# Simulating Running with AI-Powered Prosthetic Legs

How Reinforcement Learning Helps Amputee Athletes Find the Right Prosthesis

Simplified version of: Simulation of Adaptive Running with Flexible Sports Prosthesis using Reinforcement Learning of Hybrid-link System (arXiv:2604.08882, Jun 2026)

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This paper presents a simulation framework that combines reinforcement learning with biomechanical modeling to help amputee athletes find the optimal prosthetic leg stiffness. Instead of trial-and-error testing of different prostheses, the system simulates running with virtual prosthetic legs of varying stiffness and measures energy cost to find the sweet spot.

# Background: Sports Prosthetics

Running-specific prostheses have enabled amputee athletes to achieve remarkable performance in parasports. These carbon-fiber blade prostheses store and release elastic energy during each stride, acting like a spring. However, choosing the right prosthesis is difficult:

- There are many available prosthetic limbs with different material properties, geometric configurations, and mounting angles.
- The optimal prosthesis depends on the individual's body weight, running style, and residual limb characteristics.
- Currently, selection relies on trial-and-error, meaning athletes may not always use the most suitable prosthesis.

## Why Simulation Matters

Testing physical prostheses is expensive, time-consuming, and limited to what's commercially available. A simulation framework could:

- Test virtual prostheses with stiffness values that don't exist in commercial products
- Predict energy cost without requiring the athlete to physically run with each option
- Provide insights into how prosthetic properties interact with the athlete's biomechanics

But previous simulation approaches had a critical limitation: they modeled the prosthesis as rigid, ignoring its flexibility.

# The Solution: Flexible Prosthesis Modeling

The key innovation is modeling the prosthesis as a flexible structure using the Piece-wise Constant Strain (PCS) model, integrated with a rigid skeletal model through a hybrid-link system.

## The PCS Model

The prosthesis blade is divided into 6 segments. Each segment has a constant strain value (how much it bends). The total prosthesis has 18 degrees of freedom (DOFs) — 3 per segment × 6 segments. This captures the actual bending behavior of the carbon-fiber blade during running.

## The Hybrid-Link System

The complete model combines:

- Rigid skeletal system: 9 DOFs for hip, knee, and ankle joints on both legs
- Flexible prosthesis: 18 DOFs for the blade's deformation
- Base link: 6 DOFs for the pelvis position and orientation

Total: 33 DOFs. The model captures how the prosthesis bends during ground contact and how that bending interacts with the rest of the body's motion.

## Why Rigid Models Fail for Running

The paper demonstrates that rigid-body models cannot reproduce running motion accurately. During running (unlike walking), the prosthesis undergoes significant flexible deformation. A rigid model misses this deformation, leading to inaccurate force and motion predictions.

# Reinforcement Learning Framework

The system uses reinforcement learning (RL) to learn a control policy that reproduces the amputee's running motion. Here's how:

## State and Action

State: The agent observes the pelvis position, pelvis velocity, joint angles, and joint velocities. Notably, the prosthesis strain is NOT included in the state — this mirrors how humans don't consciously control prosthetic deformation.

Action: The agent outputs reference joint angles for PD control (a common robotics control method). The PD controller converts these to joint torques.

## Reward Function

The reward function encourages the agent to mimic the measured motion from a real amputee runner:

- Joint angle matching: How close are the simulated joints to the measured joints?
- Joint velocity matching: How close are the joint velocities?
- End-effector matching: How close are the hand and foot positions?
- Base link matching: How close is the pelvis position and velocity?

Each term uses a Gaussian reward function: closer match = higher reward.

## Two-Stage Training

To handle the computational expense of flexible deformation simulation:

- Stage 1 (Pre-training): Train the policy using a rigid-body prosthesis model. This is fast (82,000 episodes, ~33 hours).
- Stage 2 (Fine-tuning): Fine-tune the policy using the full hybrid-link system with flexible deformation. This is slower (88,000 episodes, ~102.5 hours) but starts from good initial parameters.

# Results: Simulated Running Motion

The trained policy successfully reproduced walking, running, and sprinting motions of a 15-year-old male transtibial amputee using a leaf-spring sports prosthesis (Ottobock Runner 1E91).

