective search dimension; parameters held fixed per terrain class are indicated in Table 2. Speed and CoT are raw simulation metrics corresponding to the representative Pareto solution.

Terrain	Gait	d	ω_{st}	ω_{sw}	μ	λ_{cpl}	A_{fore}	A_{hind}	A_{hip}	Speed (m s ⁻¹)	CoT
Rigid (flat)	Diag	5	4.943	2.368	1.178	0.778	0.500	1.500	0.823	0.0706	2.366
	Sync	5	2.698	4.324	1.178	0.714	0.500	1.045	0.841	0.0347	3.769
Sand	Diag	5	5.000	2.196	1.151	0.752	0.682	1.500	0.336	0.0590	3.144
	Sync	5	3.969	1.451	1.176	0.661	0.500	0.400	1.276	0.0247	2.499
Water	Diag	5	0.628	3.916	1.274	0.728	1.359	1.290	0.537	0.0273	2.770
	Sync	5	5.000	3.159	1.205	0.817	1.800	0.618	1.300	0.1150	2.682
Down 10°	Diag	6	5.000	5.000	0.300	0.778	0.500	1.375	0.893	0.0687	1.790
	Sync	6	3.918	3.306	0.300	0.728	0.952	0.400	1.190	0.0628	1.237
Down 20°	Diag	6	5.000	3.084	0.300	0.771	0.500	1.500	1.082	0.0566	1.462
	Sync	6	5.000	4.697	0.300	0.728	1.017	0.400	1.066	0.0917	1.260
Up 10°	Diag	6	5.000	3.295	0.300	0.722	0.671	1.198	0.300	0.0349	2.413
	Sync	6	3.546	3.523	0.785	0.640	0.500	1.126	0.886	0.0319	4.007
Up 20°	Diag	6	5.000	3.505	0.300	0.791	0.500	0.997	0.401	0.0294	2.304
	Sync	6	4.689	5.000	0.977	0.640	0.500	0.764	0.848	0.0259	6.229
Rocks	Diag	6	4.303	0.500	1.307	0.672	0.500	1.062	0.846	0.0136	4.218
	Sync	6	3.378	0.500	0.805	0.100	0.842	0.400	0.778	0.0103	3.145

that the initial GP surrogate covers the full parameter range and that the MOBO phase focuses its budget on refining the Pareto frontier rather than exploring degenerate regions.

5.4 Pareto Front Analysis and Knee Selection

Figure 6 shows the resulting Pareto fronts and performance envelopes. For each terrain-gait condition, the representative solution is selected from the Pareto set using a closest-to-ideal rule. The ideal point is defined component-wise as $\mathbf{y}^{\text{ideal}} = (\max J_{\text{speed}}, \max J_{\text{eff}})$ over the Pareto set. After min-max normalization of each objective within the Pareto set, the representative knee solution is

$$\mathbf{x}^{\text{knee}} = \arg \min_{\mathbf{x} \in \mathcal{P}^*} \left\| \mathbf{1} - \frac{\mathbf{J}(\mathbf{x}) - \mathbf{J}^{\min}}{\mathbf{J}^{\max} - \mathbf{J}^{\min}} \right\|_2. \quad (23)$$

For swimming results, the same closest-to-ideal rule is applied after restricting the candidate Pareto set to locomotion-relevant solutions satisfying $\bar{v}_x \geq 0.75 \bar{v}_{x,\max}^p$. This prevents slow, low-energy motions from being selected as representative swimming gaits while retaining a Pareto-based selection criterion. The optimized knee-point parameters for all terrain-gait combinations are collected in Table 3.

5.5 Key Results and Terrain-Dependent Gait Preferences

5.5.1 Terrain family effects

Downhill conditions produced the highest forward-speed envelope, with the synchronous gait on the 20° downhill slope reaching the largest speed among the representative solutions. These conditions also showed low CoT relative to uphill and rocky terrain, consistent with gravity-assisted forward motion. Because gravitational potential energy contributes to downhill displacement, downhill CoT values are interpreted as terrain-specific efficiency measures rather than direct indicators of actuator efficiency alone. Uphill conditions show the reverse: steep inclines cut maximum speeds by 50 – 65% relative to flat terrain and raise CoT sharply, with Up 20° sync reaching a CoT of 6.23 at the knee solution. Rocky terrain is the hardest condition by both metrics: maximum speeds are $< 0.03 \text{ m s}^{-1}$ and CoT

exceeds 3.0 in both gait classes.

