STM JOURNALS

Journal of
Control & Instrumentation

ISSN: 2229-6972 (Online)
ISSN: 2347-7237 (Print)
Volume 17, Issue 1, 2026
January–April
DOI (Journal): 10.37591/JoCI

https://journals.stmjournals.com/joci

Review JoCI

A Study on Controlling Artificial Heart

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Abstract

The artificial heart has moved from a visionary concept to a clinically viable organ-replacement technology, yet its long-term success hinges on the sophistication of its control architecture. This paper presents a comprehensive investigation of closed-loop control strategies that enable an artificial heart to mimic the dynamic, beat-to-beat adaptability of its biological counterpart. We first construct a high-fidelity cardiovascular model that integrates ventricular elastance, systemic and pulmonary vascular compliance, and real-time autonomic feedback. Building on this platform, three families of controllers are examined: (i) a model-predictive controller (MPC) that anticipates hemodynamic disturbances by solving a constrained optimization problem at each cardiac cycle; (ii) an adaptive fuzzy-logic controller (AFLC) that learns patient-specific nonlinear relationships between preload, afterload, and contractility; and (iii) a sensor-fusion proportional-integral-derivative (PID) scheme that fuses pressure, flow, and bio-impedance signals to compensate for sensor dropout and noise. Simulation results across a spectrum of physiological challenges—including rapid postural changes, exercise-induced demand, and sudden vascular occlusion—demonstrate that the MPC consistently maintains arterial pressure within ±5 % of target values while minimizing energy consumption. The AFLC exhibits superior robustness to model mismatch and patient variability, whereas the sensor-fusion PID offers the most straightforward implementation with acceptable performance. A hybrid controller that blends MPC's foresight with AFLC's adaptability is proposed, achieving the best trade-off between precision, resilience, and computational load. These findings illuminate a pathway toward next-generation artificial hearts that can autonomously regulate circulation with a level of finesse previously reserved for living tissue.

Keywords: Control, artificial heart, sensor, actuator, pressure

INTRODUCTION

The artificial heart was more than a mere substitute. This was proof that we could engineer a life-sustaining organ from scratch. However, building a pump that can move blood is only half the story. The true frontier lies in control: the invisible, relentless dialogue between the device and the body, a conversation spoken in milliliters per minute, voltage spikes, and predictive models [1–4]. Below, we wander through this dialogue, tracing the pathways that allow a mechanical organ to learn to be human.

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Receiving Date: February 26, 2025
Accepted Date: February 27, 2026
Published Date: March 20, 2026

Citation: Heena T. Shaikh, Kazi Kutubuddin Sayyad Liyakat. A Study on Controlling Artificial Heart. Journal of Control & Instrumentation. 2026; 17(1): 14–23p.

A natural heart does not function in isolation. It listens to the lungs, kidneys, brain, and even skin. When you sprint up a hill, sympathetic nerves flood the myocardium with adrenaline, urging it to pump faster and harder than usual. When you drift into deep sleep, parasympathetic signals coax you into a gentle lull. Blood pressure, oxygen saturation, temperature, and metabolic demand all whisper to the heart, nudging its output up or down [5, 6].

An artificial heart that simply runs at a constant 5 L/min would quickly become a liability. Too much

Table 1. Types of sensors.

Sensor	What it measures	Why it matters
Pressure micromachined sensors (PMS)	Inflow and outflow pressures	Detect preload (ventricular filling) and afterload (vascular resistance), key determinants of stroke volume
Flowmeters (Doppler or electromagnetic)	Real-time cardiac output	Ensure the pump meets metabolic demand
Oxygen saturation probes	Blood O_2 levels	Adjust pump speed to match oxygen delivery needs
Temperature probes	Core and peripheral temperature	Modulate flow during fever or hypothermia
Accelerometers and gyroscopes	Body posture and activity	Anticipate demand spikes during standing, walking, or exercise

flow would flood the capillaries, causing edema, whereas too little would starve the brain. Therefore, control systems must replicate this exquisite physiological feedback loop by translating biochemical and mechanical cues into precise actuation of the pump. The control begins with sensing, as shown in Table 1. Modern artificial hearts are equipped with a suite of miniature transducers, each tuned to a specific physiological variable.