## Motion Accuracy

The simulation achieved:

- Joint trajectory RMSE: 9.2% (root mean square error relative to measured range)
- Ground reaction force RMSE: 10.9%
- Joint angle confidence intervals: 2.0 degrees average

The simulated prosthetic strain and ground reaction forces closely matched the measured data, even though strain was not explicitly included in the reward or state.

## Rigid vs. Flexible: Why It Matters

| Metric | Rigid Model | Flexible Model | Difference |
|---|---|---|---|
| Average propulsion force | 92.9 N | 187.5 N | 2x more |
| Contact time | 0.20 s | 0.26 s | 23% longer |
| Time to peak GRF | 0.065 s | 0.13 s | 2x longer |

The flexible model produces twice the propulsive force and longer ground contact time — effects that can only be captured by modeling prosthesis deformation.

# Effect of Prosthetic Stiffness

The key practical question: how does prosthesis stiffness affect running performance? The researchers simulated running under three stiffness conditions:

| Condition | Stiffness Change | Energy Cost (CoT) | Key Observation |
|---|---|---|---|
| Nominal | Standard (SPR-3) | 4.3 J/kg·m | Lowest energy cost |
| Compliant | -10% | Higher | More deformation, more energy |
| Stiff | +10% | Higher | More impact force, more energy |

Key Findings:

1. Moderate stiffness minimizes energy cost. The Nominal condition (4.3 J/kg·m) had the lowest metabolic cost of transport. Both more compliant and more stiff prostheses increased energy cost.
2. Compliant prostheses deform more. Under the Compliant condition, the prosthesis showed up to 32% greater strain than the Stiff condition. While more elastic energy is stored, the body must supply more energy to control and propel, increasing overall cost.
3. Stiff prostheses increase impact. Under the Stiff condition, the horizontal braking force at ground contact was 35% higher, requiring greater propulsive effort.

4. Energy cost matches real-world data. The simulated CoT values (4.3 J/kg·m) fall within the range reported in prior experimental studies of amputee runners.

# Robustness of the Trained Policy

A practical question: how wide a range of stiffness values can the trained policy handle without retraining?

The researchers varied stiffness from -40% to +50% of the nominal value and found:

- The policy works well within ±20% of nominal stiffness (corresponding to approximately ±20 kg body weight difference).
- Beyond ±20%, reward values and episode lengths gradually decrease.
- Since ±10% stiffness change corresponds to ±10 kg body weight in commercial prostheses, the policy can handle body weight variations of about ±20 kg without retraining.

## Practical Significance

This robustness means the simulation framework could be used to:

- Screen multiple prosthesis options without retraining for each one
- Predict performance changes when an athlete gains or loses weight
- Compare prostheses from different manufacturers under the same conditions

The framework handles stiffness variations that span approximately 2-3 commercial prosthesis categories.

# Limitations

Joint Torques, Not Muscles: The skeletal system uses joint torques for actuation rather than muscle-based actuation. The energy cost calculation doesn't account for negative work, co-contraction, or energy transfer by multi-articular muscles. This likely causes an overestimate of metabolic cost.

Single Subject: The imitation learning and evaluation are based on motion data from a single 15-year-old male amputee. The resulting simulations are limited to reproducing this individual's movement.

Simplified Skeletal Model: Only 9 DOFs (pitch-rotation joints) were used for the skeletal system. While this was sufficient for sagittal-plane running, 3D analysis would require more DOFs.

## Future Directions

The authors plan to:

- Investigate a wider range of prosthetic parameters: viscosity, geometry, mounting height, and alignment angle
- Extend to muscle-actuated models for more accurate energy cost estimation
- Include multiple subjects to improve generalizability
- Enable 3D analysis by adding more skeletal DOFs

# Conclusion

This paper presents a simulation framework that combines reinforcement learning with flexible prosthesis modeling to help amputee athletes optimize their prosthetic leg stiffness. The key findings:

- Flexible prosthesis modeling is essential for accurate running simulation — rigid models fail to capture the deformation effects that dominate running biomechanics.
- The trained policy achieves 9.2% RMSE for joint trajectories and 10.9% for ground reaction forces, matching real-world measurements.
- Moderate stiffness (matched to body weight) minimizes energy cost — both more compliant and more stiff prostheses increase metabolic cost.
- The policy is robust across ±20% stiffness variations, covering approximately ±20 kg body weight range.

This framework could eventually replace trial-and-error prosthesis selection with virtual testing, helping athletes find their optimal prosthesis faster and more systematically.