5.5.2 Simulation-predicted gait preference and Pareto structure

The representative Pareto solutions in simulation show that gait preference depends on both terrain mechanics and the optimized CPG parameter regime. Diagonal coordination is favored on rigid substrates, sand, uphill inclines, and rocks when balancing forward speed and energy economy, whereas synchronous coordination is more effective in water and on downhill slopes. This indicates that no gait pattern is globally superior in the simulated environments; instead, each gait occupies a different region of the speed-CoT tradeoff depending on the surrounding mechanical environment.

Figure 6C illustrates this terrain dependence through the vector shift from the synchronous knee solution to the diagonal knee solution. On rigid and sand substrates, the shift is primarily rightward, indicating that diagonal coordination improves forward speed while maintaining comparable or improved energetic cost. On inclined terrain, the shift rotates toward lower CoT, suggesting that diagonal coordination improves energy-normalized progression more strongly than raw speed under certain slope conditions. Water shows the opposite trend: synchronous coordination is Pareto-dominant in both objectives, indicating that coordinated bilateral flipper motion is more effective when propulsion is mediated by fluid thrust rather than substrate anchoring.

5.5.3 Parameter trends across optimized solutions

The optimized Pareto solutions were consistent with the earlier sensitivity analysis. Across terrestrial conditions, stance frequency and hindflipper amplitude were the parameters most consistently differentiated between high- and low-performing Pareto solutions, indicating that terrestrial locomotion performance was primarily shaped by propulsive timing and hindflipper stroke amplitude. In water, the optimized synchronous solutions shifted toward stronger foreflipper and hip actuation, consistent with the transition from ground-contact-based to fluid-mediated propulsion.

6 Hardware Validation of MOBO-Selected Controllers

The MOBO results define a set of open-loop CPG controllers that represent different speed–efficiency tradeoffs for each terrain–gait condition. In this section, these controllers are evaluated on the physical robot to determine whether the simulation-derived gait preferences transfer to hardware. This validation stage focuses on qualitative transfer of gait rankings, parameter regimes, and performance trends rather than exact numerical agreement between simulation and hardware, since the physical platform includes unmodeled losses from servo electronics, flipper compliance, waterproofing materials, substrate rearrangement, and fluid drag.

Hardware experiments will be conducted on five terrain classes corresponding to the simulation environments: rigid substrate, sand, rocks, inclined rigid surfaces, and water. The rigid testbed provides a repeatable baseline with minimal substrate deformation. The sand testbed evaluates locomotion on a yielding granular medium, where flipper intrusion, scooping, and slip influence forward displacement. The rock testbed introduces irregular contacts and local height variations, providing a rough-terrain condition in which flipper placement and body stability become more variable. Inclined trials are conducted on rigid ramps set to 10° and 20° in both uphill and downhill directions. Water trials are conducted in a shallow pool with sufficient depth to permit flipper-driven propulsion without intentional ground contact.

For each trial, the robot is placed at a fixed starting location and aligned with the terrain reference axis. The CPG is first allowed to complete a 3 s warm-up interval so that the oscillators reach their intended phase relationships before performance measurements begin. The same 3 s warm-up interval is used in the simulation trials. The robot then executes a fixed-duration evaluation trial using the selected CPG parameter vector. Between trials, the robot is returned to its initial pose, and deformable substrates, such as sand, are leveled to reduce history effects. Each terrain–gait condition was repeated three times to estimate trial-to-trial variability due to initial contact conditions, battery state, local substrate rearrangement, and actuator properties.

6.1 Open-Loop Transfer of Representative Pareto Solutions

The first hardware experiment evaluates fixed-parameter transfer of the MOBO-selected controllers. For each terrain–gait condition, the representative Pareto solution identified in simulation is executed open-loop on the physical robot. The same CPG structure, gait phase offsets, and group-level amplitude scaling used in simulation are retained. This isolates the transfer performance of the optimized controller parameters before adding feedback adaptation.

In addition to the representative Pareto solution, selected speed-prioritized and efficiency-prioritized Pareto solutions are tested to determine whether the simulated performance envelope is preserved on hardware. The speed-prioritized solution tests the maximum locomotor capability available within a gait class, while the efficiency-prioritized solution tests whether lower-energy behaviors remain effective when actuator and substrate losses are present. These additional tests are especially important for sand and water, where the Pareto fronts show a clear separation between fast and energy-conservative solutions.