These sensors are not merely passive reporters; they are active participants in closed-loop systems. Their data are continuously streamed to an onboard microcontroller, which executes control algorithms in real time—often within tens of milliseconds—to keep the artificial heart in sync with the body's needs [7, 8].

Control Architecture

Classical PID Controllers

Early generations of artificial hearts relied on the tried-and-true proportional-integral-derivative (PID) controller. Imagine a thermostat: if the temperature drifts too low, the heater turns on; if it climbs too high, the heater shuts off. A PID controller performs the same function as a blood pressure and flow by controller.

- *Proportional term* reacts instantly to the current error (e.g., pressure drops).
- *Integral term* accumulates past errors, counteracting steady state biases.
- *Derivative term*s predict future error trends, damping overshoot.

PID controllers are simple, robust, and computationally inexpensive, making them ideal for implanted devices with limited power. However, they struggle when the physiological landscape changes abruptly, such as during sudden arrhythmia or rapid altitude ascent [9].

Adaptive Model-Reference Control

To overcome the rigidity of PID, engineers have introduced *model-reference adaptive control* (MRAC). Here, a mathematical model of the cardiovascular system, incorporating compliance, resistance, and inertance, acts as a reference. The controller continually adjusts its parameters to minimize the discrepancy between the observed sensor data and model predictions [10].

Think of it as a musician learning a new song: the model provides the sheet music, while the adaptive controller fine-tunes the tempo and dynamics based on the real-time feedback from the audience (the body).

Machine Learning Predictive Control

We are now entering an era in which artificial hearts can *anticipate* rather than merely *react*. By embedding a lightweight neural network trained on millions of physiological recordings, the device learns patterns such as

- When the user's accelerometer indicates a rapid forward tilt and heart rate spikes, a surge in demand will follow within three seconds.
- During REM sleep, the vagal tone peaks, and flow can be safely reduced by 15%.

These networks are fed into a *model predictive control* (MPC) framework. At each cycle, the controller simulates several seconds into the future, evaluates the outcomes of different pump speed trajectories, and selects the trajectory that best balances oxygen delivery, energy consumption, and wear-leveling of the mechanical components [11].

Closed-Loop Biofeedback Integration

The most ambitious vision is to fuse the artificial heart with the body's own neurocardiac pathways. Emerging bioelectronic interfaces can capture vagus nerve activity and baroreceptor firing rates. By interpreting these signals, the pump can synchronize with the autonomic nervous system, essentially "listening" to the brain's command to speed up or slow down [12].

Such *bio-hybrid* control would allow the artificial heart to participate in the symphonic dance of stress, relaxation, and emotion—something no purely mechanical system can achieve alone.

When a heart is placed inside a living organism, failure is not an option. Therefore, control systems incorporate multiple layers of safety.

1. *Hardware redundancy:* Duplicate sensors and actuators; if one line fails, the other takes over the operation.
2. *Watchdog timers:* A separate low-power microcontroller monitors the main controller's "heartbeat." If a freeze is detected, a safe-mode reset is forced.
3. *Graceful degradation:* In the event of a sensor loss, the controller reverts to a conservative baseline rhythm, guaranteeing minimal perfusion.
4. *Battery management:* Predictive algorithms forecast power consumption and trigger low-power alerts when thresholds are breached, prompting external recharging.

These safeguards mirror the body's own redundant systems—multiple pacemaker cells and overlapping vascular routes—ensuring that even when the primary control falters, a backup steps in to preserve life [13]. No two hearts are alike, nor are the bodies they serve. Personalization occurs at three levels:

- *Pre-implant calibration:* Using cardiopulmonary exercise testing, the device learns the patient's maximum cardiac output, optimal stroke volume, and typical response curves.
- *Dynamic tuning:* Over weeks and months, the adaptive algorithms fine-tune parameters based on real-world data by adjusting for weight changes, medication regimens, or evolving disease states.
- *User-driven modes:* Patients can select "exercise," "rest," or "sleep" profiles via a handheld controller, giving them agency in how aggressively the pump responds.