The open-loop validation tests three main transfer hypotheses. First, diagonal coordination is expected to remain preferable on

a rigid substrate, sand, and uphill inclines, and rough terrain because these conditions require alternating substrate engagement and recovery. Second, synchronous coordination is expected to remain preferable in water and downhill locomotion, where bilateral flipper motion can produce stronger fluid-mediated thrust or more stable gravity-assisted descent. Third, although absolute speed and CoT values may differ between the simulation and hardware, the relative performance ranking of the representative, speed-prioritized, and efficiency-prioritized Pareto solutions should remain qualitatively consistent within each terrain class.

6.2 Hardware Performance Metrics

Hardware performance is evaluated using the same metric categories used in the MOBO study: forward speed, lateral deviation, energy consumption, and cost of transport. The robot trajectory is expressed in a terrain-aligned coordinate frame, with the forward axis defined by the initial commanded heading. The mean forward speed is computed as

$$\bar{u}_{\text{hw}} = \frac{\Delta x_{\text{fwd}}}{T}, \quad (24)$$

where Δx_{fwd} is the signed forward displacement and T is the evaluation duration. For the hardware trajectories, lateral deviation is evaluated relative to the terrain-aligned forward axis defined by the robot’s initial heading. The hardware lateral RMS deviation is

$$\delta_{\text{lat,hw}} = \sqrt{\frac{1}{N} \sum_{k=1}^N y_k^2}, \quad (25)$$

where y_k is the lateral displacement from the initial forward axis at the k -th tracked trajectory point.

Electrical energy is estimated from the actuator power rail using the measured voltage and current,

$$E_{\text{elec}} = \int_0^T V(t)I(t) dt. \quad (26)$$

The corresponding hardware cost of transport is

$$\text{CoT}_{\text{elec}} = \frac{E_{\text{elec}}}{mg|\Delta x_{\text{fwd}}|}, \quad (27)$$

where m is the total robot mass and g is gravitational acceleration. Electrical CoT is used for the hardware experiments because electrical energy consumption can be measured directly and consistently from the servo supply rail using the INA260 power monitor. The supply-level voltage and current measurements therefore provide a more direct measure of the total energy drawn by the physical actuation system during each trial. The resulting electrical CoT is not expected to match the simulated mechanical CoT exactly because it also includes motor and servo-electronics losses. It is therefore used primarily to compare hardware trials within the same experimental protocol.

6.3 Hardware Results and Terrain-Dependent Gait Trends

The hardware experiments evaluated representative terrain–gait controllers selected from the simulation-guided MOBO workflow. The goal was to test whether the optimized gait families and terrain-dependent performance trends remained meaningful on the physical platform, rather than to reproduce the exact numerical performance values obtained in simulation. This distinction is necessary because the hardware platform includes actuator deadband, servo electronics losses, flipper compliance,

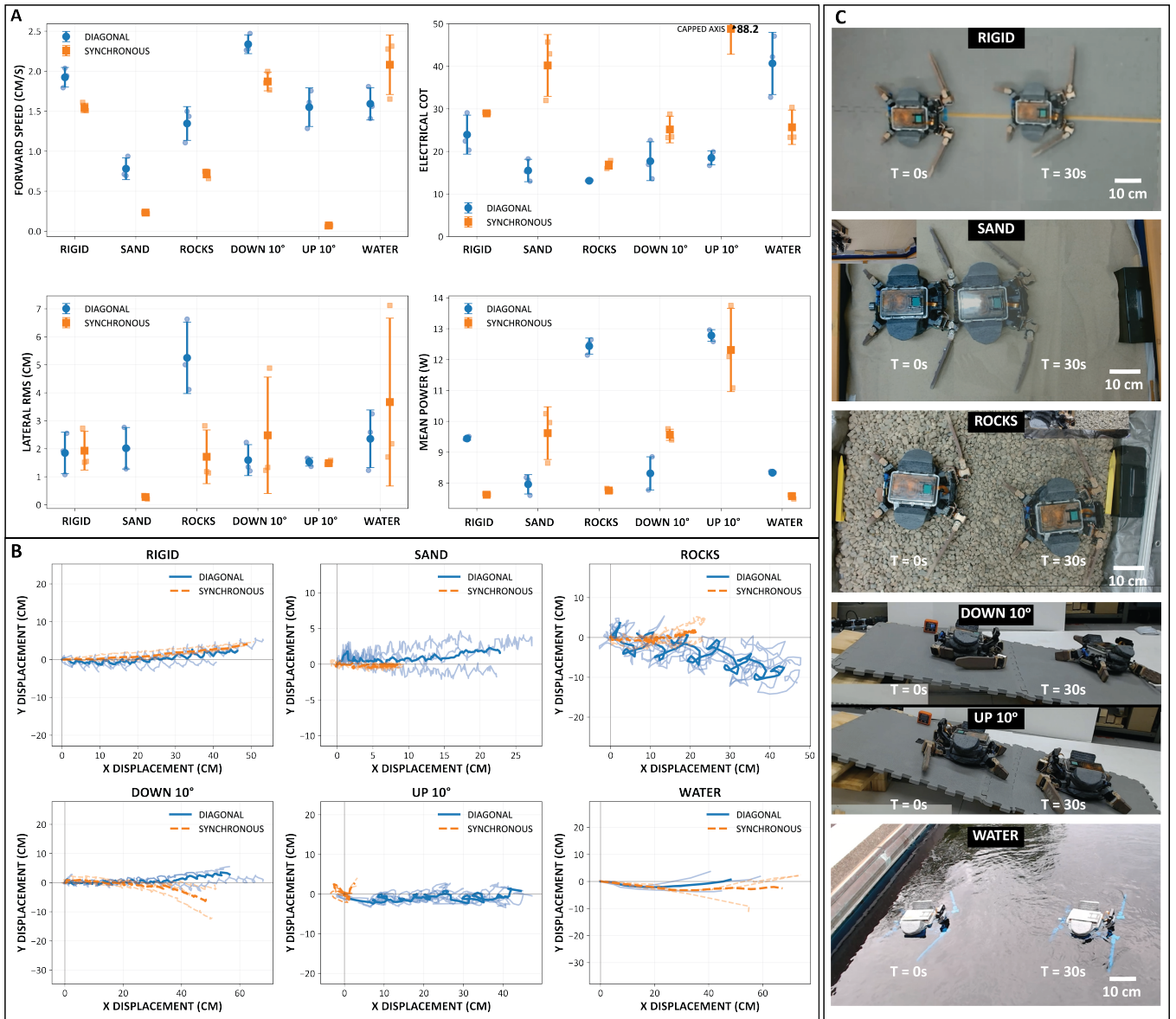


FIGURE 7 | Hardware validation of terrain-dependent gait performance. **A:** Forward speed, electrical cost of transport (CoT), lateral RMS deviation, and mean electrical power measured on the physical robot for diagonal and synchronous gaits across rigid, sand, rocks, 10° downhill, 10° uphill, and water testbeds. Markers show the mean across three hardware repeats, and error bars denote one standard deviation. The CoT axis is capped for readability, and the annotated value indicates the true out-of-range CoT for the 10° uphill synchronous condition. **B:** Overhead-tracked robot trajectories for each terrain condition. Thin curves show individual trials, while thick curves show the mean trajectory after aligning each trial at its initial position. **C:** Representative hardware trial snapshots at $t = 0$ s and $t = 30$ s for each terrain condition. The scale bar denotes 10 cm. The hardware results show that diagonal coordination generally improved terrestrial, granular, rocky, and inclined locomotion, whereas synchronous coordination was more effective in water.

terrain-contact effects, and fluid drag that were not fully captured by the simulation model.

During transfer to hardware, the Hopf-CPG structure, gait phase relationships, stance and swing frequencies, oscillator parameters, coupling strength, and relative foreflipper, hindflipper, and hip amplitude gains were retained. Because the relationship between commanded joint excursion and effective physical flipper motion differs between the simulated joints and the servo-driven platform, a hardware amplitude scaling factor, s_{hw} , was applied uniformly to the commanded joint amplitudes. This factor was determined empirically in short preliminary hardware trials to provide sufficient flipper excursion and terrain engagement

while avoiding repeated joint saturation or mechanically constrained motion.