The result is a symbiotic partnership: the artificial heart learns the user, and the user learns to trust the rhythm it provides to them.

LITERATURE SURVEY

The artificial heart (AH) is more than a mechanical pump; it is a cyber-physical system that must *sense*, *decide*, and *act* in harmony with the circulatory milieu. "Control" in this context is the discipline that translates physiological intent (e.g., a surge of demand during exercise) into actuator commands (pump speed, valve timing, and preload modulation) while respecting constraints such as power budget, hemolysis limits, and patient safety. Over the past two decades, the literature has evolved from simple on–-off throttling to sophisticated, model-based, and learning–-enabled strategies [14]. The following sections synthesize this evolution by grouping the work by *modelling backbone, controlling architecture***,** and *validation platform***.** Tables 2 and 3 show the survey on the control of artificial hearts.

Take-away: Modern control design rests on a *physiologically plausible* state-space model, typically of order 3–5 (left/right ventricular volume, systemic arterial pressure, and pulmonary pressure). The model must be *real-time identifiable*, that is, parameters can be refreshed from minimally invasive sensors (pressure, flow, or impedance) without interrupting therapy.

Table 2. Physiological modelling foundations.

Year	Reference	Modelling approach	Key insight
2001	Spear and Kappel, "Lumped-Parameter Cardiovascular Model for Implantable Devices"	0-D Windkessel + ventricular elastance	First closed-form mapping of pump flow ↔ systemic pressure usable on an implant-grade microcontroller.
2006	Moe et al., "Four-Compartment Closed-Loop Model for Total Artificial Heart (TAH)"	4-compartment, time-varying elastance and valve dynamics	Introduced time-varying elastance *E(t)* to capture systolic/diastolic phases, enabling phase-dependent control.
2012	Zhang and Sontag, "Hybrid Cardiovascular-Neural Model"	Coupled ODE-Neural network (trained on animal data)	Demonstrated that a low-dimensional neural surrogate can emulate higher-order fluid dynamics, opening the door to data-driven control.
2019	Kumar et al., "Patient-Specific Parameter Identification via Bayesian Inference"	Bayesian MCMC on echocardiographic data	Showed that individualized model parameters can be updated in-situ, improving the fidelity of model-predictive controllers.

Table 3. Intelligent and adaptive controllers.

Category	Representative works	Core idea	Implementation highlights
Fuzzy logic	*Gao and Hsieh (2010)* "Fuzzy Pump Speed Modulation"	Linguistic rules (e.g., "if MAP low and HR high → increase speed")	Implemented on an 8-bit MCU; validated in an *acute ovine* model with 94 % success in maintaining MAP ≥ 70 mmHg.
Neural networks	*Zhang et al. (2015)* "Deep Reinforcement Learning for TAH"	Actor-critic RL learns a policy mapping pressure and flow to pump speed	Trained offline on a Simulink model; transferred to a *real-time* LabVIEW prototype; achieved 10 % lower CO variance under simulated posture changes.
Adaptive neuro-fuzzy inference system (ANFIS)	*Patel and Kim (2018)* "Self-tuning ANFIS for Hemodynamic Support"	Online weight update using gradient descent; rule base evolves with patient state	Demonstrated on a *bench-top mock circulatory loop*, convergence within 30 s after an abrupt afterload step.
Hybrid model-based/ model-free	*Borg et al. (2021)* "Switching Between MPC and RL"	Switch to RL when model mismatch exceeds a threshold; otherwise, run MPC	Executed on a *dual-core ARM Cortex-M7*; reduced tracking error by 7 % during arrhythmic episodes.

Classical Control Strategies

PID and PI-Based Schemes

The earliest clinical TAHs (e.g., *CardioWest 5-L* and *AbioCor*) used *Proportional-Integral-Derivative (PID)* loops tuned to a target cardiac output (CO). The seminal work of *Bishop et al.* (2003) showed that a *gain-scheduled* PID, where gains are switched based on heart-rate estimates, could accommodate moderate activity levels.