The calibration was used to account for actuator and terrain-interaction effects that were not fully reproduced in simulation, rather than to re-optimize the CPG controller on hardware. Once calibrated, the resulting controller was held fixed across the three repeated trials for each terrain-gait condition. The resulting hardware controllers therefore retained the simulation-selected CPG parameter values, with the principal sim-to-real modification being the global amplitude scaling applied during conversion to physical joint commands; the corresponding simulation-to-hardware parameter comparison is provided in

the Supplementary Information.

Figure 7 summarizes the physical validation experiments, including scalar performance metrics, overhead-tracked trajectories, and representative trial snapshots across all hardware testbeds. Representative terrestrial trials for the diagonal and synchronous controllers on rigid, sand, rocky, and inclined terrains are shown in Supplementary Movie S2. “

6.3.1 Terrestrial and granular locomotion: rigid, sand, and rocks

On the rigid substrate, the diagonal gait achieved a mean forward speed of $1.92 \pm 0.12 \text{ cm s}^{-1}$, compared with $1.54 \pm 0.06 \text{ cm s}^{-1}$ for the synchronous gait. The diagonal gait also reduced electrical CoT from 28.95 ± 0.29 to 23.95 ± 4.58 , while using slightly higher mean electrical power. This indicates that the additional actuation effort associated with the diagonal gait produced useful forward progression rather than only increasing energy consumption. The tracked trajectories in Fig. 7B show that both gaits remained relatively straight on the rigid surface, but the diagonal gait advanced farther over the same evaluation duration. This agrees with the simulation-guided trend that alternating substrate engagement is favorable on level rigid terrain.

The sand trials showed a stronger separation between the two gaits. The diagonal gait reached $0.78 \pm 0.14 \text{ cm s}^{-1}$, while the synchronous gait produced only $0.23 \pm 0.01 \text{ cm s}^{-1}$. The corresponding electrical CoT was 15.52 ± 2.63 for the diagonal gait and 40.20 ± 7.26 for the synchronous gait. Although the synchronous gait had lower lateral RMS deviation on sand, its small forward displacement shows that this apparent straightness was not associated with effective locomotion. The robot largely failed to convert synchronous flipper motion into net forward travel on the yielding substrate. In contrast, the diagonal gait produced greater forward displacement with moderate lateral variation, suggesting that alternating flipper engagement helped the robot generate usable thrust despite substrate deformation and slip.

On the rock testbed, the diagonal gait also outperformed the synchronous gait in forward progression and CoT. The diagonal gait achieved $1.35 \pm 0.21 \text{ cm s}^{-1}$, compared with $0.72 \pm 0.05 \text{ cm s}^{-1}$ for the synchronous gait. CoT was lower for the diagonal gait, 13.12 ± 0.08 compared with 16.79 ± 0.96 . However, the diagonal gait produced greater lateral RMS deviation, $5.25 \pm 1.28 \text{ cm}$ compared with $1.71 \pm 0.96 \text{ cm}$ for the synchronous gait. The trajectory overlays show why this distinction matters: diagonal coordination enabled greater forward displacement over the irregular rock field, but the robot experienced larger heading variation due to intermittent and asymmetric flipper contacts. Thus, on rocks, diagonal coordination improved speed and energy-normalized progression, but at the cost of reduced path straightness.

Taken together, the rigid, sand, and rock trials support the same qualitative conclusion observed in simulation: terrestrial locomotion benefits from diagonal coordination when forward progress depends on alternating substrate engagement. The magnitude of the benefit, however, depends on the terrain. The rigid surface produced the most repeatable straight trajectories, sand reduced absolute speed because of substrate yielding, and rocks increased lateral drift because of irregular contact geometry.

6.3.2 Inclined locomotion: downhill and uphill ramps

Inclined locomotion further separated the gait behaviors. On the 10° downhill ramp, both gaits produced measurable forward progression, but the diagonal gait remained faster and more energy efficient. The diagonal gait achieved $2.34 \pm 0.12 \text{ cm s}^{-1}$,

compared with $1.87 \pm 0.12 \text{ cm s}^{-1}$ for the synchronous gait. Electrical CoT was also lower for diagonal coordination, 17.71 ± 4.56 compared with 25.16 ± 3.13 . Because gravity assisted motion in the downhill direction, both gaits were able to move forward, but the diagonal gait still provided better controlled progression per unit electrical energy.

The 10° uphill condition produced the clearest hardware difference between gait classes. The diagonal gait maintained a forward speed of $1.55 \pm 0.24 \text{ cm s}^{-1}$, whereas the synchronous gait produced only $0.07 \pm 0.02 \text{ cm s}^{-1}$. This low displacement caused the synchronous uphill CoT to rise to 88.21 ± 5.96 , compared with 18.50 ± 1.65 for the diagonal gait. The trajectory overlays show that the synchronous gait produced little net forward progression on the uphill ramp, whereas the diagonal gait maintained measurable forward progress. This suggests that uphill locomotion was limited by effective traction and recovery timing rather than by electrical power alone.

Although the simulation study included both 10° and 20° inclines, the hardware validation focused on the 10° uphill and downhill cases as representative physical incline tests. This angle introduced clear gravitational loading and traction demands while remaining repeatable on the current hardware platform. In preliminary testing, the 20° condition approached the robot's observed incline slip limit, leading to reduced traction and less repeatable locomotion, with increased likelihood of tipping, boundary contact, or actuator saturation. The 20° condition is therefore treated as a future robustness test following further mechanical and controller tuning.

The incline results support the simulation-guided interpretation that gait choice becomes especially important when terrain loading changes the balance between support, recovery, and slip. Downhill locomotion allowed both gaits to progress, but diagonal coordination remained more efficient. Uphill locomotion required alternating contact timing and sufficient stroke authority, which the diagonal gait provided more effectively than the synchronous gait.

6.3.3 Aquatic locomotion

Water was the only hardware environment in which synchronous coordination outperformed diagonal coordination. The synchronous gait achieved $2.18 \pm 0.37 \text{ cm s}^{-1}$, compared with $1.59 \pm 0.20 \text{ cm s}^{-1}$ for the diagonal gait. It also reduced electrical CoT from 40.68 ± 7.30 to 25.68 ± 4.04 , while using lower mean electrical power. The trajectory overlays and trial snapshots show that the synchronous gait produced the longer forward displacement in water, consistent with the scalar speed and CoT results. Representative aquatic trials for both gait conditions are shown in Supplementary Movie S3

This reversal is mechanically consistent with the change from substrate-mediated propulsion to fluid-mediated propulsion. On land, alternating flipper engagement helps maintain contact and recovery timing. In water, the robot does not rely on anchoring against a solid substrate. Instead, propulsion depends on generating fluid thrust while limiting yaw-inducing asymmetries. Coordinated bilateral flipper motion can therefore produce more balanced forward thrust, whereas diagonal timing can introduce alternating lateral components that reduce net forward swimming efficiency. This result is consistent with the broader simulation-guided conclusion that gait selection should depend on the environment rather than on a single globally preferred coordination pattern.

A two-way ANOVA with terrain and gait as fixed factors was used to support these hardware trends. The terrain–gait interaction was significant for forward speed ($p = 6.5 \times 10^{-8}$), electrical CoT ($p = 1.7 \times 10^{-13}$), energy consumption ($p = 1.3 \times 10^{-12}$), and mean electrical power ($p = 1.1 \times 10^{-9}$), indicating that the effect of gait depended strongly on the locomotor environment. The interaction was also significant for lateral RMS deviation ($p = 2.5 \times 10^{-2}$), although this metric was interpreted alongside forward displacement, as low lateral deviation can occur when the robot barely advances. Because each terrain–gait condition contained three hardware repeats, the statistical tests were used to support the observed trends rather than replace direct interpretation of the measured means, variability, and trajectories.

6.3.4 How hardware-calibrated CPG parameters shaped gait behavior

The hardware-calibrated CPG parameters help explain why gait performance changed across terrains. The diagonal and synchronous controllers differed in phase relationships as well as in stance and swing frequencies, oscillator amplitude parameter μ , coupling strength, and group-level amplitude gains for the foreflippers, hindflippers, and hip joints. These parameter differences shaped how the robot interacted with each environment.

On rigid terrain, the diagonal controller used a high stance frequency with a lower swing frequency, increased foreflipper gain, strong hindflipper scaling, and moderate hip motion. This parameter regime produced alternating propulsive strokes with sufficient hindflipper contribution for forward progression. The synchronous rigid controller used a lower stance frequency but a higher swing frequency, with smaller foreflipper and hindflipper gains. Although this produced coordinated bilateral motion, it resulted in lower forward speed and higher CoT. This suggests that on rigid terrain, alternating contact timing and stronger posterior push-off were more useful than faster bilateral recovery.