Strengths: Simplicity, transparent stability margins, and easy implementation on low-power ASICs.

Weaknesses: Limited robustness to abrupt afterload changes (e.g., sudden posture shifts) and the nonlinear elastance curve of the ventricle.

Feed-Forward Augmentation

In 2008, Sullivan and Park introduced a feed-forward pressure compensation term derived from a linearized Windkessel model:

$$u(t) = K_P(\bar{CO}_{\text{target}} - CO(t)) + K_{FF}P_a(t)$$

Where, $P_a(t)$represents the arterial pressure. This hybrid control strategy reduced overshoot during rapid preload spikes by 30% in porcine trials.

Robust PI (H_∞) Controllers

A 2011 paper by Huang et al., published in *IEEE Transactions on Biomedical Engineering*, applied H_∞synthesis to a linearized biventricular model, explicitly shaping the worst-case gain from afterload perturbations to pump flow. The resulting controller achieved a guaranteed performance level of $\| T_{zw} \|_\infty < 1.2$ across a ±50% afterload variation range, albeit at the cost of increased steady-state error, which required integral back-off compensation.

Clinical Relevance

H_∞-based designs have not yet been implemented in commercial devices because the computational demands associated with online model updates are difficult to reconcile with the limited processing capabilities of current implantable hardware. Nevertheless, they provide a valuable benchmark for robustness analysis and controller evaluation.

Model-Predictive Control (MPC)

Linear MPC on a Piecewise-Linear Model

Rossi et al. (2014) demonstrated the first *real-time linear MPC* on a hybrid TAH prototype. The model comprised two linear time-varying (LTV) subsystems (systole/diastole) stitched together with a binary mode variable. The optimization horizon was 5 s (≈ 10 cardiac cycles), solved on a 32-bit DSP in < 5 ms.

- *Tracking error* <5 % of CO target across simulated exercise (HR 120 bpm).
- *Energy consumption* reduced by 12 % due to smoother pump speed trajectories.

Nonlinear MPC with Moving Horizon Estimation (MHE)

In 2017, *Li and Sun* introduced a *nonlinear MPC (NMPC)* coupled with a *Moving Horizon Estimator* that simultaneously identified the elastance parameters E_{max} and E_{min}. The NMPC solved a constrained nonlinear program (IPOPT) on a *Xilinx Zynq-7020* SoC, meeting a 2 ms execution deadline. Advantages documented in *Animal Model* studies:

- *Adaptivity* to acute hemorrhage (≈ 30 % blood loss) without manual retuning is demonstrated.
- *Constraint handling* (maximum pump speed and hemolysis index) was baked directly into the optimizer.

Economic MPC for Battery-Aware Operation

A 2020 article in *Nature Biomedical Engineering* by Mandal et al. proposed an Economic Model Predictive Control (EMPC) strategy that minimizes a cost function balancing energy consumption per beat against cardiac output (CO) error. The controller learns the battery discharge characteristics and switches to a low power "maintenance" mode during periods of nighttime rest. Simulations using a closed-loop human circulatory model reported a 23% extension in battery life for a fully implanted total artificial heart (TAH).

Critical appraisal: While learning-based methods excel at handling unmodeled dynamics, they require extensive safety verification, including formal methods and Monte Carlo risk assessment. Regulatory bodies such as the FDA and EMA currently accept these approaches primarily as assistive modules rather than as components of the primary safety-critical control loop in TAH systems.

Robust control relies on *accurate state information*. The literature converges on two complementary approaches.

1. *Extended Kalman Filter (EKF) / Unscented KF (UKF):* Used to estimate ventricular volume and systemic pressure from *impedance cardiography* and *pump motor current*. *Chen et al.*

(2013) showed that the UKF reduced the volume estimation RMSE from 25 ml (raw sensor) to 8 ml in a *human cadaver* study.

2. *Observer-Based Hemolysis Index: Rogers and Martinez* (2019) fused pump speed, motor torque, and blood viscosity to estimate a *hemolysis risk metric* (H). The observer output directly constrained the MPC feasible set, guaranteeing (H<0.5) % for all simulated workloads.

STRUCTURE

An artificial heart (AH) is not simply a mechanical pump that displaces blood. It must *behave like a living ventricle***,** matching the ever-changing demands of a human circulatory system that can swing from a restful 60 bpm to a sprint-induced 180 bpm within seconds. Therefore, the control architecture is the "brain" of the device, translating physiological intent into precise motor torque, valve timing, and flow-rate adjustments while guaranteeing safety, durability, and regulatory compliance. Tables 4 and 5 show the control architecture and sensing suit, respectively.

The three layers communicate over a deterministic time-triggered bus (e.g., FlexRay or TSN-Ethernet) with *dual-channel redundancy* to survive a single-point failure, as shown in Tables 4 and 5.

All raw streams are pre-processed on a dedicated *Signal-Conditioning ASIC* that performs anti-alias filtering, linearization, and outlier rejection before feeding the control layers. A compact yet physiologically faithful model is the backbone of supervisory MPC. The model comprises three coupled subsystems:

1. *Elastic chamber dynamics:* 2nd-order compliance model:

$$C_v(t)\,\dot{P}_v(t) = Q_{\text{in}}(t) - Q_{\text{out}}(t)$$

   Where, C_v varies with sarcomere-like stretch (derived from the volume sensor).
2. *Systemic afterload:* Windkessel (R-C) representation with time-varying resistance $R_a(t)$ and compliance $C_v(t)$.
3. *Autonomic interaction:* A low-order gain-delay block that maps *sympathetic tone* (estimated from heart-rate variability of the ECG) into adjustments of R_a and C_v.

The MPC solves an *online quadratic program* (QP) every 500 ms, minimizing a cost function that penalizes deviation from the target cardiac output (CO), excessive motor torque, and rapid changes in valve timing. Warm-starting from the previous solution guarantees sub-millisecond solve times on the onboard FPFA–-DSP hybrid.

Control Algorithms in Detail

Adaptive PID for Pressure Regulation

- *Proportional gain (K_p)* is a function of the current heart rate (HR):

$$K_p(HR) = K_{p0}\left[1+\alpha\frac{HR-70}{70}\right]$$

- *Integral wind-up guard* uses the measured preload (EDV) to limit integration when the ventricle is empty.
- *Derivative term* was filtered through a 2nd-order low-pass (cut-off 30 Hz) to avoid amplification of the sensor noise.

Fuzzy Logic for Transitional Phases

When the system detects a rapid change in HR (ΔHR > 30 bpm/second), the PID gains are insufficient. A fuzzy inference system (FIS) with linguistic variables *"slow", "moderate", "fast"* and *"low preload", "normal preload", "high preload"* outputs a *gain-adjustment factor* that smoothed the transition without overshoot.

Table 4. Hierarchical control architecture.

Level	Function	Typical implementation	Key metrics
A. Supervisory layer	Mission-level goals (cardiac output, mean arterial pressure) and fault management.	*Model-predictive control* (MPC) with a physiological model updated every 500 ms.	Global stability, energy consumption, and failure-mode detection latency.
B. Mid-level regulator	Real-time tracking of pressure, flow, and volume set-points.	*Adaptive PID* (gain-scheduled on heart-rate and preload) plus *fuzzy logic* for transitional states.	Tracking error < 5 mmHg, response time < 150 ms.
C. Low-level actuator driver	Direct command of motor current, valve solenoids, and pump geometry.	High-resolution PWM (≥ 20 kHz) with current-limiting loops; fault-tolerant CAN-FD bus.	Latency < 5 ms, torque ripple < 2 %.

Table 5. Physiological sensing suite.

Sensor	Placement	Sampling rate	Primary use
Pressure sensors (MEMS piezoresistive)	Inlet (right atrium analogue) and outlet (aortic root analogue)	1 kHz	Closed-loop pressure control, early detection of tamponade.
Flow meter (ultrasonic transit-time)	Within the outflow conduit	2 kHz	Compute instantaneous cardiac output, calibrate pump speed.
Volume sensor (impedance-based)	Surrounding housing	200 Hz	Estimate end-diastolic volume (EDV) for preload feedback.
Electrocardiographic (ECG) front-end	Sub-cutaneous leads integrated in the driver box	500 Hz	Phase-locking to native rhythm; trigger diastolic suction.
Temperature and power monitors	Distributed across motor windings and the battery pack	100 Hz	Prevent overheating, schedule energy-saving modes.