On sand, the diagonal controller used high stance frequency, moderate swing frequency, and large hindflipper gain. This combination likely helped the flippers penetrate and push against the yielding substrate. The synchronous sand controller used lower front and hind gain scales and relied more on hip motion, which produced a straighter but much shorter trajectory. The sand results therefore, show that low lateral deviation is not sufficient for effective locomotion; the controller must generate enough substrate interaction to overcome granular yielding and slip.

On rocks, the diagonal controller emphasized alternating contact with a high stance frequency and moderate hindflipper and hip scaling. This helped the robot find intermittent propulsive contacts on the irregular surface, improving speed and CoT. The same interaction also increased lateral drift because individual flipper contacts depended on local rock placement. The synchronous rock controller produced less lateral deviation but lower forward progression, suggesting that symmetric motion was more stable but less effective at exploiting uneven contacts.

For the inclined trials, the hardware-calibrated parameters show why uphill and downhill locomotion differed. Downhill motion benefited from gravity, so both gaits could move forward, but the diagonal gait maintained lower CoT. Uphill motion required larger effective stroke authority and alternating support. The diagonal uphill controller used stronger amplitude scaling and maintained forward progress, while the synchronous controller generated little net displacement. This indicates that the uphill failure of the synchronous gait was not simply a power limitation; it reflected insufficient conversion of cyclic motion into

terrain-anchored forward progression.

In water, the synchronous controller used a coordinated bilateral pattern with a high stance frequency, lower swing frequency, balanced hindflipper scaling, and large hip gain. This parameter regime produced greater forward speed and lower CoT than the diagonal water controller. In contrast to the terrestrial cases, increasing alternating stroke activity did not improve swimming performance. The aquatic result shows that the same CPG architecture must be parameterized differently when the dominant environmental interaction changes from solid contact to fluid thrust.

Overall, the hardware-calibrated parameter trends support the central premise of the study. Terrain-dependent locomotion requires coordinated changes in gait timing, phase relationships, and amplitude distribution. Diagonal timing was more effective for terrestrial, granular, rocky, and inclined locomotion because it supported alternating substrate engagement and recovery. Synchronous timing was more effective in water because bilateral flipper motion improved fluid-mediated propulsion. These results motivate the next stage of the platform: integrating onboard terrain recognition and sensor feedback so that the robot can select or adapt gait parameters online rather than relying on a single open-loop gait across all environments.

7 Conclusion and Future Work

This study presented a simulation-guided and hardware-validated framework for terrain-dependent gait optimization in a sea turtle-inspired amphibious robot. The robot uses six actuated joints to coordinate foreflipper, hindflipper, and hip motions through a Hopf-CPG controller. By combining terrain-specific simulation, parameter sensitivity analysis, and multi-objective Bayesian optimization, the study examined how gait timing, amplitude distribution, and phase coordination influence locomotion across rigid, granular, rocky, inclined, and aquatic environments.

The sensitivity analysis showed that no single CPG parameter dominated performance across all terrain and gait conditions. Instead, parameter relevance depended on both the locomotor environment and the objective being evaluated. Stance and swing frequencies were important contributors to forward-speed variation in several conditions, while foreflipper, hindflipper, and hip amplitude gains had stronger effects on energy-normalized performance in terrain- and gait-specific cases. The coupling parameter showed comparatively weak first-order sensitivity across most conditions, supporting its reduction or fixation during the subsequent optimization stage. These results motivated a lower-dimensional optimization problem in which the most influential frequency and amplitude parameters were tuned for each terrain–gait setting.

The MOBO results identified terrain-dependent tradeoffs between forward speed and cost of transport. Across simulated terrestrial and inclined conditions, diagonal coordination generally produced stronger forward progression and more favorable speed–efficiency tradeoffs. In water, however, synchronous coordination became more effective, consistent with the shift from substrate-mediated propulsion to fluid-mediated thrust generation. These findings indicate that effective amphibious locomotion requires gait selection and parameter adaptation rather than a single globally preferred coordination pattern.