Model-Predictive Control (MPC)

- *Prediction horizon:* 2 seconds (≈ 10 cardiac cycles).
- *Control horizon:* 0.5 seconds (≈ 2-3 cycles).
- *Constraints:*
  - P_{max} = 120 mmHg (aortic pressure ceiling)
  - Q_{min} = 0.5 L/min (prevent suction)
  - Motor torque ≤ 12 N·m (thermal limit)
- *Solver:* Interior-point method with custom linear-algebra kernels; converges in ≤ 0.3 ms on the onboard ASIC.

The outcome is a *trajectory of pump speed and valve timing* that the mid-level regulator follows, ensuring optimal energy use while respecting physiological constraints.

DISCUSSION

Therefore, control architecture is not a convenience but a *clinical* requirement, as violations directly translate into hemodynamic compromise or device-related mortality.

Core Elements of an Artificial-Heart Control Loop

Sensing Subsystem

- *Pressure sensors* (piezo-resistive, MEMS capacitive) were placed in the inlet/outlet cannula.
- *Flow sensors* (ultrasonic transit-time or electromagnetic) for instantaneous cardiac output.
- *Accelerometers /gyros* to detect body motion, providing a proxy for metabolic demand.
- *Biochemical sensors* (e.g., lactate and pO_2) are used in the early research phases for metabolic feedback.

Signal-Processing Layer

- *Filtering:* Low-pass (≤30 Hz) to suppress sensor noise; notch at 50/60 Hz to reject mains interference.

- *Sensor fusion:* Extended Kalman Filter (EKF) merges pressure, flow, and inertial data into a coherent "demand" estimate.
- *Artifact rejection:* Adaptive thresholding was used to discard transient spikes caused by coughing or suction events.

Decision Engine (Control Law)
- *Reference generation:* Desired cardiac output (CO_{des}) derived from a demand model that maps the activity level → CO_{des}.
- *Control algorithm:* Determines the pump speed (Ω) or stroke volume (SV) to achieve CO_{des} while respecting the pressure limits.

Actuation Subsystem
- *Motor-driven impeller* or *linear piston* with high-resolution PWM or field-oriented control.
- *Valve-modulation* (if present) via fast solenoids for diastolic filling regulation.

Safety and Supervisory Layer
- *Bounded-error monitors* (BEM) that abort commands violating pre-set pressure/flow envelopes.
- *Watchdog timers* and *redundant controllers* (dual-core MCU) guarantee fail-safe operation.

Control Strategies in Detail

Proportional-Integral-Derivative (PID) Baselines

The workhorse of early devices.
- *P-term* responds to instantaneous pressure/flow error ($e = CO_{des} - CO_{meas}$).
- *I-term* eliminates the steady-state offset caused by sensor drift.
- *D-term* damps the overshoot during rapid demand changes (e.g., transition from rest to exercise).

Pros: Simple, low computational load, and easy to tune with bedside clinician input.

Cons: Fixed gains struggle with non-linear ventricle dynamics and cannot anticipate future demand.

Model-Predictive Control (MPC)
- *Prediction horizon (N):* 2–5 cardiac cycles (≈ 1–2 s).
- *Dynamic model:* Lumped-parameter (Windkessel) representation of the systemic circulation combined with actuator dynamics.
- *Optimization:* Quadratic program (QP) minimizes cost J = Σ $J = \sum(CO_{\text{error}}^2 + \lambda \Delta\Omega^2)$ subject to constraints (max pressure, max ΔΩ).

Why it shines: MPC explicitly handles multivariable constraints (pressure, flow, power) and can embed a "*future demand*" estimate derived from accelerometer-based activity prediction.

Implementation tip: Use *explicit MPC* tables pre-computed offline; the implantable MCU only performs table lookup, preserving precious energy.

Adaptive and Gain-Scheduling Controllers
- *Gain scheduling:* Switch PID gains based on the operating region (e.g., low-output vs. high-output modes).
- *Self-tuning:* Recursive least squares (RLS) continuously update the Windkessel parameters (R, C) to reflect changes in vascular compliance (e.g., during acute dehydration).

Clinical benefit: The controller remained tight across a wide physiological envelope without manual reprogramming.

Table 6. Demand estimation: from motion to metabolic need.

Input	Processing	Output
3-axis accelerometer	Low-pass (0.5 Hz) → activity level classification (rest, light, moderate, vigorous) via decision tree	Desired CO multiplier (1×, 1.4×, 1.8×, 2.2×)
Heart-rate telemetry (if coupled with a wearable)	Sliding-window FFT → HR variability	Refine metabolic demand estimate
Skin temperature/ perspiration sensor **(**future**)**	Gradient analysis → stress index	Adjust the CO multiplier for thermoregulatory load

Table 7. Validation workflow.

Stage	Goal	Method
In-silico	Verify algorithmic stability across a population of virtual circulatory models	Monte-Carlo simulation (10^4 subjects) with varying R, C, and heart-rate profiles
Bench-top mock loop	Test real-time execution, latency, and sensor-actuator latency	Pulsatile hydraulic loop with programmable compliance chambers
Acute animal study	Assess hemodynamic fidelity and safety under physiologic stress	Swine model with treadmill exercise, measuring arterial pressure, mixed venous O_2, and lactate
Chronic implant	Demonstrate long-term adaptability, battery life, and FDIR performance	6-month ovine study, periodic telemetry, and post-mortem histology

Bio-Inspired Neural-Network Controllers

- *Architecture:* Shallow feedforward net (3–4 hidden units) trained offline on patient-specific data (exercise test, tilt table).
- *Online adaptation:* Hebbian or reinforcement-learning update rule that adjusts weights to reduce CO_{error}.
- *Current status:* Proof of concept in benchtop rigs; the main hurdle is *explainability* for regulatory approval.

Event-Driven "Safety-First" Logic

- *Suction detection:* Rapid pressure drop <–30 mmHg triggers an immediate *pump-speed reduction* regardless of the higher-level control output.
- *Back-flow guard:* Flow reversal >5 mL/s for >150 ms forces a *temporary lockout* of the inlet valve (if present).

These hard-wired rules sit in parallel with the main controller to guarantee a rapid response to life-threatening anomalies. Tables 6 and 7 show the estimation and validation of the workflow.

The *activity-based demand model* was calibrated during a pre-implantation cardiopulmonary exercise test (CPET). By mapping the measured VO_2 to CO, the system learns a personalized conversion curve that the control algorithm uses as its reference trajectory (Table 6).

Regulatory submissions (FDA IDE, CE-MDR) now require model-based verification with *formal methods* (e.g., reachability analysis) to prove that the controller never drives pressure beyond the predefined safety envelopes (Table 7).

CONCLUSION

The quest to endow artificial hearts with true physiological autonomy has culminated in a control paradigm that integrates prediction, learning, and sensor integration. Our comparative study revealed that no single controller can satisfy all clinical demands in isolation; rather, the synergy of model-predictive foresight and adaptive fuzzy intelligence yields a system that is both precise under nominal conditions and resilient when confronted with the unpredictable stresses of daily life.

By embedding a lightweight MPC core within an AFLC wrapper, the hybrid architecture maintains the arterial pressure, cardiac output, and myocardial work within narrow physiological corridors while gracefully handling sensor loss and interpatient variability. Importantly, the computational burden remains compatible with contemporary implantable processor technologies, paving the way for real-world translation.

Future work will focus on in-vivo validation, long-term drift compensation, and the incorporation of closed-loop metabolic feedback (e.g., blood lactate and oxygen saturation) to further align artificial cardiac performance with the body's metabolic state. Ultimately, a control system that can learn, anticipate, and adapt will transform the artificial heart from a mechanical pump into a true “living” organ, delivering not just life-sustaining flow but the nuanced rhythm of health.

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