Hardware validation further supported this terrain-dependent interpretation. The physical robot was tested using simulation-guided, hardware-calibrated representative CPG controllers

across rigid, sand, rocks, 10° downhill, 10° uphill, and water testbeds. Diagonal coordination produced higher forward speed and lower electrical CoT on rigid terrain, sand, rocks, and inclined ramps. The difference was especially pronounced on sand and uphill terrain, where the synchronous gait generated limited net forward displacement and therefore high electrical CoT. In contrast, synchronous coordination outperformed diagonal coordination in water, producing higher forward speed and lower electrical CoT. The tracked trajectories confirmed that the scalar performance metrics reflected meaningful terrain-specific differences in forward progression, lateral drift, and trial-to-trial variability. These results show that the simulation-guided optimization captured useful gait families that transferred qualitatively to hardware after calibration, even though exact numerical performance differed because of unmodeled actuator losses, flipper compliance, substrate rearrangement, and fluid effects.

Several limitations remain. First, the current optimization and hardware validation relied primarily on open-loop CPG control. Although the optimized controllers produced terrain-dependent behavior, they do not yet adapt online to changes in substrate, slip, flipper loading, or body orientation. Second, the hardware validation used representative controllers rather than the full speed-prioritized and efficiency-prioritized Pareto sets. As a result, the present hardware results validate the main terrain-dependent gait trends, but they do not yet characterize the complete physical speed–efficiency envelope. Third, the hardware incline tests focused on 10° uphill and downhill conditions. These tests provided a repeatable physical incline validation with clear gravitational loading, but steeper slopes such as 20° remain to be tested for robustness after additional mechanical and controller tuning. Fourth, the simulation model does not fully capture the electrical losses, servo behavior, compliant flipper deformation, granular substrate dynamics, and fluid–structure interactions observed on the physical robot.

Future work will focus on closing these gaps through integrated sensing, adaptive control, and expanded hardware testing. A first direction is to extend the hardware experiments to include speed-prioritized and efficiency-prioritized Pareto controllers, additional incline angles, longer-duration aquatic trials, and more repeated runs per terrain–gait condition. These tests will provide a fuller comparison between the simulated Pareto fronts and the physical performance envelope.

A second direction is to incorporate onboard sensing into the locomotion loop. The current robot platform includes an onboard Raspberry Pi camera, inertial sensing, water-contact sensing, and electrical power measurement. These signals can be used to classify terrain, detect water entry, monitor body motion, estimate performance degradation, and trigger gait switching.

A third direction is to develop terrain-recognition-based gait selection. The planned workflow is to collect onboard camera videos across rigid, sand, rocks, water, and inclined testbeds; extract labeled image frames; train a lightweight terrain classifier; and deploy the classifier on the Raspberry Pi for real-time gait selection. In this framework, the robot would use the classifier output to select the appropriate hardware-calibrated CPG controller, while water-contact and obstacle sensors provide additional safety and mode-switching cues. This would move the platform from preselected open-loop trials toward autonomous terrain-aware locomotion.

A fourth direction is to redesign the CPG controller using reinforcement learning or other policy-search methods. Rather

than optimizing only a fixed set of frequency and amplitude parameters, future controllers can treat phase relationships, stance–swing timing, recovery duration, and joint-mapping functions as learnable policy components. This would allow the robot to learn more expressive flipper behaviors, such as maintaining limb elevation longer during recovery, increasing propulsive stroke authority during stance, or adapting left–right amplitude asymmetry for turning and obstacle avoidance. Simulation environments such as Webots can be used for initial policy training, with hardware experiments used for validation and refinement.

Overall, this work demonstrates that morphology, gait coordination, and environmental interaction must be considered together when designing amphibious robotic locomotion. The results show that the same flipper-based robot requires different coordination strategies across land, granular media, rocks, inclines, and water. By combining simulation-guided optimization with hardware validation, the study provides a foundation for terrain-adaptive amphibious robots capable of selecting and refining their locomotion strategies in complex heterogeneous environments.

Author Contributions

N.C. conceived the study, designed and fabricated the robotic platform, developed the CPG control framework, implemented the simulation and optimization workflow, conducted the hardware experiments, analyzed the data, generated the figures, and wrote the initial manuscript draft. Y.O.-A. supervised the project, contributed to the research direction and experimental design, provided resources and funding support, and reviewed and edited the manuscript. All authors discussed the results, contributed to the interpretation of the findings, and approved the final version of the manuscript.

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Financial Disclosure

None reported.

Conflicts of Interest

The authors declare no conflicts of interest.

Code and Data Availability

The source code and data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.